A26 A11L.UAV.74 Establish Pilot Proficiency Requirements: Multi-UAV Components
Final Report

November 11, 2022

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16. Abstract

The A26 project focused on understanding the human performance proficiencies necessary for a single human to supervise a system of multiple unmanned aerial vehicles in the national airspace. An extensive literature review identified major gaps that informed the development of domain relevant use cases for both Loosely and Tightly Coupled tasks, the analysis of hazards that impact human performance, an analysis of critical aptitude measurements, and the development of representative computational models. Extensive experiments were conducted for the Loosely Coupled task models and the Tightly Coupled task models to identify factors that impact the human's performance and inform which factors are critical for future human-in-the-hardware loop evaluations. Overall, the project resulted in a very large number of key findings and research gaps.

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TABLE OF ACRONYMS

AGL	Above Ground Level
ASSURE	Alliance for System Safety of UAV through Research Excellence
ATC	Air Traffic Control
C^2	Command and Control
CFR	Code of Federal Regulations
FAA	Federal Aviation Administration
IMPRINT	Improved Performance Research Integration Tool
NAS	National Air Space
SAFTE	Sleep, Activity, Fatigue, and Task Effectiveness
UAV	Unmanned Aerial Vehicle
UE	Unexpected Event

EXECUTIVE SUMMARY

Commercial and public safety Unmanned Aircraft Vehicles (UAVs) are currently limited by the Title 14 Code of Federal Regulations (CFR) §107.35 prohibition on operating multiple aircraft by one person. The public as well as UAV commercial operations in applications such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, wildland fire response, and infrastructure inspections, will benefit from modification to this prohibition. The Federal Aviation Administration (FAA) Center for Excellence for Unmanned Aircraft Systems Research, Alliance for System Safety of UAV through Research Excellence (ASSURE) study that this model development and analysis supports will help to inform FAA regulations and industry standards addressing single pilot and multi-UAV operations.

The A26 project focused on understanding the human performance requirements for single human multiple UAV systems in the national airspace. The project was designed to identify human factors limitations associated with one human to multiple UAV domains, relevant use cases, and open research questions. The project's three tasks each provided key findings and gaps.

The systematic literature review (Task 1) provided a broad, but deep understanding of the existing research into single human multiple UAV systems. The literature review incorporated approximately 100 manuscripts. Previous works mostly focused on human-in-the-loop studies, with an emphasis on human factors limitations for operating and monitoring multiple UAVs conducting surveillance, reconnaissance, target detection/classification, and/or search missions.

Task 2 focused on assessing the human factors limitations when monitoring multiple UAVs by first developing representative use cases with an associated task analysis. The Loosely Coupled use case involves a single human supervising up to 100 homogenous autonomous UAVs conducting independent tasks (e.g., drone package delivery) in a climate-controlled workspace. The Tightly Coupled task focused on smaller teams of heterogenous autonomous UAVs (up to 11) conducting a ridgeline aerial ignition task in difficult environmental and terrain conditions. The task analyses informed the identification of potential hazards with respect to human performance limitations, resulting in nine hazard mitigation classes that the FAA can enact. A review of existing measurements highlighted critical aptitudes, such as workload, situation awareness, and attention, but it is unclear which aptitudes play a critical role, singly and/or in combination.

The computational modeling efforts (Task 3) developed Loosely and Tightly Coupled task models provided results that demonstrate a human Supervisor's ability and limitations to safely monitor multiple UAVs in the national airspace. Importantly, the model results inform the types of human-in-the-loop evaluations that are needed to investigate 1:N UAV systems.

Key findings and knowledge gaps related to human performance when a single human Supervises multiple UAVs were identified across each task. As well, expectations about UAV capabilities necessary for such systems were identified. The A26 results generated additional questions to be resolved before the FAA is able to institute substantial regulations and guidelines for 1:N UAV systems. However, the project's results provide the ASSURE researchers and the FAA sponsors clearer understanding of what further insight is necessary to safely permit multiple UAVs to operate in the nation's airspace.

1. INTRODUCTION & BACKGROUND

Several organizations have identified human factors issues unique to UAV, including the US Air Force Accident Investigation Board, the National Transportation Safety Board, the US Department of Transportation, National Aeronautics and Space Administration, Radio Technical Commission for Aeronautics Special Committee (SC)-228, the National Academies of the Sciences, Engineering, and Medicine, and others. The A26 project addressed gaps in knowledge that are currently a barrier to the safe, efficient, and timely integration of systems composed of multiple UAVs into the National Air Space (NAS), namely the operation of multiple aircraft by one person.

The research was intended to answer the following research questions:

1. What are the human factors limitations for a single crew member/supervisor when operating and monitoring multiple Unmanned Aerial Vehicles (UAVs)?
2. What are relevant NAS integration use cases?
3. What are the open research questions to be addressed in order to adequately inform regulations, standards, and guidance for integration of multiple UAV systems into the NAS?

The previously conducted ASSURE projects utilized the following operating limitations, which were also applied to this research:

a. Day, visual meteorological conditions operations only, with potential for night visual meteorological condition operations enabled by new standards and rules.
b. UAV operations will be conducted from the surface to 500' Above Ground Level (AGL), with additional evaluation of the potential for operations up to 1,200'AGL.
c. UAV operations will be conducted over other than densely populated areas, unless all UAV comply with potential criteria or standard that demonstrates safe flights over populated areas.
d. UAV will not be operated close to airports or heliports. 'Close' is initially defined as less than 3 miles from an airport unless permission is granted from Air Traffic Control (ATC) or airport authority. A distance of greater than 5 miles will be examined if needed to support an appropriate level of safety.
e. Small UAV are potentially designed to an Industry Consensus Standard and issued an FAA Airworthiness Certificate or other FAA approval.
f. The multiple UAVs may be operating in scenarios that include *n* UAV that have *n* unique paths distributed over an area of operation.

The research project incorporated three primary tasks:

- Task 1: Literature review.
- Task 3: Assess the human factors limitations when monitoring multiple UAVs.
- Task 4: Assess the required aptitude and human factors differences for a crew member controlling multiple UAVs.

2. TASK 1: LITERATURE REVIEW

Commercial and public safety UAVs are currently limited by the Title 14 CFR §107.35, which prohibits operating multiple aircraft by one person; however, operational concepts are being developed that support M:N operations, where M represents one or more humans who have responsibility for two or more (N) aircraft. A modification to Title 14 CFR §107.35 will benefit the public as well as UAV commercial operations in applications, such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections. The full literature review is provided as Supplementary Document 1.

Multiple UAV systems require potentially multiple human roles, where the autonomous and semi-autonomous UAVs' primary flight phases are supervised by the humans. The autonomy embedded within the control station and the UAVs supports the human Supervisor(s). As a supervisor supported by autonomy, a person can define the mission goal, specify constraints and parameters that impact meeting the mission objectives, plan the mission, monitor the (semi-)autonomous system and the mission environment, detect degraded performance and failures, as well as make necessary adjustments. The A26 project uses the term *Supervisor* to differentiate this supervisory role, rather than the term pilot or crew. The literature review began with approximately 200 papers that were vetted down to approximately 100 papers for inclusion in the review. This review was designed to (1) inform ASSURE researchers and FAA sponsors on findings from published studies, and (2) identify research gaps that are outside the scope of the A26 project, but need further investigation in order to safely integrate multiple UAV operations into the NAS.

The literature review addressed a set of characteristics to inform FAA regulations and industry standards addressing a single person or multiple people and multiple UAV operations. The literature review report identified the methodological approaches employed in the studies to help to identify the fidelity of the published work. The majority were human-in-the-loop studies and there were no field studies with vehicles flown in missions similar to what is envisioned for actual operations.

The literature review also focused on the types of evaluation measures used in the studies, including characterizing them as objective or subjective and whether they can be used to measure aviation safety, as well as human's capability, efficiency, and productivity. While many of the reviewed evaluations addressed objective measures related to accuracy, very few addressed safety measures, such as UAV to UAV damage and UAV to hazard damage, UAV loss, and airspace related violations. Some studies considered objective workload measures (e.g., neurophysiological, physiological, and behavioral sensors). However, the predominate measures in the reviewed studies were subjective performance and usability measures, where the most frequent cited measures assess perceived workload as measured via NASA-TLX, different types of trust in automation, and different situation awareness measures. While subjective measurement of relevant human factors issues can provide useful insight into general task perceptions, the over-reliance on subjective assessments of human factors poses a pressing challenge to effective evaluation of humans' needs in M:N UAV systems.

The literature review also addressed the human specific characteristics that can help to define requirements for training and certification, as well as a specific focus on training interventions for M:N UAV systems. Generally, the multiple UAV human-in-the-loop study participants did not have Title 14 CFR §107.73 certifications, nor any traditional piloting or other related aviation experience. Additionally, a few studies specifically collected measures related to visual skills, spatial ability, working memory, attentional control, stress, or other factors that can impact performance when supervising multiple UAVs.

Characterizing the generalizability of the published works, the review addressed the system and aircraft characteristics with respect to architecture and small UAV heterogeneity. Most of the reviewed human-in-the-loop studies relied on simulations that did not model realistic aircraft control and dynamics, nor did they include algorithms and displays validated in field studies. The N component of M:N can range from two to many; thus, the reviewed literature also addressed aircraft group characteristics. The simulated vehicle types in the reviewed human-in-the-loop studies included a single UAV, homogeneous groups of UAVs, unmanned ground vehicle systems, computer software agents, simulated spaceships, as well as heterogeneous groups composed of three different vehicle types (e.g., one study used a UAV, unmanned ground vehicle, and manned ground vehicle, while another incorporated a humanoid robot, UAV, and an unmanned ground vehicle). The group sizes span from two to twenty vehicles. Some of the studies did not address the unmanned systems control, but rather focused on the video feeds.

As M:N UAV systems may employ high levels of autonomy on the aircraft as well as within the control station, the review also focused on autonomy and human-autonomy teaming, and the control station characteristics. While there is a significant body of research addressing different autonomous functions, associated level of autonomy, and human-autonomy related measures, there are currently fewer manuscripts that specifically address human roles, including supervisory control, in M:N systems. Many of the human-in-the-loop studies focused on the use of different forms and mixes of information analysis, decision alternative generation, decision selection, and decision execution autonomy integrated into the control station to support the human Supervisor's tasks. A finding was that there has been less emphasis on the aircraft's required autonomy and the associated information requirements, with the exception of detect and avoid operations.

Due to the different types of M:N UAV scenarios or domains, the review also addressed missions and associated task characteristics that can inform research related procedures and scenario definition. No validated task taxonomy for M:N UAV systems exists and there are no common operational procedures for the related scenarios. Common M:N UAV system mission scenarios included surveillance, reconnaissance, target detection/classification, and search. There was limited focus of the types of tasks that may be important in M:N UAV system supervision, such as eximulti-tasking and task sequencing.

The literature review provided an insightful examination of the results of past research and identified large gaps in understanding. These gaps must be addressed before the FAA will be able to lift the restrictions laid out in Title 14 CFR §107.35 and develop regulations and guidelines regarding M:N UAV systems operations. Based on these findings, the ASSURE team began to fill those gaps through modeling and case study validation. Within the review of previous work, the team found that most research was conducted around human-in-the-loop and the human factor limitations for operating and monitoring multiple UAVs. These predominately simulation-based evaluations used some objective performance measurements (e.g., target detection rates and response times), and relied heavily on subjective measurements (e.g., perceived workload, trust in automation, and situational awareness).

3. TASK 2 OTHER POTENTAIL MULTI-UAS RESEARCH AREAS

Task 2 focused on the peer scope review and developing an FAA approved research technical plan. The peer scope review was conducted in May 2021. The research technical plan was approved in November 2020. The research technical plan was revised in September 2021 to expand Task 4 and remove Task 5.

4. TASK 3 ASSESS THE HUMAN FACTORS LIMITATIONS WHEN MONITORING MULTIPLE UAVS

Task 3 focused on the human factors limitations to supervising multiple UAVs, to include the identification of potential hazards, mitigations, and controls for the mitigations. The identification of potential hazards, mitigations, and mitigation controls leveraged the literature review results and incorporated three subtasks. Subtask 3-1 focused on developing potential operational scenarios (use cases) that were validated by subject matter experts. Subtask 3-2 addressed the associated human factors limitations to monitoring multiple UAVs and associated potential hazards, mitigations, and controls. Finally, Subtask 3-3 reviewed existing aptitude measurements. The full Task 3 final report is provided as Supplementary Document 2.

4.1. Subtask 3-1 Operational Use Cases and Task Analysis

Two use cases were developed, a Loosely Coupled task and a Tightly Coupled task. A Loosely Coupled task exists when all UAVs in the system have independent goals that can be achieved without coordinating with other UAVs in the system. A Tightly Coupled task requires UAVs in the system to coordinate, to some level, to achieve the common mission goal, as well as their individual UAVs' goals. Ultimately, the decision to include both the delivery and disaster response domains facilitated insights about these two different ends of the problem spectrum.

The Loosely Coupled scenario focuses on delivery drones and originated from interests expressed by the FAA. The use case was developed based on publicly available information and interviews with industrial subject matter experts. Utilization of UAVs in a delivery setting assumes the following: 1) UAVs will operate in populated areas in which the environment does not change frequently, 2) the weather is predictable, and 3) communication with other parties is reliable. The enroute flight phase for delivery drones was considered the primary scope for the task analysis based on FAA input. However, the other flight phases are discussed in the nominal use case for completeness. An example nominal use case, thirty-eight unexpected event use cases and ten example distraction use cases were developed.

The FAA expressed a preference for the Tightly Coupled task to focus on disaster response. After consulting with various subject matter experts, the team focused on the ridgeline aerial ignition scenario. The use of UAVs in this scenario assumes UAV operations occur in sparsely populated areas with minimal to no communication and potentially unpredictable weather. The Tightly Coupled scenario requires more coordination and supervisory attention than the Loosely Coupled task. The Tightly Coupled task requires more autonomous cooperation between UAVs than is necessary to complete Loosely Coupled tasks. The example Tightly Coupled nominal use case was detailed and high-level descriptions of seven example distraction use cases are provided. The sixteen high-level Unexpected Event (UE) use case descriptions include a subset of the Loosely Coupled task's UEs (e.g., Command and Control Station Link Loss), and UEs that are unique to the domain (e.g., Ignition within the sphere dropped on the UAV).

Based on the Loosely and Tightly Coupled use cases, this subtask also conducted a task analysis. A Supervisor Task Taxonomy was generated based on the task analyses, one for each of the Loosely and Tightly Coupled tasks.

4.2. Subtask 3-2: Identify Potential Hazards, Mitigations and Controls

This task focused on identifying the human factors limitations when monitoring multiple UAVs, including the potential hazards, mitigations, and mitigation controls. This analysis was conducted for each task type (i.e., Loosely and Tightly Coupled) independently.

The Supervisor's actions, or tasks, were decomposed and classified. Each of the Supervisor's tasks within the Loosely Coupled scenario were decomposed into up to four cognitive sub-tasks: information acquisition, assessment, decision, and execution. These sub-tasks reflect the fundamental perception, interpretation, judgment, and action stages of any activity. The taxonomy was expanded when considering the Tightly Coupled scenario to include four possible Supervisor task categories: communication (sender), communication (receiver), discrete control, and monitoring/situation assessment. The Supervisor's communicating as the sender task category was decomposed into three sub-tasks: generate, transcribe, and transmit. As well, the Tightly Coupled scenario's Supervisor's communicating as the receiver task category was decomposed into three sub-tasks: perception, encoding, and interpretation. The Supervisor's discrete control tasks category was decomposed into four cognitive sub-tasks: information acquisition, assessment, decision, and execution. Finally, the monitoring and situation assessment Supervisor task category was decomposed into three cognitive sub-tasks: information acquisition, assessment, and decision.

Identifying hazards required determining the ways in which cognitive sub-tasks may succeed or fail. Successful outcomes indicate nominal performance and are not hazardous. Failed outcomes indicate an error occurred, causing a potential hazard to the mission. Errors may also occur between Supervisor tasks. Therefore, a taxonomy of procedural-level errors applicable to all Supervisor tasks was incorporated. The procedural errors describe process errors between tasks or within tasks (i.e., between sub-tasks) through skips, repeats, omissions, and intrusions; which may be combined to describe sequential errors, such as performing a procedure's steps out of a prescribed order.

The team defined all failed outcomes and procedural errors as hazards. A taxonomy based on the Human Factors Analysis and Classification System was used to categorize the hazards. The classes of outcomes that each cognitive sub-task may yield were enumerated for each Supervisor task based on a taxonomy of *commission* and *omission*. Commission refers to an outcome caused by the Supervisor's action, and omission refers to an outcome caused by the Supervisor's inaction. There is no wrong way to perform the simplest sub-tasks; therefore, the Supervisor's action (commission) or inaction (omission) directly determines whether the sub-task succeeds or fails. More complex sub-tasks may succeed and/or fail due to both commission and omission.

A series of mappings were conducted in order to determine which mitigations may reduce the hazards' risks. The team generated exemplars, or excerpts, for each mapping from the cause category definitions, which was done to facilitate review. The hazards were first mapped to their possible causes, followed by categorizing the causes to reduce the mapping space dimensionality. Next, the cause categories were mapped to mitigations. Finally, the mapping chains were traced and aggregated in order to reveal each hazards' possible mitigations. A specific design implementation is not assumed by the A26 team; thus, the team identified *mitigation classes* (i.e., categories of controls and mitigations) that may be employed to reduce the likelihood or severity of a hazard. There are nine hazard mitigation classes that the FAA can enact: workspace design, control station design, display design, procedure design, training, UAV autonomy, decision support, organizational support, and personnel selection.

The hazard-cause-mitigation mappings were traced in order to determine which mitigations are associated with which hazards. The results suggested that all nine mitigation strategies may be useful for controlling each of the six hazard classes. Although no particular mitigation strategy for a class of hazards based on this aggregate-level analysis can be recommended, the approach can be used to inform a more specific analysis of individual hazard instances. Take for example the case of an autonomy-related decision error. Seventy-eight possible causes of decision errors were identified, which may be mitigated by a wide variety of interventions; however, only eighteen causes relate to interactions with automation specifically. Four of these eighteen causes relate to hardware or software failures, while the remainder relate to human biases regarding automation, specifically trust or understanding of the automation. The mitigation to a hardware or software issue may be organizational support in the form of equipment repair or replacement, while biased decisions involving the automation may be better mitigated through training or a more transparent design of the decision aid.

The Tightly Coupled task is more complex than the loosely coupled scenario, requiring the Supervisor to complete nearly twice as many unique tasks with each task having slightly more potential outcomes, both nominal and non-nominal, and more potential hazards. Generally, decision and skill-based errors are more prevalent, than perception or knowledge errors for both scenarios. Skill-based errors, and to a lesser degree, decision errors, are substantially more likely in the Tightly Coupled task, because of the higher levels of coordination needed to complete the ridgeline aerial ignition mission. These skill-based errors arise in the communication tasks required to coordinate actions among human teammates and in the many assessment and control tasks required to command multiple types of UAVs conducting different operations (e.g., ignition and surveillance) simultaneously. A caveat to this analysis is that the likelihood of particular hazards occurring was not considered; hence, it cannot be concluded that decision or skill-based errors are expected to occur more frequently or to have greater severity. However, mitigations, such as robust autonomy and decision aids, may reduce the number of ways something can go wrong. Training of rote knowledge, beyond what is needed to complete the Supervisor's tasks may be less important than training Supervisors to recognize and evaluate mission-critical situations.

The analysis was conducted at a sufficiently high level of abstraction to be generally applicable to a wide variety of operational domains and implementations. However, this high-level approach required many assumptions to be made regarding the capabilities of the automation available. Systems employing a lower level of autonomy may encounter additional hazards as the human takes on duties that could be offloaded to a higher level of autonomy. Analysis beyond the scope of the A26 project will be required to determine implementation-specific interventions for more well-defined system designs. This approach provides constraints that may help guide such investigations.

The A26 research was restricted to the human factors limitations of a single human supervising multiple UAVs in the enroute phase for package delivery and ridgeline aerial ignition scenarios. For the package delivery scenario, future work beyond the scope of the A26 project needs to consider other flight phases, and alternative human roles (e.g., flight assistant or ground crew). The ridgeline aerial ignition case provided more task complexity. However, in both cases, limited consideration was given to the cooperation between multiple Supervisors; the analysis focused primarily on handoffs and elementary communication, such as team readiness. Future work, beyond the scope of A26, needs to address the human factors of coordinated teams of Supervisors (i.e., M:N UAV control). Several potential causes of hazards that relate to organizational influences (e.g., policy and culture) and personnel factors (e.g., illness and demographics) were identified that are outside the scope of the chosen use case and hazard taxonomy.

4.3. Subtask 3-3 Aptitude Measurements and Gaps Taxonomy

A review of the existing aptitude measurements was conducted in order to inform the gaps with respect to multi-UAV control. A list of the aptitudes was generated, along with the associated subjective, objective, or composite measurement types. Besides workload, the majority of objective measures address the allocation and control of attention, situation awareness, and efficiency, which is not surprising given the complexity associated with monitoring and assessing the behaviors of multiple moving objects. The majority of the subjective measures involve different types of rating scales. The total number of individual aptitudes and measures highlight the complexity in addressing human limitations with respect to multi-UAV control. Further, the lack of a specific multi-tasking aptitude and associated measures means that any analysis will be multi-variate.

5. TASK 4: ASSESS THE REQUIRED APTITUDE AND HUMAN FACTORS DIFFERENCES FOR A CREW MEMBER CONTROLLING MULTIPLE UAVS

Task 4 focused on developing computational user models that provide a predictive analysis of the human-in-the-loop human factors considerations for a human responsible for supervising and monitoring multiple UAV systems. The results from Tasks 1 and 3 directly influenced model development, specifically, the task analysis and use cases directly informed the development of the models. The models focused on workload and incorporated some aspects of environmental conditions, shift characteristics, mission duration, and number of vehicles. This task had two primary subtasks. Subtask 4-1 focused on identifying an appropriate modeling tool in which to create the computational models. Subtask 4-2 is a complex task that focused on creating the models for each of the Loosely and Tightly Coupled nominal use cases, distraction events, and Loosely Coupled task unexpected events. This task also required running the model experiments and analyzing the results. The Task 4 final report is provided as Supplementary Document 3.

5.1. Subtask 4-1: Identify Modeling Tool

While a number of cognitive modeling tools are available, the Improved Performance Research Integration Tool (IMPRINT) Pro was used when developing the models for the A26 effort. IMPRINT Pro was developed by the Army Research Laboratory, Human Research and Engineering Directorate to support manpower and personnel integration and human systems integration. IMPRINT Pro incorporates network modeling and can accommodate dynamic, stochastic, discrete events. The resulting models can help develop system designs by modeling the interactions between humans and systems. IMPRINT Pro can inform system requirements; identify human performance driven system design constraints; and evaluate the potential personnel training capabilities and manpower requirements to effectively operate and maintain a system under environmental stressors. A number of plugins can provide additional capabilities, including unmanned systems, fatigue, and training effects.

IMPRINT Pro does not actually develop a model representing a user interface, but rather makes assumptions about the types of potential interactions a user may have with the respective system. As such, the developed models do not assume particular user interface designs, but rather consider a set of the potential interactions the Supervisor may have with a Command and Control (C^2) station. The developed models focus on the predominant human factors results developed for A26 via Tasks 1 and 3.

More specifically, IMPRINT Pro permits the simulation of human behavior for a variety of conditions through the representation of task and event networks. IMPRINT Pro includes a number of pre-defined human performance moderators (e.g., workload) and permits the incorporation of those performance moderators not already pre-defined via the User Stressors module. IMPRINT Pro provides the capabilities to set up complex task networks, model workload, and incorporate other human performance moderators (e.g., heat, cold, protective gear, sleepless hours, noise, whole body vibration, military rank, and training). Any human performance moderator can be added to the model via the User Stressors module, but the workload models are already integrated into the system.

Models built in IMPRINT Pro use atomic task time, task ordering, number of crew members, training, equipment, stressors, and operator mental workload for each task as the model's inputs. Model outputs include values that measure mission success, mission time, and an individual's workload per unit of time. The stressors contained in IMPRINT Pro include a variety of human performance moderator functions (e.g., ambient temperature and humidity, whole body vibration, and noise level). Stressors can affect the timing and accuracy of tasks, which affects the number of tasks that can be accomplished in a certain amount of time by an individual and that individual's overall mental workload level during a mission.

5.1.1. Workload Models

The IMPRINT Pro tool was developed for different purposes than supervising multiple UAVs, and uses a linear model of overall workload. This linear model results in the same workload being added for each new UAV the Supervisor is assigned, irrespective of the mission domain. However, this linear overall workload model is not representative of the expected actual Supervisor workload for the use cases associated with A26. As such, the team investigated how to derive a relevant workload model. IMPRINT Pro is not unique in this limitation when attempting to model and assess human factors performance as the number of UAVs are scaled.

The A26 literature review (Task 1) determined that the majority of the related human subject evaluations were conducted in simulation, most of which do not provide the necessary kinematics and dynamics for the UAVs, and as such, often lack ecological validity. Further, the majority of the evaluations focus on the collection of subjective metrics, rather than objective metrics that can be used to adequately develop a workload model for the A26 effort. Specifically, tasks with larger numbers of UAVs (>10-15) are not represented in the literature with the data necessary to develop an appropriate workload model for either the Loosely or Tightly Coupled use cases. Further, in addition to the insufficient number of vehicles deployed and the subjective data collection issue, reported experiments also often conducted trials that are too short in duration to adequately model workload. Given these A26 Task 1 findings, the team investigated alternative literature in order to determine if a relevant model was available.

During the additional literature review, it was determined that visual tracking of multiple objects plays an important role in the Supervisor's workload. As such, the model had to incorporate visual search time as part of the workload. The analysis led to the conclusion that workload in both the Tightly and Loosely Coupled tasks will vary linearly in relation to visual search time, and a logarithmic function was chosen; however, the log rate must be estimated based on set-size gradients.

5.2. Loosely Coupled Task Model

The Loosely Coupled use case was modeled for an exemplar nominal situation (i.e., nothing goes wrong), three unexpected events, and two distraction events across a number of independent variables, including the number of UAVs supervised, up to 100 UAVs. The models focus on the enroute portion of the use case only.

5.2.1. Nominal Model

The Nominal use case experiments focused on the enroute deployment (i.e., outbound and return flight phases) and supervision of the delivery drones without any disruptions from unexpected events or distractions. The basic research questions were:

- Do any specific independent variables dramatically impact the Overall Workload and number of UAVs a single Supervisor can manage?
- How do the work period elements (i.e., Ramp up, Steady state, and Ramp down) impact the dependent variables?
- As the number of UAVs supervised increases, does Overall Workload increase?
- Given that Overall Workload is expected to increase as the number of UAVs increases, is there a significant difference in the conditions impact on workload?
- How do the different Ramp up and Ramp down parameters impact Supervisor Overall Workload?

The model includes multiple states representing different Supervisor shift stages. The *Ramp up* state occurs when the Supervisor first comes on shift, and occurs each time the Supervisor returns from a break. The Ramp up state gradually increases the number of UAVs the Supervisor is responsible for based on the values used for Ramp up specific independent variables for each experiment.

The duration of the *Ramp up* stage is based on the three independent variables: the Maximum number of UAVs, the Time to Launch a Wave of UAV(s), and the Maximum number of UAV(s) that can be Launched Simultaneously. Typically, a low Maximum number UAVs paired with a high Maximum number of UAVs that Launch Simultaneously results in short Ramp up durations. Meanwhile, a high Maximum number UAVs paired with a low Maximum number of UAV(s) that Launch Simultaneously results in a longer Ramp up duration. For example, if the Supervisor is to monitor at most 50 UAVs, the Ramp up launches ten UAVs simultaneously and the time to launch a wave is 30 seconds, then 2.5 mins is required to launch the vehicles. Using the same parameters to launch 100 UAVs will result in a total Ramp up duration of 5 mins. The short Ramp up period ensures that both trials launch the majority of their UAVs before UAVs begin returning. However, if the Ramp up for 100 UAVs only launches one UAV at a time using the same 30 second time to launch a wave, then the Ramp up duration will be 50 mins. Since the Ramp up duration is longer than the maximum delivery mission (i.e., 20 mins), UAVs begin returning from their delivery mission before the Ramp up period is completed. While this situation represents the extreme case, Ramp up periods greater than five mins can experience previously launched UAVs returning prior to the completion of the Ramp up. The Ramp up state is considered complete only after the Maximum number of UAVs has been launched.

The *Steady state* occurs once the Ramp up period is completed and the Supervisor is monitoring up to the maximum defined number of UAVs, as defined for each experiment. During this time, the Supervisor is responsible for the UAVs that are cycling in and out of the enroute phase of the delivery mission. The enroute outward bound phase assumes that the UAV flies out to the delivery location and then returns to the launch area. It is assumed that the delivery occurs, but this aspect was considered out of scope by the FAA and is not included in the model of Supervisor performance. When a UAV takes off and is assigned to the Supervisor, it is generally assumed that this Supervisor will monitor the UAV throughout the entire enroute mission phases.

The *Ramp down* state occurs when the Supervisor is approaching a designated break period or the end of a shift. Ramp down begins 20 mins before either the start of a scheduled break period or the end of a shift. Further, it is assumed that the Supervisor will supervise all UAVs until their mission is completed. During the Ramp down period the only new UAV deliveries generated and assigned to the Supervisor are those that can complete their delivery mission within the Ramp down period. The gradual decrease in UAVs continues until there are no active deliveries, which always concludes before the end of the Supervisor's work period. The start of the break period or end of the shift marks the end of the Ramp down state.

The Loosely Coupled nominal use case model is composed of a total of 2,740 unique lines of code. This value excludes code native to IMPRINT Pro. The unique lines of code define the numerous features of the nominal model (e.g., simulation initialization, UAV mission generation, Ramp up and Ramp down activation, break activation, the logarithmic linear scanning workload adjustment).

A total of 400 independent variable combinations were possible, but only 355 were simulated. This number of combinations excludes forty-five independent variable combinations that truncated the final working period before shift Ramp down. Some combinations with a truncated final work period resulted in work periods without a Steady state shift condition, because the Ramp up shift state lasts until the start of the Ramp down shift state, 20 mins before the break. Therefore, the forty-five combinations without a Steady state shift state in the final work period were excluded. Each combination of independent variables was run for 25 trials in order to account for variability in the model distributions. A total of 8,875 trials were run (355 x 25 = 8,875).

The manipulation of shift characteristics did not have a significant impact on the estimated Overall Workload. Conversely, manipulation of task characteristics did have a significant effect on Overall Workload. However, despite these reliable effects for task characteristics, a majority of effect sizes were small to non-existent. The Maximum number of UAVs and Maximum number UAVs to Launch Simultaneously often produced the largest impact on the Overall Workload estimates, and it is recommended that focusing on these variables, and their interactions with time, may identify those cases where these variables have the largest effect.

5.2.2. Unexpected Events

The UE use case experiments focused on the impacts on the Supervisor's performance in response to three unexpected events, assuming the best case and worst-case scenarios. The fundamental research questions were:

- How does Overall Workload differ from the nominal use case results?
- How do different Unexpected Events impact Overall Workload and the number of UAVs a Supervisor can manage, both for the best case and worst-case use case requirements?

- What is the impact of an Unexpected Event occurring during the Ramp up, Steady state, or Ramp down on the Supervisor's performance and the number of managed UAVs?

A complete and detailed analysis of all Unexpected Events for the Loosely Coupled scenario are not within the A26 project's scope. Three UE use cases were modeled: Emergency in the Airspace, C^2 Link Loss, and Mid-air Collision. The UE use case models leverage the nominal use case model. Each UE use case model was developed based on its specific characteristics. The model implementations generally require the same model elements, atomic tasks with associated timings, and Overall Workload component values as the nominal use case. However, a more realistic representation of Overall Workload required a looping module of linear scanning tasks that capture the Overall Workload associated with the Supervisor's monitoring the UAVs.

The occurrence of a UE, such as C^2 link loss or Mid-air collision, can result in the Supervisor multitasking between linear scanning the unaffected UAVs, while also completing tasks to address the UAV affected by the UE. Properly modeling multitasking in IMPRINT Pro proved to be difficult to implement; therefore, the current model assumes that the Supervisor does not attempt to multitask and attempts to complete all the UE related tasks before returning to nominal monitoring of the unaffected UAVs. While completing the UE related tasks, the Supervisor continues incurring Overall Workload associated with the monitoring task.

Each UE was chosen to represent different types of Supervisor responses. Further, best-case and worst-case scenarios have differing impacts on the Supervisor. For example, the C^2 link loss does not dramatically change the number of UAVs the Supervisor is monitoring. The worst-case requires the Supervisor to continue working with the UAVs, while the best case reassigns the UAVs in question to the UE Supervisor, and the primary Supervisor is simply assigned new UAV(s) to monitor. However, an Emergency in the Airspace does directly impact the number of UAVs the Supervisor is monitoring. The best-case scenario hands-off responsibility for the UE to the UE Supervisor, resulting in an immediate reduction in the number of UAVs the Supervisor is responsible for monitoring. However, that decrease in the Supervisor's UAVs differs for the worst-case scenario in which the Supervisor's immediate response is to ground all UAVs in the area of the Emergency. The Supervisor's secondary responsibility is to monitor and ensure that all of the Supervisor's UAVs outside of the Emergency area hold in place and do not enter the Emergency area. If the Emergency is quick, then the holding UAVs can continue their delivery missions. Otherwise, the UAVs consume their power sources and return to launch or land at a secondary launch area. Thus, the worst-case path results in a different pattern. Once the emergency is over, the Supervisor is assigned new UAVs to monitor.

The UE model was developed specifically to reuse the nominal model, but the UEs introduce 1,298 new unique lines of code. The UE model's unique code is responsible for the initialization, activation, and execution of each UE use case as well as the logging of UE model data. The UE model in total is composed of about 4,078 unique lines of code, not inclusive of IMPRINT Pro's inherent programming code.

A total of 720 independent variable combinations are possible; however, to condense the data collection time, UE instances were consolidated into a single trial for the Ramp up or Ramp down shift state instances. Trials of said consolidated combinations have the UE occur twice in the 2nd and 4th working period, once in the Ramp up shift state and once during the Ramp down shift state. This consolidation is possible because the UEs are discrete instances that have a finite impact on the model's outputs. This consolidation lowered the total number of combinations to 480. Among the 480 combinations, 12 were considered invalid because they result in trials with very short Steady state shift states (1 minute). If a UE was to occur within the 1 minute Steady state, the majority of the Supervisor's response to the UE will occur during the subsequent Ramp down shift state, an undesirable characteristic for data analysis. It is noted that UEs will occur such that they cross between shift states during actual deployments, but the analysis of such cases was outside the scope of the A26 effort. The A26 effort required that the UE occurrences arise and are handled during the specific shift states, as this ensures that appropriate data and results are generated to reflect the impact of the UE on the Supervisor within a given shift state. Each valid combination of independent variables was run for 25 trials in order to account for variability in the model distributions. A total of 11,700 trials were run (468 x 25 = 11,700).

The analysis of the three types of UEs (C^2 link loss, Emergency in the airspace, Mid-air collision) yielded task factor results for the Maximum number of active UAVs, Maximum number of UAV(s) to Launch Simultaneously, and Time to Launch a Wave of UAV(s), as did the analysis of the nominal use case. These results for both the nominal UE scenarios found that many of the effect sizes were small to non-existent; thus, even though the actual Overall Workload differences were significant, they were not always interesting in a practical sense.

What is more interesting is that the analysis of the three types of UEs all showed that the protocols used to address the UEs have a great impact on Overall Workload. The best-case scenarios for all UEs do not require the Supervisor complete any UE-related tasks, since the affected UAV(s) is handed off immediately to the UE Supervisor, which only causes a small increase in workload. The worst-case C^2 link loss and Mid-air collision UEs increased Overall Workload more than the best-case, because the Supervisor completes additional tasks to address the UE, while still performing their nominal duties (e.g., visual monitoring). The Emergency in the airspace UE had a qualitatively opposite effect on Overall Workload compared to the other two UEs. Generally, although the Supervisor experiences a short, small increase in Overall Workload from handing off UAVs to the UE Supervisor, the Supervisor experiences a much longer and larger decrease in Overall Workload from having fewer UAVs to monitor. This effect is relative: the more UAVs for which the Supervisor is responsible, the greater their Overall Workload will decrease. These outcomes occur due to the fact that the Emergency in the airspace UE requires UAVs to be grounded; thus, reducing the number of UAVs for which the Supervisor is responsible. Specifically, the Emergency in the airspace worst-case UE requires the Supervisor to ground the impacted aircraft, while maintaining responsibility for any UAVs unaffected by the emergency. After the Supervisor grounds UAV(s), responsibility for the grounded UAV(s) is handed off to the ground recovery team. However, the Supervisor is still responsible for UAVs that were not grounded, which means the decrement in workload is not a great as in the best-case scenario. Generally speaking, the Supervisor's Overall Workload is related directly to the number of UAVs the Supervisor monitors; thus, grounding UAV(s) reduces the experienced Overall Workload. This result indicates that UE protocols are worthy of deeper investigation and that addressing the UAV(s) differently based on features, such as proximity for Emergencies in the airspace, may require additional autonomy and decision support in order to allow the Supervisor to address the situation.

Comparing the mean Overall Workload for three types of UE trials during periods when the UEs occurred and when they were not also highlighted that differences in UE type can have an impact even when they are not occurring. The Overall Workload during the non-event control periods was lower for the Emergency in the airspace trials than for C^2 link loss and Mid-air collision UEs during Ramp down. This result is likely an artifact of the analysis caused by differences in the durations of the three UE types. The C^2 link loss and Mid-air collision UEs are relatively short in duration, resulting in the control intervals to which the UEs are compared being fairly consistent in terms of Overall Workload. However, when the Emergency in the airspace UE occurs during Ramp down, the UAVs are always handed off to the UE Supervisor, as the UE frequently lasts longer than the Ramp down period and the time remaining in the Supervisor's shift. The Overall Workload, when averaged over the entirety of the Ramp down period, will tend to be less than when averaged over a shorter interval earlier in Ramp down. Future work needs to explore alternative operational definitions for the shift states to eliminate this confound.

5.2.3. Distraction Events

Ten distraction event use cases were developed by the A26 team as part of Task 3. It is infeasible within the scope of the A26 effort to model and fully analyze all ten distractions. As a result, and based on industrial and FAA feedback, the team modeled two distractions: Mindwandering and Fatigue. Three research questions were generated:

1. Do distractions reduce Overall Workload relative to normal baseline values, both overall and channel?
    a. What is the impact of a short vs. long Mindwandering event?
    b. What is the impact of reduced numbers of hours of sleep over the last four days?
2. Does the type of distraction differentially influence any observed impact on Overall Workload?
3. Do distractions interact with the current state of UAV operation (Ramp up, Steady state, Ramp down)?

The distraction event use case models leverage a majority of nominal use case model and incorporate the looping linear scanning task introduced for the UE use case model.

5.2.3.1. Mindwandering

The *Mindwandering* distraction was implemented as a togglable event that randomly occurred during the Ramp up state, Steady state, or Ramp down state. The distraction events were implemented to occur during the Supervisor's 2nd and 4th shift working periods. No Mindwandering events occurred during the shift's 1st and 3rd working periods. Given that the model does not degrade the Supervisor's performance over time, the occurrence of distraction events within a trial, either a single event across the entire trial or a single type of event within a work period, does not change the model outcomes. As a result, multiple distraction events with unique independent variables can be generated within a trial, based on different work periods.

The activation of Mindwandering causes a decrease in Supervisor workload and an increase in the linear scanning task duration, for a period of time. A short Mindwandering event lasts 30 seconds, while a long Mindwandering event lasts 2 minutes (i.e., 120 seconds). Supervisor workload is decremented by 10% during both short and long Mindwandering events; however, during short Mindwandering, the duration of the linear scan task is increased by 10%, whereas the duration of the linear scan task is increased by 50% during a long Mindwandering event.

Distraction events do not result in any change to the Supervisor's assigned or to be assigned UAVs. This model assigns UAVs to the Supervisor in the same manner as the nominal model. A distraction does not result in UAVs being unassigned to the Supervisor. As a result, there is no visible change in the number of active UAVs enroute. The predominant phenomenon from a distraction is a decrease in the Supervisor's workload due directly to the distraction event. This decrement in Overall Workload is visible for long and short duration Mindwandering distractions, during the 2nd and 4th work periods.

The Mindwandering distraction model was developed to reuse the majority of the nominal model and UE model codebase, with about an additional 30 unique lines of code. The new code is responsible for the initialization and activation of the Mindwandering distractions and the logging of the distraction's effects on Supervisor performance. The exact number of unique lines of code that compose the distraction model is difficult to estimate, as only a portion of the UE model's code was reused.

The change in Overall Workload caused by the Mindwandering distraction was smaller than expected. As a result, no relationship between Mindwandering and the task characteristics was established. Future work needs to investigate additional methods for modeling this type of distraction.

5.2.3.2. Fatigue

The fatigue distraction research questions were the same as for Mindwandering. The Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) algorithm is an IMPRINT Pro plugin that predicts changes in human performance based on the number of hours slept each of the last four nights. The SAFTE algorithm plugin creates fatigue-related degradations in performance over the course of the Supervisor's shift. The algorithm incorporates quantitative information related to circadian rhythms, sleep inertia, and recovery and decay rates in order to predict human performance. The model permits specifying 8, 6, 4 or 2 hours of sleep each of the last four nights in order to understand the corresponding implications.

The SAFTE algorithm is an IMPRINT Pro plugin; thus, no changes were required to operate the plugin with the nominal use case model. The SAFTE algorithm generally is applied to an entire trial, and is not a discrete event that occurs randomly throughout a trial for a period of time. Rather, the algorithm is enabled at the start of a trial with a specified number of hours of sleep for the preceding four nights.

The Fatigue distraction event does not change the Supervisor's assigned or to be assigned UAVs. This model assigns UAVs to the Supervisor in exactly the same manner as the nominal model. A high-level of fatigue does not result in UAVs being unassigned to the Supervisor. As a result, there is no visible change in the number of active UAVs en-route.

The SAFTE plugin provides all the necessary code to support the Fatigue distraction. The nominal and UE models are leveraged as is for the Fatigue distraction.

A total of 120 independent variable combinations are possible for the Fatigue distraction model, for which 25 trials were completed per relevant independent variable combination. The SAFTE model was enabled at the start of each trial and has a continuous impact on the Supervisor's performance, as a result, it is applied to each shift state for a single trial. The Fatigue model trials' independent variables closely mimic those of nominal model trials; however, the maximum Shift Duration, Duration of the Supervisor's Working Period, and Duration of the Supervisor's Breaks independent variables were fixed to 10 hours, 120 minutes, and 30 minutes, respectively. The number of possible values for the Maximum number of Active UAVs and Maximum number of UAV to Launch Simultaneously were reduced. The Fatigue trials do not include UE or distraction events (i.e., Mindwandering) that may impact workload. A total of 25 trials were run for each of the 120 variable combinations, resulting in a total of 3,000 completed trials (120 x 25 = 3,000).

The Fatigue distraction results did not yield the expected effects based on the number of hours slept each of the last four nights and the work period. While the main effect and some interaction effects were significant, the effect sizes were negligible. Future work consisting of additional analyses of other measures, such as time to complete tasks or accuracy, may be needed to see the effect of the built-in IMPRINT Pro models. This additional analysis is relevant, as the SAFTE model assumes additional fatigue makes the Supervisor less efficient; thus, the Supervisor will take longer to complete tasks. While the SAFTE model is common, additional different fatigue models also need to be investigated in future work.

5.3. Tightly Coupled Task

The Tightly Coupled use case was modeled for an exemplar nominal situation that assumes the Supervisor sleeps eight hours each of the preceding four nights. The Fatigue distraction was further modeled assuming six and four hours of sleep each of the preceding four nights. The Fatigue distraction is the only distraction event modeled. Further, none of the exemplar unexpected events were modeled. The models focus on the ignition mission deployment portion of the use case only.

The nominal use case experiments focused on the UAVs' mission deployment (i.e., UAVs conducting ignition and surveillance tasks) and supervision of the UAVs without any disruptions from unexpected events or distractions. The Fatigue distraction use case experiments used the exact same model and simply adjusted the SAFTE model's number of hours slept over the last four nights parameter. The basic research questions were the same for both sets of experiments:

- Do any specific independent variables dramatically impact the Overall Workload the Supervisor can manage?
- How do the modeled Supervisor activities during the mission deployment impact the dependent variables?
- As the number of UAVs supervised increases, does Overall Workload increase?
- Given that Overall Workload is expected to increase as the number of UAVs increases, is there a significant difference in the conditions impact on Overall Workload?

The model represents the Supervisor's tasks for monitoring multiple Ignition and Surveillance UAVs conducting a ridgeline aerial ignition mission. The nominal use case model assumes that a single Supervisor is responsible for managing multiple UAVs during the aerial ignition mission. The nominal use case model incorporates examples of common mission activities (e.g., adjusting ignition sphere drop density, verifying surveillance areas), but does not incorporate any unexpected events or distraction use cases. The nominal use case enables the SAFTE fatigue plugin, assuming that the Supervisor has slept 8 hours each of the last four nights.

A number of typical activities can occur during the Tightly Coupled nominal use case. These activities require the Supervisor to either take action or converse with another team member about actions to be taken. The Fatigue distraction SAFTE model parameters cause the Supervisor to be less effective as the number of hours slept over the last four nights decreases. As such, the Supervisor's activities take slightly longer to perform. While the modeled activities take longer to complete during the Fatigue distraction trials, the activities occur in the same order at the same scheduled times. However, extended activity completion times can result in some activities' steps occurring simultaneously, or overlapping.

The Tightly Coupled model leverages 37% percent of the code developed for the Loosely Coupled model. 2,494 unique lines of code were introduced for the Tightly Coupled model. The new code is responsible for necessary Tightly Coupled model features, such as generating the simulation mission plan, executing the mission, the low power UAV swap behavior, and the Supervisor's activities logic.

A total of three independent variable combinations are possible for the nominal use case (8 hours of sleep). Each combination of independent variables was run for 25 trials in order to account for variability in the model distributions. A total of 75 trials were run (3 x 25 = 75). The Fatigue distraction use case trials incorporate a total of nine independent variable combinations. Each combination of independent variables was run for 25 trials in order to account for variability in the model distribution. A total of 225 trials were run (9 x 25 = 225), of which 75 trials are the nominal use case trials.

An overall analysis of the first 83 minutes of the mission suggests that the main driver of Overall Workload is UAV Team size. While the Hours slept did impact Overall Workload, this was a very small effect. Further, an analysis of the number of swapped UAVs across the mission also appears to be highly influenced by UAV Team size, and not at all by Hours slept. The number of Hours slept did not impact Overall Workload (either across the entire mission, or by activity), but exerted its main influence in the time to complete a given activity. This result is consistent with how the SAFTE plugin influences human performance based on the number of hours slept each of the last four nights, which reduces activity effectiveness and thereby prolongings the activity Duration.

An Efficiency metric was calculated in an effort to connect the notions of Overall Workload and the activity Duration. The UAV Team size often impacted Efficiency, such that it increases the amount of work disproportionately to the simultaneous increase in activity Duration. Hours slept often impacted Efficiency as well, as fewer Hours slept produces an inflation in activity Duration. Importantly, an interaction between independent variables was observed several times, such that while Efficiency increased with more Hours slept, this effect was less pronounced if there were more UAVs flying.

Ultimately, it appears that the UAV Team size is the critical factor influencing the Supervisor's Overall Workload; however, the Hours slept can also impact the activity's duration, and the ratio of Overall Workload to time (i.e., Efficiency).

6. TASK 5 CONDUCT HUMAN-IN-THE-LOOP SIMULATION

Task 5 was removed from the original statement of work and the research technical plan in September 2021 due to the scope of the Task 4 effort expanding to conduct additional modeling. The additional modeling was intended to provide a more informed analysis that better identified the appropriate independent variables to incorporate into future human-in-the-loop evaluations. This decision was informed by the literature review, project rescoping, and the lack of available systems for human-in-the-loop evaluations.

7. RESEARCH FINDINGS/GAPS

A number of important research findings and gaps were identified throughout the entire research project. The findings and gaps are organized by task. The literature review findings and gaps are provided in

Table 1, while the Task 3 findings and gaps are provided in Table 2. Finally, the findings and gaps identified as part of the Task 4 modeling efforts are provided in Table 3.

Table 1. Literature review (Task 1) Findings/Gaps.

Phases of Flight: Very little research has focused on the takeoff and landing flight phases, and the research has focused primarily on cruise flight. These critical phases, along with preflight, climb, descent, approach, recovery, and post-flight will need to be addressed. Further, different multiple UAV domains may require unique flight phases that do not exist with crewed aircraft or generalize across multiple UAV domains.
Crew Roles: When developing crew roles, one must consider the M:N UAV ecosystem as a whole, potentially including an entire organization. Factors to consider include (1) there may be one supervisor in charge (e.g., a traditional pilot in control), or an entire crew organization, (2) how many humans are considered a part of a specific crew, and (3) what new roles need to be defined or introduced.
Training: More focus is needed to define required training. Since the systems are becoming more automated, there is less need for months or weeks of training. The future of UAV autonomy forces a more in-depth analysis of everyday citizens serving in any of the M crew roles and what the associated training needs to encompass.
System Requirements: There is little research considering the type of system, which is broken down into two distinct groups, a single UAV or a multiple UAV structure. Factors that must be further investigated within the context of both definitions include, the maneuverability, weather, and system composition. The system composition can be further decomposed into how the system responds to communication link loss, transitions through airspace, overall mission location (e.g., restricted airspace, or no fly zones), and UAV team heterogeneity.
Autonomy: The levels of autonomy will determine how many humans are needed, what training those humans will require, and what other system composition requirements will be necessary for safe flight.
Applied Domains: The existing literature is generally domain agnostic, and does not consider unique Supervisor required activities, UAV autonomy requirements, or a full scope of unexpected events and distractions. Different multiple UAV deployment domains will have different requirements that impact the Supervisor's capabilities, tasks, and training.

Table 2. Human Factors Limitations (Task 3) Findings/Gaps.

The Loosely Coupled use case's task analysis and focus on scheduled tasks highlight that monitoring, vigilance, and boredom may directly influence human performance. A gap includes the lack of studies focused on the specific effects of vigilance and boredom in multiple UAV delivery contexts.
The input from the subject matter experts may be very unique compared to what may be collected from those using other multiple UAV logistics models. As such, for the Loosely Coupled task, the developed use case is a notional use case that does not represent any specific company's UAV logistics model. Similarly, for the Tightly Coupled scenario, the developed use case is an abstracted exemplar with respect to ridgeline aerial ignition and the use of surveillance and ignition UAVs. A gap is the lack of validated use cases for a wider range of Loosely and Tightly Coupled tasks across domains for multiple UAV systems.
There are no data about how frequently the unscheduled events may occur in practice. There is a gap in understanding the necessary levels of training and expertise required for addressing the unscheduled tasks when supervising multiple UAVs.
The tasks associated with the unscheduled events were represented at a high level. For example, there may be a range of landing tasks (e.g., land immediately vs. first identifying a landing location that may be further away, fly to it and landing). For holding (i.e., hovering in place), there also may be a range of methods and some may be specific to aircraft type. Thus, a gap is identifying the full range of methods for addressing each unscheduled event and completing the analysis for each method.

Table 2. Continued
The Tightly Coupled tasks scenario added the dimension of coupled tasks with UAV heterogeneity (i.e., surveillance and ignition). While the resulting analyses addressed the different task and team work associated with the different UAV types, this work did not systematically address the complexity of supervising different UAV types with different missions and performance capabilities. Thus, a gap is analyzing the potential interaction of task, aircraft, and mission types with respect to human performance.
The research highlighted critical aptitudes, but it is not clear which aptitudes play a critical role singly and/or in combination. Aptitude measures developed under specific experimental paradigms and using laboratory tasks may not translate to applied scenarios. General measurements, such as those collected by self-reports may not be relevant in a field study. There are no meta-analyses or other literature to support making claims about exactly which aptitudes are relevant to multiple UAV supervision. Thus, there is a gap in understanding what combination of aptitudes are the most important with respect to supervising multiple UAVs.
Validated measures of multitasking for multiple UAV operations are not available. Thus, a gap is that there is no single aptitude or single validated measure that can capture all the human performance limitations related to multitasking with respect to supervising multiple UAVs.
Some aptitude measures may be difficult to obtain during real-time operations. Measures that yield results in real- or near real-time allow for interventions that support the operation as it is unfolding. Developing methods and measures to support real-world operations is a gap.
Teamwork may be an important skill for Supervisors and other roles. There is limited research on what type of coordination abilities may be important. Thus, a gap is determining the exact role for the human Supervisor for delegation.
Some aptitudes may be very sensitive to the task or domain. Thus, collecting accurate data will require specific design/implementation assumptions, including the level of autonomy and flight phase. Specific implementations will define clear Supervisor roles and support. Thus, one gap is validating what specific autonomy will be available for each task and tasks in combination. A related gap is a lack of detailed timing information for human performance of various tasks.
The type of task management strategies has not been defined for domains, such as package delivery. Thus, it is difficult to predict operator overload. Additionally, different types of autonomy may support task management. A gap is the definition of such capabilities.

Table 3. The Modeling (Task 4) key findings and gaps by overall and task type.

Overall Task 4 Modeling Key Findings/Gaps
Assuming highly autonomous UAVs, that are capable of responding appropriately to unexpected events, does permit a single human Supervisor to manage a larger number at lower Overall Workload levels.
A primary driver of a Supervisor's Overall Workload is the number of UAVs being supervised, irrespective of the specific modeled Loosely or Tightly Coupled tasks.
The statistical results, across both the Loosely and Tightly Coupled tasks, resulted in significant differences, but with small to non-existent effect sizes, which means the results are not always interesting in a practical application sense.
The common human factors modeling tools do not incorporate human performance models that account for the Supervisor's performance when monitoring more than one or a few UAVs. The Task 1 literature review also found that no reasonable models existed. The team conducted an additional investigation into the human-robot interaction research, human visual perception literature, and the human visual scanning literature, but was unable to identify any applicable models for human performance, specifically workload that are based on real systems (i.e., not simulated systems) and objective human factors results. A primary gap is the existence of representative models for the focus domains.
Many human factors modeling tools do not adequately model task switching for multiple UAV deployments. IMPRINT Pro has a task switching capability, but it was unable to be used to support this effort.
IMPRINT Pro does not adequately represent fatigue in the standard modeling tools. IMPRINT Pro does provide a plugin for the SAFTE model; however, that model has limitations. The SAFTE model does not account for other aspects of fatigue, such as long shifts or extreme working conditions. Additional different fatigue models need to be investigated or developed.
The developed models do not fully consider all of the on-board UAV engineering and monitoring requirements for a UAV to autonomously detect internal faults (e.g., difficulty managing stability).
The developed models do not incorporate cascading demands on the Supervisor, be it from normal activities, unexpected events, or distractions. Such cascading demands need to be modeled and understood.
Generally, there are no similar human factors models representative of the complexity of the Loosely or Tightly Coupled domains' tasks, particularly that model the Nominal use case, as well as the Unexpected Event and Distraction use cases.
The developed models are quite complex, but are unable to model the true complexity of the representative systems. Achieving a 100% match to the deployed systems is impractical; however, increasing the model complexity can provide additional insights. Further, the models can guide the design of human-in-the-loop evaluations by removing independent variables that had no impact on Supervisor Performance.
The provided results focus on the Supervisor's overall workload; however, workload is really a multi-factor variable that is composed of the cognitive, visual, speech, auditory, fine grained, and tactile components. A more detailed analysis of the component workload results was not completed, and is needed. Further, future work must focus on how the workload components impact overall workload. The more nuanced interactions need to be modeled, understood, and considered during Multiple UAV system development.

Table 3 Continued
Loosely Coupled Task Key Findings/Gaps
The developed models provide key insights into human performance for these single human Supervisor-multiple UAV tasks, they are simply models and cannot provide a complete picture of actual human performance. Representative systems must be built, acquired, and evaluated using actual UAVs and human Supervisors with the requisite domain training and knowledge in ecologically valid experiments.
All results based on the developed models must be verified with ecologically valid human subjects evaluations.
Industrial subject matter experts expect that the Supervisor will likely have some training, but may only have a high school level education or equivalent.
The industrial subject matter experts predict that an individual UAV will experience a UE about once per week, and that for the majority of the UEs, the UAV will autonomously respond to the UE, taking any necessary actions.
The manipulation of the shift characteristics (e.g., shift, work period, and break length) did not have a significant impact on the Supervisor's Overall Workload.
Two task characteristics had the most reliable impacts on the Supervisor's Overall Workload: Maximum number of UAVs and the Maximum number of UAVs to launch simultaneously. Larger numbers of UAVs being monitored and larger numbers of UAVs launching simultaneously increased Overall Workload.
If one considers the industrial expectation regarding the frequency of a single UAV unexpected event and also assumes that a major corporation with thousands of UAVs conducting deliveries on a daily basis, then there will be a very large number of unexpected events occurring daily. A means of ensuring that unexpected events requiring human responses or monitoring is to assign them to a UE Supervisor. The UE Supervisor handles all unexpected events in a much larger region than the Supervisors. This approach allows the Supervisors to remain focused on the monitoring task, which is considered the best-case scenario. Modeling the UE Supervisor is beyond the scope of the A26 effort.
While the goal is a clean work environment, this may be unachievable. Further, distractions can occur for many reasons. The Supervisor may be unaware that a distraction is hindering their performance. A Watch Supervisor is a necessary role to monitor the Supervisors and to take corrective actions to ensure Supervisor attention. Modeling of the Watch Supervisor is beyond the scope of the A26 effort.
Thirty-four unexpected event use cases were developed to cover a very large breadth of events. Depending on the response to the unexpected event, there may be limited, if any impact on the Supervisor's performance. However, unexpected events that are involved (e.g., Emergency in a portion of the Supervisor's airspace region) and require the Supervisor to handle the event will lead to additional workload.
The protocol used to respond to the modeled unexpected events, either handing off the unexpected event in the best-case scenario to the UE Supervisor, or in the worst case the Supervisor handing the unexpected event, impacted Overall Workload. The Supervisor's Overall Workload was least impacted, or was reduced by handing an unexpected event off to the UE Supervisor.
Ten distraction use cases were developed that include the actions to be taken by the Watch Supervisor and the Supervisor in order to ensure optimal performance. Distractions generally reduce the Supervisor's Overall Workload, since the individual is not paying attention to their tasks.
The developed Loosely Coupled task model focuses only on the enroute portion of the delivery task, and does not include the take-off, ascend to altitude (either for initial flight or post-package delivery), descent from altitude (either on return to launch or for actual package delivery), or the transition from horizontal to vertical flight and vice versa.
The Loosely Coupled task modeled enroute flights assumed that the outbound and return flight phases are equivalent; however, a number of factors can influence this flight time.

Table 3 Continued
Loosely Coupled Task Key Findings/Gaps Continued
The developed Loosely Coupled task model does not represent the breadth of intermittent communication problems that can occur in delivery environments. Built environments will result in communication drops that occur on a frequent basis.
The developed model assumes a single Supervisor; however, modeling a control room with multiple Supervisors may change some of the results.
Handoffs of responsibility between Supervisors or between a Supervisor and the UE Supervisor need to be modeled.
The unexpected events were modeled to occur completely within a Supervisor's work period; thus, unexpected events during Ramp down that continue past the current Supervisor's work period (i.e., cross between shifts or work periods) were not modeled. Such unexpected events need to be modeled.
Distractions naturally create a backlog of task duties. The developed model does not incorporate the Supervisor being required to catch up on that backlog. Further, a model that does require catching up must also incorporate the Supervisor's error rate while attempting to catch up.
The models need to be extended to incorporate additional types of unexpected events and distractions.
The modeling of the unexpected events and distractions needs to consider additional durations and timing occurrences.
The modeled unexpected events and distractions (within each use case) have fairly homogeneous magnitudes, but each use case requires modeling with varying magnitudes of impact on the Supervisor.
The models do not incorporate multiple simultaneous unexpected events, distractions, or a combination thereof. Nor did the model incorporate cascading events.
Tightly Coupled Task Key Findings/Gaps
The modeled Overall Workload was very high, often overloaded, even with four UAVs. Based of field experience, this seems to be an over prediction, and must be validated with ecologically valid human-in-the-loop evaluations.
Spikes in Overall Workload corresponded to the Supervisor's activities.
UAV Team size impacted the Supervisor's Efficiency, such that it increases the amount of work disproportionately to the simultaneous increase in activity Duration.
Hours slept often impacted the Supervisor's Efficiency, as fewer Hours slept via the SAFTE model inflated the activity Duration.
While the Supervisor's Efficiency increased with more Hours slept, this effect was less pronounced when more UAVs deployed simultaneously, either due to larger UAV Team size or more UAV swaps.
The modeled use case did not consider extreme weather conditions or other serious impacts on the Supervisor's performance, other than hours slept the last four nights. More realistic extreme deployment conditions need to be modeled.
No unexpected events were modeled for the Tightly Coupled task, which is a key gap.
Only the fatigue distraction, using the SAFTE model plugin, was modeled for the Tightly Coupled task. Additional distractions must be modeled. As noted for the Loosely Coupled task, better fatigue models are needed to cover the breadth of factors that will impact Supervisor fatigue, and performance.
UAVs are not currently used for monitoring ridgeline aerial ignition missions; human wildland responders serve in those roles. The developed scenarios were based on discussions with subject matter experts and Dr. Adams' field experience. Surveillance UAVs, as modeled, need to be evaluated in actual deployments.

Table 3 Continued
Tightly Coupled Task Key Findings/Gaps Continued
The modeled Ignition UAVs assumes that the UAVs can carry sufficient ignition spheres, such that UAVs runs out of ignition spheres at the same time the battery is depleted, resulting in a single type of swap behavior. While Ignition UAVs are being developed to hold 1,000 spheres, such UAVs will require a sphere refill before battery depletion. The result will be heterogeneous types of swap behaviors, one for ignition sphere refill and another for battery replacement. A more realistic representation of heterogeneous swaps is needed, and will impact the Supervisor's Overall Workload.
The Tightly Coupled task model incorporates very limited Supervisor multitasking. The Supervisor is modeled as completing the visual scan task, and the modeled Supervisor activities simultaneously. However, much more realistic and extensive multitasking needs to be modeled.
The developed model does not extensively model task switching, which must be modeled.
The developed model does not represent the complexity of the environmental working conditions for the Tightly Coupled scenario. It is questionable if IMPRINT Pro, or any human performance modeling tool can represent such complex working environments.

8. CONCLUSION

The A26 effort focused on the human factors requirements associated with a single human supervising multiple UAVs across two domains. The Loosely Coupled use case's focus on delivery drones facilitated scaling the number of UAVs a single human Supervisor in a control room was responsible for across nominal, unexpected events, and distraction use cases. The Tightly Coupled use case's focus on aerial ridgeline ignition considered some aspects of the unstructured environment in which the human Supervisor was located for deploying a much smaller team of heterogeneous UAVs. The research effort addressed gaps in knowledge that are currently a barrier to the safe, efficient, and timely integration of systems composed of multiple unmanned aircraft into the national air space, but the research also identified a large number of key gaps that must be addressed. The provided task reports (attached as Supplements to this document) provide significantly more details regarding the research activities and results, as well as the key findings and gaps.

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SUPPLEMENT 1: TASK 1 - LITERATURE REVIEW FINAL REPORT

A26: Establish Pilot Proficiency Requirements Multi-UAS Components

March 22, 2021

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15. Supplementary Notes

Commercial and public safety UAS are currently limited by Title 14 CFR §107.205 prohibition on operating multiple aircraft by one person. The public as well as UAS commercial operations in applications such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections would benefit from modification to this prohibition. The FAA-ASSURE study that this literature review supports will help to inform FAA regulations and industry standards addressing single pilot and multi-UAS operations. This literature review is designed to help inform ASSURE researchers and FAA sponsors on findings in other studies and to identify research gaps.

Previous works mostly focused on human-in-the-loop (HITL) studies with an emphasis on human factors limitations for operating and monitoring multiple small UAS conducting surveillance, reconnaissance, target detection/classification, and/or search missions. For these studies, researchers used performance measures including target detection rate and response times and subjective measures including perceived workload, trust in automation, and situation awareness. Some of these studies tended to use research simulators to evaluate levels of automation needed for different tasks and whether automation should be static (remain at same level) or flexible. For flexible levels of automation, previous research studied whether the operator should be in control of the change (adaptable automation) or if the change in automation level should be based on operator workload or performance (adaptive automation). While these previous studies showed some pros and cons of each, subjective measures and situation awareness tipped the balance toward operator control of the decision on level of autonomy.

Because there are few studies specifically focusing on supervisory control of multiple small UAS, the literature review team found gaps in understanding of the impacts of different operations, flight phases, flight near infrastructure and over people, UAS fidelity and heterogeneity, failure modes, environment factors, team configuration, commercial applications, training and selection.

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Table of Acronyms

Acronym	Meaning
3D	Three Dimensional
CFR	Code of Federal Regulations
DAA	Detect and Avoid
FAA	Federal Aviation Administration
HITL	Human In The Loop
ISR	Intelligence Surveillance Reconnaissance
LOA	Level of Autonomy
NAS	National Airspace System
SAGAT	SA Global Assessment Technique
SART	SA Rating Technique
sUAS	Small UAS
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle

Executive Summary

Commercial and public safety Unmanned Aircraft Systems (UASs) are currently limited by the 14 Code of Federal Regulations (CFR) Part 107.205 prohibition on operating multiple aircraft by one person. The public as well as UAS commercial operations in applications, such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections will benefit from modification to this prohibition. The FAA-ASSURE study that this literature review supports will help to inform FAA regulations and industry standards addressing single supervisor and multiple UASs, or M:N UAV systems. This literature review is designed to inform ASSURE researchers and FAA sponsors of the findings from published studies and to identify research gaps.

The research team reviewed approximately 100 manuscripts. Previous works mostly focused on Human-in-the-loop (HITL) studies, with an emphasis on human factors limitations for operating and monitoring multiple sUASs conducting surveillance, reconnaissance, target detection/classification, and/or search missions. To evaluate the effect on the humans, these studies used performance measures, including target detection rate and response times as well as subjective measures including perceived workload, trust in autonomy, and situation awareness. Some of the studies evaluated levels of autonomy needed for different tasks and others explored the effects of static (remain at the same level) or adjustable autonomy based on the human's workload or performance.

Perhaps one of the biggest findings is how little research is available on the factors, effects, and their interactions regarding the control of multiple UASs across different phases of flight (i.e., takeoff, departure, enroute, mission, arrival, landing and ground operations). Some other research gaps include the effects of different levels of education and training of crew roles (including the human supervisor in command); the minimum crew roles necessary for different types of operations, and the implications of system autonomy; climate; airspace; type of aircraft (i.e., fixed-wing, rotorcraft, hybrid); communication reliability; task/mission composition; the physical M:N UAV System composition; and more.

The ASSURE research team will begin to improve understanding of these factors by modeling loosely coupled tasks, where multiple vehicles conduct independent tasks (e.g., drone package delivery). This effort will demonstrate and provide a better understanding of the factors affecting a single supervisor's safe control of multiple UASs as well as the interactions and relationships between the key components. Additionally, researchers plan to conduct a small HITL study (e.g., on-campus UAS delivery) to demonstrate, further understand, or validate some of the modeling findings.

It is expected that this project will generate even more questions that will need to be resolved before the FAA is able to institute substantial regulations and guidelines. However, by the end of this project researchers and the FAA will have a much clearer understanding of what further insight is needed to safely allow multiple UASs operations in the nation's airspace.

1 Introduction

Commercial and public safety UAS are currently limited by the CFR Part 107.205, which prohibits operating multiple aircraft by one person; however, operational concepts are be- ing developed that support M:N operations, where M represents one or more humans who have responsibility for two or more (N) aircraft. A modification to CFR Part 107.205 will benefit the public as well as UAS commercial operations in applications, such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections. The study that this literature review supports will help to inform FAA regulations and industry standards addressing a single person or multiple people and multiple UAS operations.

These systems require potentially multiple human roles, where the the autonomous and semi-autonomous UAVs' primary flight phases are supervised by the humans [1]. The autonomy embedded within the control station and the vehicles supports the human supervisor(s) [2]. As a supervisor supported by autonomy, a person can define the mission goal, specify constraints and parameters that impact meeting the mission objectives, plan the mission, monitor the (semi-)autonomous system and the mission environment, detect degraded performance and failures, and make necessary adjustments [1–4]. This document uses the term *supervisor* to differentiate this supervisory role, rather than the term pilot. This literature review is designed to (1) inform ASSURE researchers and FAA sponsors on findings from published studies and (2) identify research gaps that are outside the scope of this project, but need further study in order to safely integrate multiple UAS operations into the National Airspace System (NAS).

2 Literature Identification

The identification of the relevant literature related to the pilot proficiency requirements for a supervisor engaged in multiple UAS operations required identifying appropriate search terminology, as shown in Table 1. The search terms focused on the type of vehicle (the *UAS* terms), on multiple vehicles (the *group* terms), and on the human serving as the supervisor (the *interaction* terms).

Table 1: Literature review search terms by category.

UAS	**Group**	**Interaction**
Autonomous micro air vehicle	Cooperative	Human-autonomy teaming
Remotely piloted aircraft	Coordinating	Human-robot teaming
Remotely piloted vehicle	Distributed	Human-swarm interaction
Uninhabited air vehicle	Multi	Multiple robot control
Unmanned aerial system	Multiple	Multiple robot control
Unmanned aerial vehicle	Swarm	Multi-robot coalition
Unmanned aircraft		Multi-robot teams

The manuscripts were required to meet explicit review criteria. The basic criteria required manuscripts written in English that appeared in peer reviewed or high quality sources between 2010 and 2020. Manuscripts were excluded if they did not provide sufficient detail (e.g., lacked a detailed experimental methodology) or contained errors (e.g., inconsistent results). The manuscript evaluations were required to focus on human performance; thus, those that failed to do so for any reason, including not reporting experimental results related to human performance, were excluded. Manuscripts were also excluded if the mission or task focus was not relevant, such as the human not directly controlling or supervising at least one UAS. The most relevant literature sources focus on human factors and robotics sources. A summary of the publication sources for the included manuscripts is provided in Table 2.

3 Review Results

This section highlights the findings from the reviewed manuscripts. The findings are organized to help inform regulations and research gaps for M:N UAV systems. The first subsection addresses the methodological approaches employed in the studies to help to identify the fidelity of the work. The second subsection highlights the types of evaluation measures used in the reviewed literature, including characterizing them as objective or subjective and whether they can help to measure aviation safety, as well as human's capability, efficiency, and productivity. The third subsection addresses a set of results related to the human specific characteristics that can help to define requirements for training and certification, followed by a subsection specifically focusing on training interventions for M:N UAV systems. The system and aircraft characteristics that can help to characterize the generalizability of the work with respect to architecture and sUAS heterogeneity is reviewed. The N component of M:N can range from two to many; thus, the sixth subsection addresses aircraft group characteristics. As M:N UAV systems may employ high levels of autonomy on the aircraft as well as within the control station, the seventh subsection focuses on autonomy and human-autonomy teaming, while the eighth subsection addresses control station characteristics. Finally, the missions and associated task characteristics that can inform research related procedures as well as scenario definition are addressed.

3.1 Methodological approaches

Considering different methodological approaches provides higher quality information and yields results that are more generalizable to the project's goals. For example, field tests in mission relevant contexts provides more directly applicable results than experiments in which the UAS's behaviors are emulated, called Wizard of Oz experiments. The vast majority of the included manuscripts were human-in-the-loop studies conducted using simulations that incorporate partial sets of required tasks, as shown in Table 3.

3.2 Evaluation measures

Gathering information that can inform regulations with respect to the humans' proficiency and training requirements, procedures, and control station requirements and guidelines for M:N systems requires understanding relevant evaluation measures, also called de-

Table 2: Manuscript sources

Publication	**Count**
ACM/IEEE Intl. Conf. on Human-Robot Interaction (HRI)	1
Cyber-Physical Systems	1
Ergonomics	2
Frontiers in Psychology	1
Human Factors	8
IEEE Access	1
IEEE Conf. on Control Technology and Applications (CCTA)	1
IEEE Intl. Conf. on Control, Automation and Systems	1
IEEE Intl. Conf. on Robot and Human Interactive Communication (RO-MAN)	1
IEEE Intl. Conf. on Robotics and Automation	3
IEEE Intl. Conf. on Systems, Man, and Cybernetics	1
IEEE Intl. Multi-Disciplinary Conf. on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)	1
IEEE Intl. Symposium on Distributed Autonomous Robotic Systems	1
IEEE Intl. Symposium on Safety, Security, and Rescue Robotics (SSRR)	1
IEEE Robotics & Automation Magazine	1
IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems	1
IEEE Trans. on Cybernetics	1
IEEE Trans. on Human-Machine Systems	5
IEEE Trans. on Robotics	1
IEEE Trans. on Systems, Man, and Cybernetics - Part A: Systems and Humans	3
Intl. Journal of Human-Computer Interaction	1
Intl. Journal of Human-Computer Studies	1
Journal of Cognitive Engineering and Decision Making	6
Journal of Experimental Psychology, Applied	1
Proc. of the American Control Conf.	3
Proc. of the Human Factors and Ergonomics Society Annual Meeting	38
Theoretical Issues in Ergonomics Science	2
Workshop on Research, Education and Development of Unmanned Aerial Systems (RED UAS)	1

pendent measures. Such measures need to support the assessment of aviation safety, the humans' capability, efficiency, and productivity [5]. The reviewed evaluations encompass a range of dependent measures related to human performance, where some were mission specific.

Measures specific to M:N systems and prediction of the human supervisor's capacity address fan-out (i.e., how many vehicles the human can supervise), neglect tolerance (i.e., amount of time a vehicle can run autonomously, before it needs human attention) [6] and associated delays in allocating attention to a vehicle [7]. Vehicle or asset idle time is a related

Table 3: Methodological approaches.

Type	Count
HITL or usability evaluation	76
Computational Model or simulation	7
Field study or demonstration	4
Interview or survey	2
Operational concept	2

measure of efficiency [8–10] in which untasked vehicles indicated human supervisor overload. For example, Donmez et al. [11] investigated human attention inefficiencies in relationship to the human's busy time, a measure that can serve as a surrogate for workload. The model was validated with data from an experiment in which the participants supervised homogeneous and heterogeneous teams of five vehicles. The *no heterogeneity* condition led to the highest vehicle utilization, while the *high heterogeneity* condition was the lowest. Neglect times increased and interaction times decreased as heterogeneity increased.

Many of the reviewed evaluations addressed accuracy [8, 12–42] and related signal detection measures, including detection or hit rate, correct rejection rate, false alarms, sensitivity, and response bias [11, 35, 42–45]. Only five evaluations addressed safety: vehicle to vehicle damage and vehicle to hazard damage [46, 47], UAS loss [34], time of safety violation condition [8], and airspace related violations (i.e., entering of "no fly" zones) [48]. Human supervisors may employ a speed-accuracy tradeoff and several evaluations considered efficiency measures, including response or task completion time [8,13–19,22–25,30–34,36,39,45,49–59]. Some researchers incorporate neurophysiological, physiological [29,30,60–63], and behavioral sensors [30, 60, 64] to measure workload load objectively. An important aspect of using such metrics is foundational research that established correlations between these objective and the subjective workload metrics specifically in the context of unmanned systems [65–68]. The accuracy and reliability of physiological and behavior objective metrics (i.e., heart rate variability, heart rate, respiration rate, posture vector magnitude, skin temperature, speech rate, number of sentence fragments, number of speech false starts, speech filler utterances, utterance lengths, noise level, postural load, task density, task switches, interruptions, and secondary task failure rates) were established for humans serving as a supervisor or a peer with unmanned systems [65–67]. This effort compared the objective metrics to common subjective metrics, such as NASA TLX. A complete review of the common objective workload metrics also incorporated fNRS, EEG, and eye tracking based metrics [68].

NASA TLX was assessed relative to eye tracking (i.e., pupil diameter, fixation duration and fixation count) [69] and the results found a correlation with existing findings [68]. Eye-tracking metrics require a dedicated interface or environment for which focal points can be established, and are difficult to use in outdoor real-world deployments due to the fundamental eye tracking technology limitations. A follow-on effort [56] hypothesized that increased transparency of the autonomy's reasoning will decrease workload. The results did not identify an effect of transparency level on workload for fixation duration, pupil diameter, saccadic amplitude, and saccade duration. However, an interaction effect was found for spatial visualization ability (i.e., mental rotation of objects) and transparency level on fixation duration and a main effect of spatial orientation ability (i.e., reorientation of an environment) on pupil diameter. The longer fixation durations may be due to increased information processing time when making allocation decisions. A larger number of UAVs (16) were incorporated into a study focused on searching an environment under four taskloads [33]. Eye tracking metrics were used to investigate how fixation duration, spread metrics (i.e., fixation point convex hull area, gaze point spatial density and area of interest stationary entropy) and direction metrics (i.e., saccade amplitude, scanpath length, saccade backtrack rate, grid cell transi- tion rate, and transition entropy) change with performance. An effect of task load level on spatial density and stationary entropy was identified. There were significant effects of task load type on the directional saccade amplitude, scanpath length per second, transition rate, and transition entropy metrics.

Eye gaze and EEG signals (i.e., alpha band (7.5Hz-12Hz), omega band (4Hz-7.5Hz)) were used to measure cognitive load [60]. An evaluation that manipulated task load (i.e., the UAVs' speed) and the level of manual control [30] used two derived measures: one for mental workload, a proxy for working memory load and cognitive processing based on a linear Discriminant Function Analysis trained on processed EEG signals; and distraction level, the inability of a subject to maintain passive attention. The study, in which two UAVs were managed for a target detect and identify task, also incorporated three eye tracking related measures: fixation rate (i.e., fixations within one second time windows), glance ratio (i.e., percent of time glances are within an area of interest), and pupil size. The manual control condition exhibited indications of higher attention demand based on EEG workload, fixation rate and pupil size. Regarding the EEG features, there was a significant main effect of manual control level on the mental workload and distraction level as well as task load on the distraction level.

Stress was manipulated in a simulated multi-tasking environment (i.e., allocating vehicles to target locations, imaging the area, monitoring vehicle health and avoiding hazardous areas) by increasing cognitive demand and providing negative performance feedback [29]. The dependent measures included: NASA-TLX workload, stress response measures and physiological responses from EEG (i.e., theta (4–8 Hz), alpha (9–13 Hz), beta (14–30 Hz), and gamma (30–100 Hz) bandwidths), ECG (i.e., mean inter-beat interval and heart rate variability), fNIR (i.e., hemodynamic changes in the prefrontal cortex) and Transcranial Doppler Sonography (i.e., cerebral blood flow velocity in the left and right hemisphere middle cerebral arteries). The stress manipulations increased EEG and heart rate variability, and were associated with higher workload, with a stronger effect for the cognitive demand manipulation.

Overall workload was measured using a multi-dimensional construct that measured cognitive, visual, speech, auditory and physical workload for humans serving as a supervisor as well as a peer to the associated UAV or ground robot [61]. This multi-dimensional workload approach incorporates multiple sensing modalities, such as ECG (e.g., heart rate variability), IMU (e.g., posture magnitude), and environmental noise [62] to measure each workload component and overall workload. The system was extended to incorporate real-time detection of speech workload metrics [64]. This system detects changes in the human's overall workload, as well as the workload components in order to intelligently adapt either the interaction or the system autonomy level in real time [62]. Current efforts are incorporating eye tracking to better assess visual workload and a decomposition of physical workload into the gross motor, fine motor and tactile workload components.

The reviewed evaluations predominately incorporated subjective performance and usability measures. The most frequent measure was perceived workload measured via NASA-TLX [70] (i.e., [12, 18–20, 24, 26–29, 38, 39, 41–43, 47, 50, 54–59, 69, 71–78]) and other common measurements [9, 14–17, 21, 36, 49, 54, 79]. A few evaluations employed related workload measures, such as perceived task difficulty [13, 15, 17, 31, 49, 74] and level of busyness [21, 79, 80]. While subjective workload metrics (e.g., NASA TLX) are very easy to use, they suffer from the common issues associated with any subjective metric (e.g., dependence on post-trial memory recall, individual response bias). NASA TLX is often believed to be a very good measure of workload, and while its metric scales capture the breadth of representative workload factors, the results obtained using it often are not representative of true workload. Subjective metrics are typically assessed after a trial and often, either for trials that are too short to truly impact the human's workload or are so long they incorporate different levels of workload, which cannot be captured by a post-trial subjective assessment tool. Therefore, it is important to use objective workload assessment metrics that more accurately and reli- ably assess workload, either by showing no difference in very short trials or clearly measure workload shifts during longer trials.

Trust in, and relative to the usage of the autonomy were measured in several studies [16, 17, 21, 25, 36, 39, 45, 49, 56, 73] using variants of Jian, Bisantz, Drury's [81] trust scale, while other studies [19, 24, 47, 48, 50, 77] used other instruments. Additional, subjective trust measures assessed compliance with the autonomy [40, 41, 47, 82], reliance on the automation [25, 27, 28, 40, 82], competence, faith in the system and perceived reliability [40, 50], among others.

Situation awareness was the third most common measure. The most common situation awareness assessment methods were subjective and include the Situation Awareness Global Assessment Technique (SAGAT) [83] (e.g., [50]), SA Rating Technique (SART) [84] (e.g., [9,24,36,54,77]) and other types of queries (e.g., [12,18,19,36,42,69,72]). Situation awareness probes, based on common subjective metrics can be collected more frequently during an evaluation without freezing the screen and causing potential issues with cognitive dissonance with regard to UAV capabilities [48]. An objective eye tracking-based measure of situation awareness was proposed [30] that measures the amount of time the user did not fixate on new visual information. Some evaluations did not specify the exact situation awareness assessment method (e.g., [15–17, 49, 79]).

Design and usability measures were employed to address algorithm parameters as well as control and display design. Objective measures addressed interaction input (i.e., keystrokes and mouse inputs, including hovering characteristics) [18, 20, 46, 54, 85] and physical input, such as required controlled forces [53] and position tracking [86, 87]. Calhoun and colleagues used adequacy of autonomy feedback [17,48, 49,79] and impact of autonomy on performance [16, 17, 49, 79]. Specific usability measures included perceived overall usability [45, 56, 59, 75, 88,89], ease of use [19,38,72,89,90], preference [31,37,44,48,59], interaction modality [20] and comfort [90]. Different types of self assessment measures were considered, including perceived task performance/accuracy [13, 16, 17, 21, 31, 37, 48, 49, 79, 80], subjective task certainty [37], perceived speed [31], self-confidence [14, 21, 24, 37, 38, 80], perceived understanding [37], and perceived responsibility for accurate performance [38].

While subjective measurement of relevant human factors issues can provide useful insight into general task perceptions, the over-reliance on subjective assessments of human factors poses a pressing challenge to effective evaluation of humans' needs in M:N UAV systems. For example, while subjective workload measures, like the NASA-TLX, often correlate with overall perceptions of a task, the fact that such assessments take place post-hoc (i.e., after task completion) and are temporally decoupled from explicit task components, makes it especially difficult to appreciate with any confidence what task components specifically drive any changes in the measures. In other words, while it is possible to detect higher degrees of workload, it is often very difficult to determine exactly what specific aspect of the task or environment may be driving the changes in workload (e.g., overload or under- load), which is naturally important for workflow optimization. This outcome is perhaps endemic of a common disconnect observed in the literature; studies often fail to simultane- ously measure objective task performance (e.g., mission time, errors) measures concurrently with subjective measurements (e.g., trust in autonomy, situational awareness or even per- ceived competency/efficacy). The omission of more objective performance criteria makes it difficult to appreciate how subjective perceptions conceptually link to, and inform, actual task completion, which becomes especially problematic when considering individual human performance differences. It is necessary to anchor subjective assessments to objective differences in performance, otherwise it becomes nearly impossible to determine whether any differences in these subjective estimates are (1) a function of user competency, or (2) driven by other more broad reactions to the task environment. Further, given the very performance driven nature of M:N UAV system domains (e.g., package delivery), it crucial to capture objective measures so that the regulatory guidance can be validated more consistently.

3.3 Human characteristics

The requirements for training and certification for M:N UAV systems are understudied. The types of individuals who will be ideal for M:N UAV operations in domains, such as package delivery, may differ significantly from current UAS supervisors engaged in domains, such as homeland security. Thus, developing M:N UAV systems' regulations for supervisor proficiency and training requires considering a range of human characteristics and associated measures. This section's findings are related to these characteristics, where performance may be enhanced or diminished due to individual differences.

3.3.1 Experience demographics

Obtaining a remote pilot certification for a single UAS requires knowledge evaluated per the requirements in 14 CFR Part 107.73 [91]. An open research question is whether the humans in M:N systems require the same level of piloting knowledge, less knowledge, or a different set of knowledge. Two evaluations mentioned unmanned vehicle experience: one reported participants with UAS experience [8]; another reported some robotics experience [37].

Generally, the multiple UAS HITLs participants did not have 14 CFR Part 107.73 certification, nor any traditional piloting or other related aviation experience. Participants were frequently students [10, 12, 20, 24, 27–30, 32–36, 39–41, 44, 45, 52, 54, 56–58, 63, 71, 76, 80, 92], or were reported as either having no pilot experience [79] or their experience was unspecified [19, 21, 25, 59, 82]. Additional manuscripts reported participants with no robot control experience [26,42,55,69], computer users [47,78], or having various backgrounds with no unmanned aircraft experience [50]. Even when the participant pools were composed of military affiliated personnel, they reported no piloting experience [9,16,17,31,38], with the exception of [13].

As the minimum autonomy requirements for the vehicles as well as the control station are undefined, it continues to be unclear what traditional piloting experience the supervisors of N UAVs require. The proficiency requirements may be related to a large number of factors, thus, it will be important to determine whether the current literature findings with the current set of participants are relevant.

3.3.2 Gender differences

The FAA predicts that the growth in the commercial UAS sector will continue [93]. Females held only 6.8% (10,818) of the 160,302 remote pilot certificates in 2019, [94]. It is unclear whether this trend will continue and whether any potential changes in gender demographics will impact the sector.

Each study tends to include more male participants. 61 studies reported participants' gender, of which four were gender balanced and 36 included more male than female participants. Relatively few studies analyzed the influence of gender for multiple UAV systems. Video game experience and gender were investigated as predictors of stress and perfor- mance [27] in an evaluation that explored the effect of workload and Level of Autonomy (LOA) on participants' performance using a simulated multiple UAV supervisory control station. Gender differences were not evident when the analysis was controlled for gaming experience.

An important consideration is whether the FAA and industry need to be actively working to increase the number of females seeking UAV pilot certificates. Further, analysis of such systems by the research community needs to ensure more balanced participant pools that accurately reflect the anticipated workforce pools.

3.3.3 Visual skills

Visual search and multiple object tracking are two visual skills that are important to target detection, situation awareness, and reaction time [95]. An evaluation in which two UASs were tasked to detect geometrical objects measured individual differences in visual search and multiple object tracking skills [30]. The independent variables were task types (i.e., visual scanning and manual control tasks) and task-load (i.e., video stream speed was higher or lower). Performance was evaluated using target detection, false detection, and reaction time measures and situation awareness was calculated using eye tracking data. However, humans visually perceive very large numbers of individual entities (100) differently. Visualization design for unmanned swarms was informed by a visual multiple object tracking evaluation that required humans to track the movements of data collected from biological fish swarms [96]. Participants did not visually perceive the individual swarm members, but rather the overall swarm's movements.

While participants with better visual search skills had significantly higher target detection rates and those with better multiple object tracking skills had significantly higher situation awareness for two vehicles, these results will not generalize to systems with larger numbers of UAVs. As the number of vehicles increases, humans' visual performance will change.

3.3.4 Video game experience

Video game experience is often presumed to positively influence the ability to successfully complete tasks for multiple UASs or multiple vehicle control. Experienced gamers were found to have better visuospatial attention skills than trained pilots, but have similar aircraft control skills [97]. Additional results [98] indicate that playing action games can impact sensory, perceptual, and attentional abilities, which are important for many spatial cognition tasks and likely M:N systems.

Generally, individuals with video game experience exhibit better performance and situation awareness in multiple vehicle control experiments. The participants tend to provide better subjective measures, such as perceived lower workload and higher trust in the autonomy, particularly in higher taskload environments. For example, Chen and Barnes [19] investigated participants supervising a team of ground robots with autonomy of varying reliability levels. Video gaming experience was associated with overall multitasking performance. When supported by an autonomous system, frequent video game players had significantly better perceived situation awareness than infrequent gamers. Also frequent video gamers' subjective workload assessments were significantly lower than those of infrequent gamers.

Performance benefits were identified based on video game experience for a three vehicle convoy mission [42], where gamers had higher situation awareness scores than non-gamers. Additionally, non-gamers had a liberal response bias (i.e., more likely to respond that there was a target during a target detection task). This difference in decision strategy, as a function of video game experience warrants further investigation as non-gamers may be compensating for their lack of spatial awareness or experience.

Surveillance will be a common M:N UAV system task. Video gaming expertise was correlated with performance for a surveillance task (i.e., weapon release) [27]. First-person shooter game experience predicted post-task engagement. Participants with more action game and first-person shooter game experience were more accurate, relied more on the autonomy, and exhibited less task neglect. Those participants with video game experience also trusted the autonomy more during higher task load conditions, and experienced lower stress and worry.

A multiple unmanned experimental vehicle planning task was used to examine the level of information necessary to create an effective and transparent interface that supports human-agent teaming [56]. The results showed that gamers did have faster response times, but this was confounded with other demographics.

Video game experience appears to play an important role in human performance and while this is an important finding, a gap is identifying the unique aspects of gaming experience that may benefit future human roles in M:N UAV systems. Open questions include: do gamers possess unique individual differences and what can future humans serving in the various M:N system roles, including supervisors, learn via training that permits them to be as proficient as gamers?

3.3.5 Spatial ability

Spatial awareness impacts overall aviation safety, as humans need to consider the relative locations of objects in the environment [99]. Thus, high spatial awareness may be a critical differentiator when selecting individuals human supervisory roles in M:N UAV systems.

Benefits were found for individuals controlling multiple vehicles who had better spatial ability scores as measured using tests, such as the Cube Comparison Test [100] and the Spatial Orientation Test [101]. Participants with higher spatial ability detected more targets when using robots with varying autonomous navigation reliability levels. Participants with better spatial ability also interacted more with the video feed interface than participants with lower spatial ability [19], which may indicate more effective scanning performance or capacity to consider additional visual information. While supervising a three-vehicle convoy, where autonomy fully supported the vehicles' spacing task and partially supported route planning, participants with higher spatial ability maintained higher situation awareness than those with low spatial ability [42]. Autonomy was able to improve the performance of participants with lower spatial ability. The autonomy assistance helped participants with low spatial ability, including improving their situation awareness and increasing their sensitivity during a target detection task.

Spatial ability is tied to better performance for tasks relevant to M:N UAV system operations. Additionally, it appears possible that autonomy may raise the performance floor for those with lower spatial ability. Thus, two considerations are warranted: 1) selection of personnel based on spatial ability and 2) the autonomy requirements necessary to support personnel with lower spatial ability.

3.3.6 Working memory

Working memory capacity can predict performance in many complex tasks, which may provide guidance when selecting individuals for M:N UAV system roles. It is well established across domains that working memory capacity reflects differences in the capacity to control attention with both automatic and controlled processes [102]. The reviewed literature indicates benefits of higher working memory capacity for multiple vehicle control. de Visser, Shaw, Mohamed-Ameen, and Parasuraman [52] studied working memory differences as impacted by the effects of taskload and relevant message traffic for 1:N UAVs system performance. working memory capacity was measured using Operation Span [103], which showed that eight vehicles can be monitored relatively successfully, albeit less so in higher taskload conditions.

An investigation of participants engaged in a multiple unmanned experimental vehicle planning task examined the level of information necessary to create an effective and transparent interface to support human-agent teaming [56]. Participants completed the operation span task [104], and those with higher working memory capacity had the best performance with respect to autonomy usage with an interface that had low transparency.

Panganiban and Matthews [76] conducted a study where the goal was to supervise three or six UASs to search for as many targets as possible while avoiding hazardous regions. The participants also updated a set of information held in working memory, such as a letter (i.e., Letter Memory task) or a word (i.e., Keep Track task). Participants received neutral or negative feedback regarding their performance. The ability for executive functioning, which is a critical component of working memory capacity, was measured using inhibition, switching, and updating to predict UAS supervisor performance and subjective state under stress [76]. High letter memory was associated with better performance, as measured by the command ratio (i.e., total number of target engagements divided by the number of target assignments), regardless of taskload.

Better team working memory scores were associated with superior team performance when taskload and the reliability of an autonomous decision aid's message traffic was manipulated using a multiple UASs simulation for an air defense task [92]. Thus, a participant's working memory, even when considered in combination with another team member, can enhance overall human-system performance for a supervisory control task.

Given the multi-tasking nature of M:N systems, further investigation is required regarding the impact of working memory capacity on the humans serving in the various M:N system roles, particularly supervisor selection criteria. Control station information requirements and display design recommendations need to consider how to reduce the need for superior working memory capacity.

3.3.7 Perceived attentional control and directed attention

Attentional control helps to avoid distraction and is, therefore, critical to supporting multi-tasking. Few multiple UASs studies address participants' perceived attentional control. The reviewed literature showed that participants with higher perceived attentional control measured using tests, such as the Attentional Control Survey [105], exhibited better overall multi-tasking performance.

Participants using autonomy with low reliability, who also had low attentional control, appeared to be unable to allocate as much attention to all parts of the tasking environment [19]. While performing an automated route editing task, participants with high perceived attentional control outperformed those with lower control during the low reliability miss prone autonomy condition. This result may indicate differences in the ability to detect changes [35], [44], [79].

A study that incorporated differing levels of autonomy when managing a three-vehicle convoy found that participants with lower attentional control experienced higher perceived workload than those with higher attentional control [42]. The lower attentional control participants also exhibited a liberal response bias in the target detection task, perhaps compensating for being overloaded. This interaction of individual differences and individual decision strategies/response bias warrants investigation.

The over-use of autonomy in supervisory control systems can induce boredom. Cycli- cal attention switching strategies were investigated in low task load scenarios [80]. This study determined that boredom proneness [106] was not a major factor affecting partici- pants' performance; however, an intervention with alerts and task switching was developed. The interventions supported sustained directed attention for supervisory control of multi- ple UASs. While the alerts were found to support distracted supervisors for a considerable amount of time, they may be unable to sustain directed attention for prolonged periods. This result may impact control station design and help to characterize the need for personalized alerting schemes.

There are well known issues associated with divided attention. Thus, the M:N UAV system control station requirements need to consider specification of information elements. Further, the recommended design guidance needs to address attentional demand to ensure that it does not overburden this cognitive system.

3.3.8 Vigilance

Vigilance (i.e., the need to focus attention over prolonged periods of time), and associated vigilance decrements (i.e., any performance decline due to having to complete a task over time) are important topics with regard to supervisory control tasks. Fatigue, one of the causes of vigilance decrements, has been an issue in aviation for traditional manned pilots and UAS crew members for decades [107–110]. High levels of fatigue can lead to task disengagement in addition to vigilance decrements. The introduction of autonomy can impact fatigue, as evidenced by findings with driving tasks [111]. The required autonomy necessary for supervisory control in M:N UAV systems will likely have direct implications on the human supervisor's fatigue and vigilance decrements.

Recent studies that aimed to examine sustained performance and fatigue in multiple UASs tasks required participants to maintain performance for more than thirty minutes [40, 41]. The vigilance decrements were greater for a more difficult surveillance (i.e., vigilance) task, especially when the autonomy was less reliable. However, with low reliability, participants' performance was stable for close to 45 minutes. Performance recovered near the end of the two-hour session, perhaps due to a motivational factor of anticipating the end of the experimental session. The delayed onset of the vigilance decrement is promising for UAS surveillance tasks and needs to be replicated in a more ecologically valid environment. The Sleep, Activity, Fatigue, and Task Effectiveness [112] model was used to develop a queue-based model of human supervisor fatigue while supervising autonomous vehicles over a ten-hour shift composed of fixed shifts (i.e., human supervisors work fixed shifts and all staff are replaced at shift changes) and staggered shifts (i.e., supervisors start and end at different times, thus becoming more fatigued at different times) [113]. The human supervisors were modeled as either working jointly (a multiserver queue) or separately (separate single server queues). Higher supervisor-to-vehicle ratios were achieved when any supervisor was able to supervise any vehicle as compared to a single-server queuing model Staggered shifts mitigated the impact of human supervisor fatigue. There are a number of limitations to these results. First, the analysis only included nominal conditions, and it is well known that off-nominal conditions will impact fatigue. This analysis also did not consider the human supervisor's ability to maintain situation awareness, which will also impact fatigue levels. Finally, this analysis did not include two important factors, shift breaks, which are known to mitigate fatigue, individual fatigue levels at shift start and individual circadian rhythm differences.

Managing vigilance and fatigue levels represent important factors in the design of M:N UAV system control stations. These factors will also be central to the scheduling of the human supervisors.

3.3.9 Stress

Prolonged performance of demanding vigilance tasks is hypothesized to tap attentional resources leading to an increase in extreme stress, or distress [114]. Distress may lead humans to rely more on decision support tools and related autonomy. Thus, researchers have investigated how stress can impact supervisory control of multiple UASs.

Participants engaged with a multiple task UAS simulation where two surveillance tasks were of higher priority and supported by autonomy [28]. Higher task demands impaired participants' surveillance task accuracy, increased neglect, while elevating stress and perceived workload. High demands increased task engagement in conscientious participants, and yielded higher correlations between stress and lower task accuracy as well as between task engagement and lower neglect. Distress correlated negatively with dependence on autonomy, perhaps because integrating the autonomy's recommendation created an additional task demand [115]. Neuroticism was positively correlated with distress, where those with higher neuroticism achieved higher accuracy for the more demanding surveillance task while under high task demand.

Two evaluations investigated the relationship between dispositional worry, metacognition, resilience, and stress responses when operating multiple UASs for reconnaissance and surveillance tasks [29] [76]. Traits associated with resilience predicted subjective and physiological responses to negative feedback and cognitive demand stressors in a simulation with two and six UASs. Worry traits, such as meta-worry, were generally associated with higher levels of situational stress, whereas hardiness and grit appeared to be protective. The Anxious Thoughts Inventory [116] measures were generally associated with higher state worry.

It is unclear how the impact of stress will change as the number of vehicles increases. These studies incorporated a very small number of vehicles, especially relative to the number of vehicles a human supervisor is predicted to supervise in some domains, such as package delivery. The implications of M:N UAV System task characteristics on human supervisor stress will be important considerations for the development of effective multiple UAS autonomy and control stations.

3.3.10 Resilience

There has been limited research with respect to psychological traits of perseverance for M:N UAV System applications. It is unclear whether the various challenges of UAS operation and traits for resilience predict objective performance as well as subjective responses. A simulator-based study found that assessment and prediction of resilience may be useful for assessment in training programs and evaluation of fitness to cope with stress in the mission context [29]. The results showed that hardiness and grit correlated negatively with the Anxious Thoughts Inventory worry scales, which indicates that maladaptive metacognitive style may impair development of a resilient personality.

The literature lacks reliable and repeatable measures of resilience. The development of such measures is needed in order to better characterize what impacts resilience and can realistically be assessed, particularly in relation to the impacts on human performance for M:N systems.

3.3.11 Culture

As the UAS industry grows, the demographics of the M humans will likely shift to include a broader set of individuals from more diverse cultures. There have been few cross- cultural studies in the domain of supervisory control of M:N systems. Chien and colleagues [47] investigated the effects of transparency, by culture, with respect to readiness to trust autonomy, and the degree of transparency required to use an autonomous path planner. Using participants from different cultures, the experiment varied transparency and the degree of autonomy, while assessing the willingness to use systems with high degrees of autonomy. Participants from a face culture (i.e., where one's dignity and prestige is derived in terms of one's social relationships [117]) exhibited bias by accepting recommendations from the autonomy, whereas those from dignity (i.e., one's self-worth is derived internally) and honor (i.e., self-worth is dependent on interactions with others and one's perception of self) cultures were less likely to trust or accept recommendations on this basis.

As more autonomy is incorporated into unmanned aircraft and their associated ground control stations, it is prudent to include participants from different cultures who may exhibit a range of responses with respect to autonomous system behaviors. Also, few training interventions exist that consider cross-cultural issues, which may be important for ensuring good training outcomes.

3.4 Training

The literature includes few studies focused on training for supervisory control of M:N systems. The need for additional research regarding redesigning training to accommodate new task requirements in the presence of increased autonomy has been noted [8]. The authors investigated the impact of including or removing control device training. The exper- imental design considered combinations of the presence or absence of unreliable automated target recognition autonomy that assisted with imagery search tasks and skill-based trackball training: a) Skill-based trackball training with automated target recognition, b) Skill-based trackball training without automated target recognition, and c) automated target recognition without skill-based training. Participants with no automated target recognition autonomy panned and zoomed more to find targets than those who used the automated target recognition autonomy. Thus, the impact of the device training may manifest as a critical factor for human supervisor performance. The lack of skill-based training with the control device did not affect the target search time. However, what device training needs to be required for autonomous, or semi-autonomous tasks is an open question.

There is an increasing need for the FAA to standardize training requirements [118]; however, the only existing training knowledge requirements for single UAS control are specified in 14 CFR Part 107.73 [91]. Studies that investigate the trade-offs between training, additional autonomous capabilities for the UAS and in the control station, as well as fundamental control station design are warranted.

3.5 System architecture and aircraft characteristics

The FAA develops system architecture and aircraft related regulations to ensure public safety as well as the safety and efficiency of the United State's national airspace. For example, the final remote identification of unmanned aircraft rule [119] recently modified the 14 CFR Part 107 rule. The final rule for operation of sUAS over people [120] recently modified the 14 CFR Part 107 requirements by including provisions for operations at night. These final rules mandated equipment, UAS design and production, as well as other requirements relevant to system architecture and aircraft characteristics. Similarly, additional system and aircraft related regulations may also be required for M:N UAV system operations.

Most of the reviewed HITLs used simulations that did not model realistic aircraft control and dynamics, nor did they include algorithms and displays validated in field studies. The one exception is provided by Clare, Cummings, and Repenning [21]. The on-board planning system for unmanned vehicles supporting expeditionary reconnaissance and surveillance [121] was the computer simulation. These decision support displays allowed participants to operate small unmanned air and ground vehicles in real time [122].

The predominate simulation based evaluations do not provide high degrees of ecological validity and the necessary generalizability needed for real world M:N UAV system applications. The aircraft, the control stations, the associated autonomous capabilities, and the environments have been idealized.

3.6 Aircraft group characteristics

CFR 14 Part 107 does not restrict the types of sUAS an individual can fly. M:N systems may be composed of homogeneous vehicles or may be heterogeneous. Heterogeneous M:N systems may incorporate combinations of fixed winged and multi-rotor UAS models, UAS with differing sensor and actuator payloads, as well as combinations of propulsion types from different manufacturers. Heterogeneous systems, irrespective of aircraft performance may add significant additional complexity to the human supervisors' tasks.

The simulated vehicle types in the reviewed HITLs included single UAS, homogeneous groups of UASs, unmanned ground vehicle systems, computer agents, simulated spaceships groups, as well as heterogeneous groups composed of three different vehicle types (e.g., one study used a UAS, unmanned ground vehicle and manned ground vehicle, while another incorporated a humanoid robot, sUAS and an unmanned ground vehicle), and an unmanned ground vehicle and an UAS pair. The group sizes span from two to twenty vehicles. Some of the studies did not address the unmanned systems control, but rather focused on the video feeds.

Several researchers included explicit changes to the number or type of agents supervised, either between trials or during a trial. An investigation into the effect of aircraft heterogeneity found that as the level of heterogeneity increased, the participants had fewer interactions with the vehicles, as measured by longer neglect time and shorter interaction periods [11]. A simulated military target tracking scenario evaluation that incorporated UAVs to serve as communication relays when the target moved out of the vehicles' communication range [51]. The roles of the homogeneous UAVs differed, requiring the human supervisor to manage the relay UAVs and the roving UAVs. A one relay-rover pair was compared to a two relay-rover pair with different relay task function allocations (i.e., manual relay vehicle positioning, management by consent LOA for relay navigation and fully autonomous relay navigation). Autonomous relay behaviors were necessary for the two relay-rover pairs. Moacdieh, Devlin, Jundi, and Riggs [33] studied the effects of workload transitions that were gradual and sudden. Participants simultaneously controlled and managed three to five UASs, 13-16 UASs, or a number of UASs that transitioned between the lower and higher group sizes. The response time during the target detection task was shorter and detection accuracy was higher with the lower number (three to five) of UASs.

Human supervisor performance for two adaptable autonomy configurations was evaluated by requiring participants to control one, two, three or four ground robots in a search and exploration mission [10]. The control modes were teleoperation, shared-control (i.e., supervisor sets a target point that the robot tries to reach it autonomously), and full autonomy (i.e., robot navigates autonomously, trying to maximize the explored area). The participants tended to use different control modes when supervising different numbers of robots. Participants almost always used the teleoperation mode when working with one robot, but relied primarily on shared control and sending parameters sequentially when working with three or four unmanned ground vehicles. Better mission performance was achieved with three robots. Chen and Barnes [19] manipulated the number of ground robots (i.e., four and eight robots) in order to understand the effects of autonomy reliability (i.e., false alarm vs. miss prone) on multitasking performance. Participants detected fewer targets, had poorer situation awareness, and reported higher perceived workload when completing the tasks with eight robots compared with four. During the miss prone condition, participants had lower detection rates, but better situation awareness scores, than during the false-alarm prone condition. The latter result was due to more frequent map scanning during the miss prone condition.

The effects of autonomy reliability and adaptive autonomy on human-system performance for different taskload levels were examined [24]. Participants supervised heterogeneous groups: a) two experimental unmanned vehicles and one UAS or b) four experimental unmanned vehicles and two UASs. Autonomy reliability varied from 30% (low) to 70% (medium) to 100% (high) during the autonomous target recognition task. A significant interaction existed between reliability and taskload. During the medium reliability condition, target detections increased as taskload increased, but detections decreased as taskload increased when using the low reliability autonomous target recognition. An important finding is that taskload, or span of control, can be influenced due to other factors, not simply the number of UASs. These other factors can include mission type, task difficulty, task-to-robot ratio, and autonomy reliability.

It was infeasible to make inferences about the number of vehicles for two evaluations in the multiple vehicle domain, because other parameters changed with the number of vehicles. Panganiban and Matthews [76] investigated whether measures (i.e., inhibition, switching, and updating) of executive functioning predict UAS supervisor performance and subjective state under stress in a simulated multiple UASs task environment. There were either a) three UASs, eight hazards, randomly expiring initial targets (between 60-90 seconds), and new targets that expired after 60 seconds, or b) six UASs, fourteen hazards, and short target expiration times, 45-60 seconds for initial targets and 45 second for subsequent targets. Command Ratio appeared sensitive to individual differences in executive functioning. An additional evaluation investigated the relationship between dispositional worry, metacognition, resilience, and stress responses when operating multiple UASs for reconnaissance and surveillance [29]. Using a similar design, there were either a) two UASs, nine hazards, fourteen targets, targets that expired after 60 seconds, and hazards that expired after 5 seconds, or b) six UASs, fourteen hazards, eighteen targets, targets (45 seconds expiration), and hazards (5 seconds expiration). Higher taskload significantly increased stress, situational uncontrollability, and subjective workload.

A varying number of cyber assets were used to investigate human performance and cognitive outcomes [9]. Participants controlled 4, 8, 12 or 16 computer agents using a set of commands, to monitor the progress and state of varying missions, and communicate with a mission commander to obtain permission to execute restricted commands. Participants struggled with the task independent of the number of agents, including the lowest level, four. It is unclear if a performance increase with a smaller number of agents exists, given the evaluation design.

These evaluations demonstrate that researchers tend to not systematically investigate varying the number of UASs. Additionally, few evaluations systematically investigate the effect of a mixed fleet of sUAS. The reviewed manuscripts make clear the importance of studying group size in the context of other factors.

3.7 Autonomy, human-autonomy teams, and human-autonomy interaction

Researchers have studied crew and staffing requirements in unmanned operations, but less so with respect to envisioned multiple UASs applications and related UASs' autonomy [123]. It is noted that 14 CFR Part 107 mentions operator roles, such as the remote pilot and "the person manipulating the flight controls of the small UAS," but these roles are not inclusive of all the anticipated human roles for M:N system deployments. M:N systems that incorporate more than a very small number of UASs will necessarily incorporate greater use of autonomous flight control and navigation as well as higher levels of autonomy. The human will serve in a more supervisory role. As such, "the person manipulating the flight controls of the small UAS" will either be a) the remote supervisor, b) the autonomy, or c) both. For example, sUASs flying in close proximity may employ cooperative methods to maintain separation autonomously without human oversight. While there is a significant body of research addressing different autonomous functions, associated level of autonomy, and human-autonomy related measures (e.g., [2, 56, 81, 88, 115, 124–155]), there are currently fewer manuscripts that specifically address human roles, including supervisory control, in M:N systems.

3.7.1 Human-robot team configuration

The overall organization and composition of the M:N team will be an important consideration for pilot proficiency requirements [156]. The span of more traditional human-robot interaction roles, from teleoperator to supervisor, will have to be considered for M:N UAV system integration into the national airspace. Further, new roles are likely to arise that will be domain specific or domain agnostic.

An important consideration for M:N systems will be a question of whether the assignment of UASs supervisors to operational tasks will be fixed, or whether such responsibilities change based on scheduling or other contexts. A team approach to supervisory control of M:N systems using a shared pool of human supervisors, based on call centers, was investigated [26, 55]. The approach incorporated a queue to allocate vehicles to a shared pool of human supervisors. The hypothesis was that this approach better used supervisors and managed workload; however, this strategy did not provide performance benefits over a dedicated assignment of supervisors. The assigned-robot condition supervisors planned paths and controlled twelve robots each. The diffusion of responsibility for the shared human supervisor pool actually led to performance decrements. For example, when robots were not clearly addressed by one supervisor, another did not automatically supervise it. It appears that M:N systems that incorporate teams of human supervisors require more specifically constrained roles and responsibilities.

The human supervisor and UASs roles can be assigned by multi-agent planning and scheduling algorithms that account for expected human performance [157]. The humans were modeled as dynamic agents with an associated likelihood of the human making a correct decisions when allocating tasks between the human and the UAVs.

These examples highlight the need to investigate assignment strategies as well as the necessary procedures and training when selecting UASs to human supervisor assignment methodologies, especially if the assignments vary with time or task demand. Unlike queuing models with independent tasks, explicit mechanisms for assigning robots to human supervi- sors are needed.

While the human-robot interaction community has continued to develop metrics, some specific to assessing human to robot (i.e., M:N) ratios [156], there are no concrete algorithms or formulas that accurately predict that ratio by capturing the complexity of systems, the contingencies that can arise, and the levels of autonomy. However, the literature demonstrates that given certain scenarios and control capabilities, human supervisors were able to control approximately ten robots in a simulated first response environment [158]. The shared human supervisor pool condition, where supervisors were added without assigning robots, had fewer (eight) robots controlled, on average. This decrement was attributed to diffusion of responsibility, a cost of human-to-human coordination. Viewed from a broader perspective, none of this prior research supports claims as to a safe humans-to-UASs ratio, regardless of whether the assignment of UASs to human supervisors is fixed or flexible.

3.7.2 Autonomy

Supervisory control of M:N UAV systems requires autonomy. Many of the HITLs focused on the use of different forms and mixes of information analysis, decision alternative generation, decision selection, and decision execution autonomy integrated into the control station to support the human supervisor's tasks. There has been less emphasis on the aircraft's required autonomy.

Some HITLs focused on what level of autonomy is needed to support each task, including whether the level of autonomy (LOA) was static or flexible. If the LOA is flexible, then the research questions considered whether the human supervisor control of the autonomy changes, or are *adaptable* (e.g., [88]), or whether the system changes the level based on context, such as human supervisor taskload or performance, which is referred to as *adaptive autonomy* (e.g., [49]). Adaptable autonomy allows the user to tailor the level of autonomy, while adaptive autonomy uses parameters, such as the human supervisor's performance or other context, to change the autonomy level. The adaptive autonomy design must consider the threshold for adaptivity and setting it accurately to determine how best to balance workload and performance [17].

A human supervisor's ability to detect changes in the system state is critical. The act of delegating LOAs may improve situation awareness, especially with regard to unexpected events. While change blindness may be mitigated by interventions (e.g., [35]) focusing the human supervisor directly on system operations may better support performance.

Calhoun, Ruff, Behymer, and Frost [159] present design considerations and an interface paradigm for supporting human-autonomy teaming for air, ground, and surface unmanned vehices that support unmanned vehicle management using an adaptable autonomy control scheme [160]. The Playbook® concept supports human-autonomy communication and teaming by developing generalized plays representing more complex actions, inclusive of execution instructions (e.g., asset allocation, and routing) that a human supervisor can issue as is (i.e., default parameters) or can customize to the current situation [161–163]. The design processes included ecological interface design constructs, and generation of unmanned vehicle and task-related pictorial symbology (e.g., [13] and [31]).

Predefined autonomous robot behaviors are often brittle [32], which is an important consideration for the delegation-based control provided by the Playbook®. Plays are defined based on expected deployment conditions using default parameters, since uncertain environments will present unanticipated conditions. The human supervisor can adjust the plays' parameters to customize the play as needed [162]. Supporting the plays demands that some action and decision-making autonomy be delegated to intelligent subordinates. However, circumstances will arise for which the plays are not applicable, such circumstances are "non-optimal play environments," where the human supervisor must abandon play usage and rely on more primitive behavior commanding. The autonomy appeared to free cognitive resources during routine events, which may have improved situation awareness to support non-routine circumstances. The delegation-based control (i.e., play calling and adaptable autonomy) holds promise for supervisory control of M:N UAV systems, and may even provide benefits for cases when predefined plays do not exist.

Another set of research questions addressed LOA across synchronous and sequential tasks. Specifically, the LOA for concurrent tasks and sequential tasks needs to be considered as a joint design decision, as demonstrated via an investigation in which participants supervised three UASs [16]. The performance on both the primary tasks and many secondary tasks was better when the LOA was the same across the two sequential primary tasks, which implies that the LOA needs to be similar across closely coupled tasks in order to reduce mode awareness problems.

The literature review did not identify results that systematically automate the full range of activities that the human supervisor must attend to within M:N UAV systems. However, this finding is understandable given the breadth of UASs, their capabilities, and the complexity of M:N UAV systems with regard to size, task domains, and applications.

3.7.3 Reliable Autonomy and Trust in Autonomy

The reliability of autonomous systems has been a topic of general research for over a decade. Many of the questions related to validation and verification of autonomous systems are left unanswered and directly impact UASs. Perceived reliability of autonomy, and the subsequent trust placed in these autonomous systems, is particularly important given the need for autonomy to manage the high task demands of M:N UAV systems.

One concern is whether humans will even use less than perfect autonomy. A supervi- sory route planning task was used to evaluate compliance and reliance [82]. The results indicated relatively high compliance (i.e., above 60% and below 80%) and reliance rates (i.e., between 60% and 70%). Algorithms that generated paths similar to previous paths developed by the participant resulted in the highest compliance and reliance rates, while the lowest rates were recorded for paths that were very different from the participant generated paths. Hussein and colleagues [25] examined whether autonomy reliability or transparency can influence human reliance behavior (i.e., reliance rate and proper reliance) and mission performance. These scenarios required supervising twenty UASs executing image retrieval and object identification tasks. It was found that enhanced reliability of a supervisory control decision aid led to enhanced overall accuracy, but also increased human complacency and overtrust. Similarly, when using robots to detect information [20], lower system reliability resulted in participants making more camera selections, indicating that an unreliable system led to more active supervision of robot status and system performance. Naturally, this addi- tional supervision provided increased detection opportunities, but also had the unfortunate consequence of increasing workload, which may impact trust in autonomous systems.

Indeed, it has been found that taskload can interact with the degree of autonomy to impact trust. Prinet, Terhune, and Sarter [34] compared re-planning and target detection performance in supervisory control with multiple UASs that incorporated video feeds from nine UASs. The re-planning task was evaluated at three LOAs (i.e., manual, intermediate, full) where the autonomy was not perfectly reliable due to missing information, called partial observability. Re-planning and target detection performance was evaluated in low and high taskload conditions. The fully autonomous re-planning aid resulted in the fastest completion time and re-planning score, although the intermediate LOA was equivalent in terms of target detection. However, re-planning scores for the two autonomous conditions were highest when the taskload was also high. During the high workload conditions, the humans over-relied on the autonomy by choosing the first, or only option, without careful review. As such, more than half the participants trusted the manual mode most, and placed the intermediate mode third. The effects of task sequencing on workload, with differing LOAs, has also been investigated [16]. An early sequence of autonomous tasks may be favored by human supervisors and free them to focus on subsequent tasks. However, unreliable autonomy can also increase the human's workload required to monitor the autonomous behaviors, which can far outweigh any performance benefits. This finding suggests that design aids for facilitating monitoring of autonomous decisions are warranted.

Human's preferences for autonomy may also need to be considered when choosing a LOA. For example, participants who play computer and video games frequently had a higher propensity to overtrust autonomy [21], and a context-sensitive approach to choosing the LOA may realize the benefits of autonomy while avoiding its potential costs. Trust was manipulated in an evaluation during which participants guided an automated scheduler to create, modify and approve schedules for a team of UASs using positive priming, negative priming, or no comments about the automated scheduler [21]. Participants with computer and video game experience tended to overtrust the automated scheduler and when exposed to a positive priming intervention, they had fewer interactions to engage the autonomy. Priming gamers to lower their initial trust to a more appropriate level, the system performance improved by 10%, as compared to that of gamers who were primed to have higher trust in the autonomy. These results have implications for training as well as for personnel selection for supervisory control of M:N UAV systems. Priming during training and operations may help to overcome overtrust of autonomy.

The research suggests that placing humans in what are perceived to be either highly demanding or highly reliable autonomous situations can led to overtrust in these autonomous systems, which may negatively impact the ability of personnel to monitor and intervene in task duties when necessary. Conversely, unreliable systems lead to lower levels of trust, but often are accompanied with heightened levels of perceived workload to compensate for the unreliable autonomy. Trust in autonomy, particularly over- or undertrust is very important in M:N UAV system deployments. Overtrust in various domains has shown that people are out-of-the-loop and frequently unable to respond appropriately or quickly to incidents and off-nominal conditions from which the vehicle or system is unable to recover autonomously. At the other end of the spectrum is undertrust, which often results in humans micro-managing systems in ways that can lead to incidents.

3.8 Control station standards and guidelines

The final reports for projects A7 [164] and A10 [165], tasks CS-1 through CS-5 indicate a need to develop recommendations for minimum UAS control station standards and guidelines for single UAS systems, respectively. This need also exists for M:N UAV systems; however, it may be significantly more difficult to do so given broad differences in future multiple UASs capabilities and applications.

3.8.1 Information elements

The M:N UAV systems operational concept assumes the UASs' provided information will be presented at the control station. Thus, defining what information is to be available to the human supervisor is critical.

3.8.1.1 Minimum information requirements

Different efforts are developing information requirements for UAS control. Projects A7 [164] and A10 [165] as well as others [166] provided minimum information requirements for UAS tasks when controlling a single larger UAS. UAS Detect And Avoid (DAA) operations represent one of the more common autonomous behaviors.

The RTCA Special Committee 228 (SC-228) developed minimum operational performance standards for large UAS DAA system operation in the enroute flight phase. SC-228 adopted a quantitative definition of "well clear" and developed alerting criteria for DAA encounters and UAS pilot interaction with DAA systems [167], accommodating encounters with both cooperative (i.e., an on-board operational electronic means of identification) and non-cooperative (i.e., no electronic means of identification aboard) aircraft. Additionally, alerting criteria needed for specifying event sequencing in UAS DAA encounters and UAS pilot interaction with a DAA system have been developed to guide the human's response during potential encounters with intruder air traffic. The quantitative "well clear" criteria specifies minimum time-based and distance-based thresholds for horizontal and vertical separation. While automated response to advisories is optional, ACAS XU supports automated DAA avoidance maneuvers for large UAS en-route at cruise altitude [168].

Human subjects evaluations have focused on identifying minimum DAA information requirements, maneuver guidance, and display design recommendations for single UAS (e.g., [169–173]). However, there have been no comprehensive studies addressing the minimum information requirements for M:N UAV systems.

3.8.1.2 Transparency

Transparency is an important factor for controllability by humans of autonomous sys- tems and can potentially mitigate some of the issues with less than perfect autonomy. The Situation Awareness-based Agent Transparency model, see Figure 1, supports human aware- ness in human-agent teams [174]. The situation-awareness-based agent transparency model, originally designed for single robot systems, is useful for facilitating shared understanding and calibration of trust in human-multiple robot teams.

Situation Awareness-based Agent Transparency

Level 1: Goals & Actions

Agent's current status/actions/plans

- Purpose: Desire (Goal selection)
- Process: Intentions (Planning/Execution); Progress
- Performance
- Perception (Environment/Teammates)

Level 2: Reasoning

Agent's reasoning process

- Reasoning process (Belief/Purpose)
- Motivations
    - Environmental & other constraints/affordances

Level 3: Projections

Agent's projections/predictions; uncertainty

- Projection of future outcomes
- Uncertainty and potential limitations; Likelihood of success/failure
- History of Performance

Figure 1: Situation awareness-based agent transparency model, adapted from [175]

Transparency plays a key role in mission performance, situation awareness, usability, trust development, correct acceptance and rejection rates, response time, efficiency and reliance. A summary of the effects of the systems reliability and transparency on the human are provided in Table 4.

Table 4: Effects of reliability and transparency on human reliance behavior and overall performance

Response variable	Impact of reliability	Impact of transparency
Reliance rate	Increases [25]	No effect [25]
Proper reliance	Increases (correct rejection) [25]	Increases [25, 39, 56, 176]
Mission performance	Increases [25]	No effect [25]
Efficiency	No effect [25]	No effect [56, 177] Decrease (uncertainty information) [39]

The task context specific mechanisms that support transparency benefits remain under investigation. For example, Mercado, Rupp, Chen, Barnes, Barber and Procci [56] investigated a planning task in order to examine the level of information necessary to create an effective and transparent interface to support a human teaming with multiple unmanned experimental vehicles. Incorporating reasoning and uncertainty information into heterogeneous tactical decision making helped the participants make better-calibrated decisions. A follow up study [39] investigated differences in projection and uncertainty from projection information alone. Participants used the autonomy's recommendations better (i.e., accepted recommendations when they were correct and rejected them when they were incorrect) when they were provided with uncertainty information; however that information also increased response time.

A related question is how does the type of transparency into the autonomy's decisions impact human's trust and can the human be persuaded to rely on the autonomy more [45]? A sequential transparency method was compared to a on-demand method of providing transparency into the autonomy. Participants who used the on-demand transparency method allowed participants to maintain or improve their performance, while improving their trust in the autonomy.

Cognitive agents have been suggested as a means to improve trust and transparency [36]. The simulated system was composed of a manned helicopter, where the supervisor was responsible for controlling multiple UAVs. The supervisor's performance (i.e., higher accuracy and faster response times) and situation awareness of the autonomy's interventions and mission planning improved with higher agent transparency. As well, subjective metrics of trust also improved.

The impacts on the human's workload of varying the transparency of an agent' reasoning were examined [58]. This evaluation also investigated how differing measures of workload compared in assessing and understanding cognitive workload. While this work addressed convoy management, access to agent reasoning did not increase overall human performance and workload. However, a comparison of the individual factor ratings to the workload measures found differences in participant behavior between transparency levels.

Transparency is a nascent topic, particularly in relation to multiple vehicle systems. Many open questions remain, including how much transparency is necessary to support M:N UAV system deployments, what is the minimum necessary for safe operation, and can there be too much transparency?

3.8.1.3 Camera video data

The M, or the human, in a M:N system can easily become overloaded with multiple sensor inputs. A common sensor feed is visual information, but future systems are expected to include traditional robotics sensors (e.g., LiDAR) and new sensors (e.g., package weight or secure package stowage). Humans working with a single UAS often view a provided video feed, however, it is unclear how to scale this type of imagery for M:N UAV systems. A critical issue occurs when the human is using views from multiple UAVs and needs to integrate the information to generate a common understanding or operational picture. Control station design strategies range from co-locating video feeds in different ways on the same workstation, to providing display augmentation, to easing the transition from one video feed to another, to developing integrated synthetic camera views.

Oron-Gilad et al. [75] investigated display support, but found that using a single window that toggled through the imagery was too slow for the pace of task demands in a dynamic operational context. Split views (i.e., two equal sized views) and combination screens (i.e., one larger and one smaller) were rated as more optimal compared to single screen displays. The combination layout provided an operational advantage over the split screen, as it can potentially be expanded to include more than one "small window" in the layout. However, the scalability of this approach will only be applicable to some M:N UAV system domains that contain a small number of vehicles, or have the capacity to integrate very large workstations. Further, the efficacy of this display approach, even within domains, will be highly dependent on the specific task objectives.

Supporting a human's understand of how different camera images are spatially related to one another was addressed in a display concept that transitioned between camera views when multiple UASs were monitoring the same object/scene [15]. While this work focused on higher altitude flight operations than what is in scope for A26, the simulation-based experimental results demonstrate the benefits of such tools to support transition aids.

Often algorithms are developed to process sensory inputs, but the implications of the algorithm's outcomes on human performance are often not understood. The algorithm design of system augmentations intended to support human performance were investigated previously [71]. An automatic target recognition system with an additional cue (i.e., a box was drawn in the region in which a possible target was detected) was expected to reduce workload and improve overall performance. However, the results indicated that the system impacted response bias. The underlying algorithm pulled images from an area, based on target detection priority and coverage, which may have attributed to the outcome in which human supervisors monitored the same area.

Many have investigated algorithms that integrated multiple camera views, or even multiple images from the same camera into a cohesive display. Abedin and colleagues [12, 78] developed an integrated synthetic view from multiple independent camera feeds. However, the researchers did not address any latency with respect to creating the 3D model and there was no consideration of the impact of potential latency in representing synthetic data to the human in near real-time. Depending on the latency duration, there are domains for which the impact can be minimal, but in others, any latency will hinder the supervisor's ability to respond appropriately.

An important issue to be addressed for control of M:N UAV systems relates to the role for video/image feeds. There has been no comprehensive study to address when imagery is absolutely necessary. It is possible that vendors may wish to supply imagery for the humans' benefit, but the notion of whether imagery must be available has yet to be proven. Understanding the necessity of imagery is crucial, since the computational and communication loads associated with imagery from M:N UAV systems will likely be very high.

3.8.2 *Input devices*

Most of the single UAS control devices support direct teleoperation, as well as graphical user interfaces with keyboard and mouse inputs. The majority of the HITLs included graphical user interfaces with keyboard and mouse inputs that allowed the human to supervise all of the vehicles from the same set of windows. Some research has addressed other modal and multi-modal interfaces, such as haptics and tactile interfaces [34, 35, 86, 87, 178], gesture and finger tracking interfaces [179–181] and voice recognition [179].

Multiple robot teleoperation schemes based on traditional personal computer (i.e., keyboard and mouse) and game console input hardware (i.e., video game controller) were compared for a 3D spatial interaction interface [90]. While the keyboard scheme exhibited shorter completion times and fewer errors, no significant differences were found for performance measures by input device. Haptic force feedback was found to support maneuverability, while velocity feedback supported perceptual sensitivity [86, 87].

Different researchers have tried to develop better control station designs to support multiple UASs operations; however, no research has addressed the question of what are the minimum device input requirements. More complex the work stations and input devices will create a greater barrier to entry and increase the need for subsequent training.

3.8.3 *Display design*

Researchers have been investigating display configurations to support UAS operations. For example, several studies have addressed DAA alerting requirements and display designs that incorporate conflict detection, resolution and execution tools (e.g., [169–171, 182–186]).

The use of mission-coded map icons to assist humans when making decisions were investigated for play-based interfaces and multiple UASs [13]. Presenting pictorial icons that represented different base defense events directly on the map reduced the time required to locate these mission relevant events. The map icons supported situation awareness, and may support better decision making for multiple UAS control.

Many open questions exist for how best to display very large multiple vehicle systems, or swarms. Five swarm visualizations, some that displayed all individual vehicles and some that abstracted away individual vehicles, were analyzed for two common multiple UASs tasks (i.e., go to a goal location and the detection and avoidance of obstacles) [37]. The video-based evaluation investigated how the visualizations impacted human's ability to identify the swarm's current task, goto or avoid, when the visualizations either included or excluded the obstacles. The three visualizations that incorporated individual agents resulted in the highest accurate recognition of the swarm's current task, while one of the abstract visualiza- tions provided similar, but lower detection accuracy. Future work needs to investigate the relationship between tasks and visualizations, since results have shown that humans perceive biological swarm movements as a complete entity, rather than the individuals [96].

Change blindness occurs when people fail to detect even large changes in a visual scene or on a display, when these changes coincide with another visual or transient event [187]. However, crossmodal change blindness occurs when the individual does not detect differences across sensory modalities. The extent that, and when, crossmodal change blindness impact human performance were investigated [35]. Specifically, this evaluation investigated touch's susceptibility to change blindness, and how global visual changes, including luminosity, impact visual change blindness, and if crossmodal change blindness occurs with the sensing modalities by manipulating tasks demands along with cue modality and transient modality type (i.e., cue-transient combination). The results demonstrated that change blindness is an issue for these multimodal displays and needs to be considered for future multimodal displays. There is a potential for training to mitigate the effects of crossmodal change blindness, but training was not incorporated into this evaluation.

Methods that direct the human's attention can improve the systems performance. The general visualization and abstraction algorithm was designed specifically to declutter and direct the human's attention [54]. This algorithm was shown to intelligently group and present complex visual information and improve situation awareness. Four attention guidance methods that differ in integration, detail and configurability were analyzed [22]. While completing a multiple UASs re-routing task, participants demonstrated better monitoring performance when their attention was directed using methods that incorporated data categorization (e.g., event prioritization) and decluttering (e.g., removed unrelated information).

While the research to date is useful, to ensure reliable and effective control displays, manufacturers will need explicit requirements in order to bring their systems to market. Manufacturers will need to know what these standards are as well as what standards are applicable to a given context. Future display design must ensure bias is not induced, either change blindness or unintentional attentional narrowing.

3.9 Mission and associated task characteristics

Researchers have considered missions and associated UAS tasks [166,167,188–197]. However, no validated task taxonomy for M:N UAV systems exists. Additionally, as described in the final ASSURE A10 project report for tasks PC-1 through PC-3 [198], there are no common operational procedures for UAS pilots operating single UAS larger than 55 pounds. This finding is also true for M:N UAV systems. Original equipment manufacturers provide inconsistent operational procedures that are unique to their UAS.

A few common M:N UAV system mission scenarios were identified: surveillance, reconnaissance, target detection/classification, and search. Table 5 lists the tasks detailed in the reviewed manuscripts, where sub-tasks of higher level tasks are denoted with a dash. Most of the literature focused on missions composed of multiple tasks. For example, surveillance

Table 5: Task frequency

Task	Count	Associated Citations
Route planning or navigation or aviation	58	[8,10,11,16–23,25–30,32–34,36–39,41, 41,46–51,53,55–58,60,63,69,71–73,77–79, 82, 85–88, 88, 90, 159, 178, 179, 181, 199, 200]
- Avoid hazard or area	18	[8, 11, 18, 19, 22, 29, 30, 36, 46–48, 50, 57, 72, 73, 86, 87, 200].
Intelligence Surveillance Reconnaissance and visual search	53	[8, 11–21, 23–30, 32–36, 38, 40, 41, 43, 44, 46–50, 53, 55, 58, 63, 69, 71, 72, 74–80, 85, 113, 179, 199]
- Search and identification (UV, target, location, threat) or classification	44	[8,11–14,18–21,23–26,29,30,32–36,38, 41, 43, 44, 46–48, 50, 53, 55, 58, 63, 69, 71, 72, 74–78, 80, 85, 113, 179]
- Camera video or image control; image analysis	33	[11,12,15–18,20,24,27–30,35,36,38,40, 41, 43, 44, 48, 49, 53, 55, 71, 72, 74, 75, 78, 79, 85, 113, 199]
- Detection or change detection	9	[16–18, 27, 28, 35, 44, 49, 79]
- Tracking	3	[32, 72, 80]
- Orientation	3	[20, 74, 75]
Vehicle allocation	26	[10,11,16,17,20,23,27–29,36,38,41,45, 49, 55, 63, 71, 73, 76, 79, 85, 159, 200–203]
- Imaging Task Allocation	12	[16,17,20,27,38,41,49,63,76,79,85,203]
Chat or other form of communication	22	[9, 13, 15, 16, 18, 19, 21, 22, 27, 28, 33, 34, 38, 39, 41, 45, 48, 52, 56, 58, 79, 92]
System status	19	[11,16,17,19,20,27,28,33,34,36,38,41, 46, 48, 49, 51, 79, 89, 202]
Monitor mission progress and state	17	[9–11, 18–20, 22, 24, 32, 34, 36, 41, 63, 76, 159, 199, 202]
Payload release and delivery	15	[11,21,27,28,32,38,40,41,46,47,52,73, 80, 92, 113]
Mission planning	12	[10,11,22,36,39,45,56,73,159,179,200, 201]
Information retrieval	9	[16, 17, 27, 28, 39, 49, 56, 57, 79]
Protect own assets	3	[45, 52, 63, 76, 92]
Procedure or checklist	3	[9, 31, 36]
Other tasks	3	Maintenance [51,202] and grasping [90]

oriented missions often required the human supervisor, usually supported by autonomy, to allocate vehicle specific new imaging tasks, re-route vehicles in response to hazards or new task demands, as well as conduct image analysis and target detection. Some tasks, such as monitoring and responding to chat, were manual. The UASs completed some tasks independently in many cases, but in other cases, the human supervisor and UASs were required to coordinate [203]. Kancler and Malek [204] interviewed subject matter experts that focused on intelligence, surveillance and reconnaissance missions in order to better understand current sUASs missions, capabilities, and expected payloads (e.g., sensor or weapon).

Limited research exists related to multi-tasking and task sequencing. As briefly mentioned in Section 3.7.2, Calhoun et al. [16] focused on level of autonomy design across sequential and simultaneous tasks as well as whether there is any effect of similar and different autonomy levels across the sequential tasks in the presence of mission-related secondary tasks. Primary tasks included assigning sensor tasks to vehicles and routing (i.e., flight plans). Secondary tasks included unidentified aircraft detection, image analysis, rules of engagement status, information retrieval, and systems status. The levels of autonomy for the two primary tasks were combined into a composite independent measure with two lev- els: global (i.e., both high or both low) and mixed (i.e., one level of autonomy is low, the other is high). One hypothesis is that if the more highly automated task occurred earlier in the task sequence, the supervisor may have more time for subsequent tasks, regardless of the subsequent tasks' autonomy level. The authors found that performance on the primary tasks and many secondary tasks was better when the autonomy level was the same across the two sequential primary tasks. That is, there was an effect of whether the subsequent task's autonomy level matched the earlier task, which means that predicting task performance is dependent upon the type of autonomy support.

There is limited research focused on providing the human supervisor with ground robot and UAS-based perspectives. However, some researchers have investigated soldiers controlling a suite of air and ground vehicles. Oron-Gilad and colleagues [74, 75] found that participants benefited from the detailed information provided by the ground vehicles. The presence of the UAS imagery perspective alone was insufficient for the human when the terrain was more open, the human supervisors gained more information from adding the unmanned ground vehicle feed [74].

Future UAS tasks may require vehicles to transition from the NAS to indoor, non-NAS environments. Search tasks [77], such as for disaster response, will require such NAS to non-NAS to NAS transitions. These transitions will impact the UAS's control and potentially communication link connectivity.

An important mission characteristic that will directly impact M:N UAV systems is common flight phases. However, very few studies specifically addressed the flight phases, such as take off and landing [36, 51, 85, 90]. Return to launch behaviors are common on most available platforms, and were analyzed using one actual UAV and two simulated UAVs [201]. Similarly, a multi-faceted return-to-launch behavior was developed for a real-world semi-autonomous heterogeneous swarm [202] The behavior to swap vehicles in order to maintain task performance used two thresholds to trigger a return-to-launch behavior: the standard low battery threshold, and a higher threshold that allowed the in-flight UAV to safely return when being replaced by a UAV with a fresh battery. The purpose of this swap behavior is to reduce human supervisor workload, while maintaining mission progress and deployment safety. Take off and landing for three minute search missions were a component of a devel- oped control architecture [85]. Roth, Schulte, Schmitt, and Brand [36] developed a symbol set to help the human supervisor to understand the autonomy's planning process, where the phase level tasks included take off, transit, detection of a landing point, and landing as well as mission tasks (recon and scout).

The research to date is helpful, but there is no comprehensive set of task analyses that have been conducted in order to support and better understand the demands of M:N UAV system. The interplay of the number of aircraft, the range of tasks, and the type of autonomy and decision support need to be addressed and considered in a holistic manner.

4 GAPS

Many wish to focus on the single crew member in control of multiple UAS, or the M:N problem, and the associated human supervisor-to-vehicle ratio; however, that ratio is highly dependent on a broad set of factors, including the overall M:N UAV ecosystem (i.e., the physical infrastructure, hardware and software systems, and personnel) and aspects that are "hidden from view" when developing such systems for a given domain. This literature review has identified a number of unaddressed gaps. The most noteworthy gaps are summarized.

1. **Entity in control**: Who or what is ultimately in control of the UASs, either individual UAS or coordinating groups of UAS, in an M:N UAV system? Some M:N UAV systems will require very high levels of autonomy, autonomy that needs to handle a breadth of adverse events. As the complexity of the M:N UAV system increases, the human will be "on-the-loop" rather than "in-the-loop," as such the human will be ill-equipped to handle an adverse event. However, depending on the domain, operational environment, or adverse events, a human entity may be best equipped to be in control, or at least maintain some authority over the system's UAS components.

2. **Crew Roles**: What are the minimal crew role types necessary to support M:N UAV systems and what is the required proficiency of each role? The crew roles specified by 14 CFR Part 107 are not necessarily relevant in the M:N UAV system domain. The common and well understood human-robot interaction domain roles, such as supervisor and mechanic (e.g., [156, 205]), are applicable, but there will be new crew roles that have not existed previously. For example, new domain uses (e.g., delivery drones) will introduce new crew roles that currently do not exist (e.g., load supervisor).

3. **Crew Composition** What are the allocations to the crew roles, more specifically, how many individual humans are required to staff each crew role? Some domains will have multiple individuals in a particular crew role (e.g., flight supervisor), but it is unclear how the ecosystem's N UASs will be allocated across the individuals in a particular crew role. What are the minimal combination of crew roles and the staffing numbers associated with those roles? What are the criteria on which the crew composition is dependent (e.g., M:N UAV system composition, domain, task complexity)?

4. **Climate Conditions**: What are the implications of the effects of weather, or geographical or human built structure induced microclimates, on crew member responsibilities? This question needs to be answered from the perspective of the M:N UAV system capabilities and well as the role-based crew member responsibilities.

5. **Flight Phases**: M:N UAV systems will have similar flight phases as single UAS operations (i.e., pre-flight, launch, take-off, climb to cruise, cruise, descent, approach, landing, recovery, post-flight). The crew role responsibilities and proficiency requirements for all flight phases, other than cruise, have not been investigated. Important issues include whether or not UAS to crew role assignments are based on flight phase, and if not, what are the implications on crew handling multiple UASs in different flight phases simultaneously? What are the adverse event flight phases and the associated implications on the crew roles?

6. **Altitude Maneuverability**: UAS have different morphologies (e.g., omni-directional multi-rotor or helicopters, fixed wing, or hybrid) that determine a particular vehicle's ability to hold a stationary position or navigate either laterally and vertically. As such, some UAS can navigate the airspace differently than manned aircraft. While these same capabilities are also available with single UAS systems, there are undetermined implications for the UAS morphologies within M:N UAV systems and the crew roles with regard to altitude and yaw control.

7. **Area of Operational Control**: Existing regulations related to the area of operation (i.e., restricted airspace or no fly zones) and geofence capabilities for single UAS will not necessarily translate to multiple UASs domains. The implications of the existing regulations on the M:N UAV system human roles is not entirely clear. Generally, the regulations can apply, but depending on domain, these operational criteria may be predefined "default settings" that change infrequently (e.g., delivery drones) or may require partial or full specification, such as a geofence, for other domains for which the area of operation cannot be prespecified (e.g., disaster response).

8. **M:N UAV System Composition**: M:N UAV systems in certain domains will be composed of 100% homogeneous (i.e., identical) UASs, where the system complexity will arise from the number of UASs and the mission complexity. However, M:N UAV systems will also be composed of heterogeneous UASs, either in morphology, payload, or even larger capacity, but all other system aspects being identical. How does system composition impact the crew roles and team compositions? Do the minimal information requirements apply across vehicle heterogeneity, in order to standardize the crew stations? Are there UAS morphology or payload characteristics that the crew role and station must accommodate, and if so, how? Do heterogeneous system compositions require different crew role competencies and training?

9. **Mission Task Composition**: How do the crew station, crew proficiency and competencies as well as the minimal requirements differ between M:N UAV systems performing a set of standardizable tasks (e.g., drone delivery) versus highly dynamic, uncertain or unpredictable missions (e.g., disaster response)? Similarly, what are the implications of loosely coupled tasks (i.e., each UAS performs an independent task) versus tightly coupled tasks (i.e., multiple UASs conduct a highly collaborative task), as well as missions composed of tasks across the task coupling spectrum? How can unexpected or emergency operations, and task compositions (e.g., unique, previously unthought of disaster response task) be accommodated safely in situ by the crew?

10. **Communication Link Loss**: Communication link loss will be inevitable in some M:N UAV system domains with standardized communication systems. What are the minimal requirements for M:N UAV systems to maintain a link to the crew and how are they defined relative to the mission tasks? Does the M:N UAV system, and hence the control stations have to accommodate intermittent lost link or allocate individual UAS to serve as ad hoc communication link relays? Do the UASs have to return to the coordinate of a last known link location before proceeding? If the UASs are capable of autonomously completing the task safely (i.e., a package delivery) do they do so and

what information must be communicated to the crew? Does the M:N UAV ecosystem require intelligent decision support to predict the likely actions of the UASs during lost link? These are just a few of the relevant questions.

11. **Airspace Transitions**: While it is noted that the FAA is focused on operations in the national airspace, it is prudent to recognize that future M:N UAV system domains will require aircraft to transition between the national airspace and non-national airspace (e.g., tunnels and building interiors). Domains, such as disaster response, will require UAS to enter non-national airspace spaces (e.g., search and rescue and structural inspections after a hurricane). The key concern is handling the transitions between these airspaces, which often require an UAS to transition between flight control methods in order to safely perform its tasks. What are the responsibilities of the crew roles and the UAS platforms in these scenarios? What are the minimal requirements to ensure safe transitions between such airspaces and what specifically must the crew roles know from the UAS and be able to control? It will be difficult for crew to control this transition, and in some cases, to even approve this transition.

12. **Function Allocation**: How are the mission responsibilities allocated between the crew roles, individual crew members within a role, the individual UASs and the M:N UAV ecosystem? This allocation will depend on many factors (e.g., autonomy level, mission task composition, crew role). The function allocation will ultimately define responsibility for the various mission and system components that may encompass legal responsibilities, a topic excluded from this literature review.

13. **Autonomy**: Autonomy is a broad concept that can control an individual UAS, including responding to off-nominal and adverse events, but will also be incorporated into the broader M:N ecosystem as intelligent processing and crew role specific deci- sions support. Fundamentally, autonomy is an aspect of artificial intelligence, which will be embedded into the ecosystem. The minimal UAS autonomy requirements and their implications on M:N UAV systems are not understood. What off-nominal and adverse events must be handled autonomously by the UAS to ensure safety and when does an UAS need assistance from a crew member or for that a crew member to as- sume control? Examples of the ecosystem autonomy include the ability to combine raw sensory information from multiple UASs into a crew accessible and meaningful operational picture, or the system planning the flight paths. Artificial intelligence methods will be necessary to perceive the environment, within the domain's context, in order to derive new knowledge and autonomous policies that are validated by humans prior to the system's UAVs performing the modified policy (e.g., a man made object ob- structs a routine flight path). As such, the required minimal autonomy will have to consider a breadth of the provided gap factors and validation methods are necessary to continuously ensure sustainment of those autonomy and safety requirements.

14. **Crew Role: Operation Station**: A breadth of crew role specific operation stations will be necessary to support the entire M:N ecosystem; however, these operation sta- tions will be difficult to regulate given vastly different domain and M:N UAV system

specific core capabilities. What are the minimal requirements are that operation stations must incorporate and how do those requirements differ by crew role and various other system and domain characteristics? Some domains will require crew roles, such as a delivery drone load supervisor, who may use a custom stationary or hand-held operation station, which differs from the enroute supervisor located in a comfortable control room using an operation station with rich input and output peripherals. Similarly, a domain's operational conditions will influence the operation station. For example, a disaster response flight supervisor may be located in an emergency response vehicle using a laptop-based operation station with limited input and output peripherals.

(a) **Operation Station: Inputs**: The most reliable and accurate control and information specification modalities for M:N UAV systems are not fully understood, as they will vary based on crew role and domain. The M:N ecosystem crew roles will require different information inputs and potentially input modalities. Broadly, what must be input and controlled is not well understood and will have to be allocated across the various crew roles. Domain characteristics will further influence what information is input by whom and when, but more importantly will influence the input peripherals and modalities (e.g., keyboard, joystick, natural language). What are the necessary crew role specific inputs? How do different input peripherals and modalities influence safety?

(b) **Operation Station: Outputs**: What is the minimal information required to complete the crew role responsibilities, which are expected to differ dramatically from single UAS deployments. How does the autonomy of the system's vehicles alter the information requirements? Do the information requirements change by flight phase or adverse event? How is the breadth of multiple UASs' sensor information aggregated and integrated into a comprehensive, meaningful presentation from which unbiased, accurate decisions can be quickly derived and appropriate, necessary actions taken? If the UASs are in control, when must they notify the human supervisor(s) of thier status and via what means? A operation station with a video feed display for each vehicle will not be useful or usable in many domains; however, maintaining access to the live video feeds may represent a minimal information requirement. A human supervsior will be unable to maintain awareness of each vehicles' status via individual video relays. Further, what is the set of standardized symbology (e.g., Mil-STD-2525D map symbology) to be used to ensure a common operating picture across M:N UAV systems and domains?

15. **Crew: Trait Selection**: The different crew roles needed to support the M:N ecosystem will require different fundamental human traits, and pre-screening for minimal basic traits needs to be considered. One such trait will be minimal level of education and demonstrated competency (e.g., high school diploma, trade skills). The traits for some crew roles require further investigation, such as the necessary level of inherent human performance capabilities (e.g., spatial awareness, reaction time, and ability to respond to stressful situations calmly). The minimal trait requirements are aspects re- quired to increase the likelihood of successfully training and attaining a minimal level of competency relevant to the crew role in the M:N UAV ecosystem.

16. **Crew: Diversity**: Females are clearly under represented in the CFR Part 107.205 remote pilot certifications, and while not reported in the literature, it is believed that other diverse groups are under represented. However, developing the workforce for M:N UAV system crew roles will require engaging all segments of the population, and not only individuals who possess certain backgrounds (e.g., gaming). As M:N UAV systems change businesses, there will be a growth in UAS crew role jobs and a decrease in others (i.e., delivery and ride share drivers). Developing and engaging interest, while keeping the barrier to entry accessible will be critical for developing a workforce.

17. **Crew: Training**: The minimal crew role traits will influence the minimal training requirements associated with each role. While the FAA ASSURE project A27 is developing a training framework for type certified UAS based on established industry UAS pilot standards, the characteristics of M:N UAV systems may differ significantly. As such, aspects of that framework may be leveraged for only a subset of crew roles in the M:N ecosystem. However, training and certification requirements across the crew roles must be commensurate with the minimum level requirements related to the crew role's traits and focus on supporting the crew role's level of control, interaction and responsibilities with respect to the M:N ecosystem (e.g., a delivery drone load supervisor requires less minimal training, perhaps two hours, than the enroute human supervisor, perhaps a few weeks). The recertification cycles and requirements will also be dependent on the crew role responsibilities. Further, some crew roles may require specialized training unrelated to UAS, such as regulatory compliance. Addressing personnel turnover will also be important, and potential career trajectories will be needed in order to retain a highly trained workforce.

18. **Crew: Competency Certification**: Validating crew role competency will encompass basic skills, and for some roles, fundamental human factors performance characteristics (e.g., workload, spatial awareness). Easily accessible minimal crew role specific competency (re)certification assessments must provide an accurate and objective validation of the skills and competencies. Skill degradation can occur for many reasons, including biologically oriented degradation (e.g., reaction time or spatial awareness). Subjective metrics dominate the literature evaluation analyses of human performance capacity; however, these metrics are insufficient for purposes of certifying competency and proficiency for M:N UAV system crew roles. A minimal set of objective validation metrics capable of mitigating individual differences are required that accurately assesses all aspects of the minimal crew role specific competency requirements are met.

10. CONCLUSION

This literature review provided an insightful examination of the results of past research and identified large gaps in understanding. These gaps must be addressed before the FAA is able to lift the restrictions laid out in CFR Part 107.205 and develop regulations and guidelines regarding M:N UAV systems operations. Based on these findings, the ASSURE team will begin to fill those gaps through modeling and case study validation. Within the review of previous work, the team found that most research was conducted around HITL and the human factor limitations for operating and monitoring multiple sUASs. These predominately simulation-based evaluations used some objective performance measurements (e.g., target detection rates and response times), and relied heavily on subjective measurements (e.g., perceived workload, trust in automation, and situational awareness).

The initial gap findings can be summarized into five main gaps:

- Phases of Flight – It is well known in the aviation industry that takeoff and landing are the two most dangerous phases of flight. This literature review highlighted that very little research has focused on these flight phases, and the research has focused primarily on cruise flight. These critical phases, along with preflight, climb, descent, approach, recovery, and post-flight will need to be addressed.

- Crew Roles – When developing crew roles, one must consider the M:N UAV ecosystem as a whole, potentially including an entire organization. Factors to consider include (1) there may be one supervisor in charge (e.g., a traditional pilot in control), or an entire crew organization, (2) how many humans are considered a part of a specific crew, and (3) what new roles need to be defined or introduced.

- Training – More focus is needed to define required training. Since the systems are becoming more automated, there is less need for months or weeks of training. Previous work looked at training considerations for CFR Part 107.205 remote pilots verses UAS degree programs. The future of UAS autonomy forces the ASSURE team to look closer at everyday citizens any of the M crew roles and what that training needs to encompass.

- System Requirements – There is little research considering the type of system, which is broken down into two distinct groups, a single UAS or a multiple UAS structure. Factors that must be further investigated within the context of both definitions include, the maneuverability, weather, and system composition. The system composition can be further decomposed into how the system responds to communication link loss, transitions through airspace, and overall mission location (e.g., restricted airspace, or no fly zones).

- Autonomy – Although this gap falls under the system requirements gap, it drives the level of impact for most of the other gaps. The levels of autonomy will determine how many humans are needed, what training those humans will require, and what other system composition requirements will be necessary for safe flight.

The researchers will use this literature review and high-level gap findings to inform a deeper gap analysis. Based on the additional gap analysis, the research team will develop a model for a case study of drone package delivery. This loosely coupled tasks case study, where multiple vehicles conduct independent tasks, will provide a better understanding of what factors impact the human to UAS (M:N) ratio for this particular domain. This model will investigate more broadly the complex relationship between the human(s) and the UASs' level of autonomy. The team will evaluate a single case HITL, focusing on validating one aspect of the complex model.

The modeling and validation of the case study will illustrate how autonomy impacts the M:N ratio for the factors associated with package delivery and begin to answer the ulti- mate question; how many vehicles can one human control, and what performance standards must be developed to properly determine a safe M:N ratios based on the aircraft's level of autonomy.

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11. BIBLIOGRAPHY

[1] W. R. Ferrell and T. B. Sheridan, "Supervisory control of remote manipulation," *IEEE Spectrum*, vol. 4, no. 10, pp. 81–88, 1967.

[2] T. B. Sheridan, *Telerobotics, Automation, and Human Supervisory Control*. The MIT Press, 1992.

[3] T. B. Sheridan, *Humans and Automation*. Wiley, 2002.

[4] T. B. Sheridan, "Adaptive automation, level of automation, allocation authority, supervisory control, and adaptive control: Distinctions and modes of adaptation," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 41, no. 4, pp. 662–667, 2011.

[5] "FAA Human Factors Policy Order 9550.8," 1993. https://www.faa.gov/documentLibrary/media/Order/9550.8.pdf.

[6] J. W. Crandall, M. A. Goodrich, D. R. Olsen, and C. W. Nielsen, "Validating human-robot interaction schemes in multitasking environments," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 35, no. 4, pp. 438–449, 2005.

[7] M. L. Cummings and P. J. Mitchell, "Predicting controller capacity in supervisory control of multiple UAVs," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 38, no. 2, pp. 451–460, 2008.

[8] M. Cummings, L. Huang, H. Zhu, D. Finkelstein, and R. Wei, "The impact of increasing autonomy on training requirements in a UAV supervisory control task," *Journal of Cognitive Engineering and Decision Making*, vol. 13, no. 4, pp. 295–309, 2019.

[9] V. F. Mancuso, G. J. Funke, A. J. Strang, and M. B. Eckold, "Capturing perfor- mance in cyber human supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 317–321, 2015.

[10] A. Valero-Gomez, P. de la Puente, and M. Hernando, "Impact of two adjustable-autonomy models on the scalability of single-human/multiple-robot teams for exploration missions," *Human Factors*, vol. 53, no. 6, pp. 703–716, 2011.

[11] B. Donmez, C. Nehme, and M. L. Cummings, "Modeling workload impact in multiple unmanned vehicle supervisory control," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 40, no. 6, pp. 1180–1190, 2010.

[12] S. Abedin, M. Lewis, N. Brooks, S. Owens, P. Scerri, and K. Sycara, "SUAVE: Integrating UAV video using a 3D model," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 91–94, 2011.

[13] J. Bartik, H. Ruff, K. Behymer, E. Frost, G. Calhoun, S. Spriggs, and T. Hammack, "Mission-coded map icon decision aids for play-based multi-unmanned vehicle autonomy delegation," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, pp. 237–241, 2017.

[14] L. F. Bertuccelli and M. L. Cummings, "Operator choice modeling for collaborative UAV visual search tasks," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 42, no. 5, pp. 1088–1099, 2012.

[15] G. Calhoun, L. Warfield, N. Wright, S. Spriggs, and H. Ruff, "Automated aid evaluation for transitioning UAS camera views," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 413–417, 2010.

[16] G. L. Calhoun, H. A. Ruff, M. H. Draper, and E. J. Wright, "Automation-level transference effects in simulated multiple unmanned aerial vehicle control," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 1, pp. 55–82, 2011.

[17] G. L. Calhoun, H. A. Ruff, S. Spriggs, and L. C. Murray, "Tailored performance-based adaptive levels of automation," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 413–417, 2012.

[18] J. Y. C. Chen and M. J. Barnes, "Supervisory control of robots using RoboLeader," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 1483–1487, 2010.

[19] J. Y. C. Chen and M. J. Barnes, "Supervisory control of multiple robots: Effects of imperfect automation and individual differences," *Human Factors*, vol. 54, no. 2, pp. 157–174, 2012.

[20] S.-Y. Chien, Y.-L. Lin, P.-J. Lee, S. Han, M. Lewis, and K. Sycara, "Attention allocation for human multi-robot control: Cognitive analysis based on behavior data and hidden states," *International Journal of Human-Computer Studies*, vol. 117, pp. 30–44, 2018.

[21] A. S. Clare, M. L. Cummings, and N. P. Repenning, "Influencing trust for human-automation collaborative scheduling of multiple unmanned vehicles," *Human Factors*, vol. 57, no. 7, pp. 1208–1218, 2015.

[22] M. B. Cook, H. S. Smallman, F. C. Lacson, and D. I. Manes, "Guided attention for autonomous system supervision," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, no. 1, pp. 408–412, 2012.

[23] J. Coyne, C. Foroughi, N. Brown, and C. Sibley, "Evaluating decision making in a multi-objective route planning-task," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, no. 1, pp. 217–221, 2018.

[24] E. de Visser and R. Parasuraman, "Adaptive aiding of human-robot teaming: Effects of imperfect automation on performance, trust, and workload," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 2, pp. 209–231, 2011.

[25] A. Hussein, S. Elsawah, and H. A. Abbass, "The reliability and transparency bases of trust in human-swarm interaction: Principles and implications," *Ergonomics*, vol. 63, no. 9, pp. 1116–1132, 2020.

[26] P.-J. Lee, H. Wang, S.-Y. Chien, M. Lewis, P. Scerri, P. Velagapudi, K. Sycara, and B. Kane, "Teams for teams performance in multi-human/multi-robot teams," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 438–442, SAGE Publications Sage CA: Los Angeles, CA, 2010.

[27] J. Lin, R. Wohleber, G. Matthews, P. Chiu, G. Calhoun, H. Ruff, and G. Funke, "Video game experience and gender as predictors of performance and stress during supervisory control of multiple unmanned aerial vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 746–750, 2015.

[28] J. Lin, G. Matthews, R. W. Wohleber, G. J. Funke, G. L. Calhoun, H. A. Ruff, J. Szalma, and P. Chiu, "Overload and automation-dependence in a multi-UAS simulation: Task demand and individual difference factors," *Journal of Experimental Psychology: Applied*, vol. 26, pp. 218–235, 2020.

[29] G. Matthews, A. R. Panganiban, A. Wells, R. W. Wohleber, and L. E. Reinerman-Jones, "Metacognition, hardiness, and grit as resilience factors in unmanned aerial systems (UAS) operations: a simulation study," *Frontiers in Psychology*, vol. 10, pp. 1–17, 2019.

[30] A. H. Memar and E. T. Esfahani, "Physiological measures for human performance analysis in human-robot teamwork: Case of tele-exploration," *IEEE Access*, vol. 6, pp. 3694–3705, 2018.

[31] E. M. Mersch, K. J. Behymer, G. L. Calhoun, H. A. Ruff, and J. S. Dewey, "Game-based delegation interface design for unmanned vehicles: Color coding and icon row assignment," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 122–126, 2016.

[32] C. A. Miller, T. Shaw, A. Emfield, J. Hamell, E. deVisser, R. Parasuraman, and D. Musliner, "Delegating to automation: Performance, complacency and bias effects under non-optimal conditions," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 95–99, Sage Publications Sage CA: Los Angeles, CA, 2011.

[33] N. M. Moacdieh, S. P. Devlin, H. Jundi, and S. L. Riggs, "Effects of workload and workload transitions on attention allocation in a dual-task environment: Evidence from eye tracking metrics," *Journal of Cognitive Engineering and Decision Making*, vol. 14, no. 2, pp. 132–151, 2020.

[34] J. C. Prinet, A. Terhune, and N. B. Sarter, "Supporting dynamic re-planning in multiple UAV control: A comparison of 3 levels of automation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 423–427, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[35] S. L. Riggs and N. Sarter, "Tactile, visual, and crossmodal visual-tactile change blindness: The effect of transient type and task demands," *Human Factors*, vol. 61, no. 1, pp. 5–24, 2019.

[36] G. Roth, A. Schulte, F. Schmitt, and Y. Brand, "Transparency for a workload-adaptive cognitive agent in a manned-unmanned teaming application," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 3, pp. 225–233, 2020.

[37] K. A. Roundtree, M. D. Manning, and J. A. Adams, "Analysis of human-swarm visualizations," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 287–291, SAGE Publications, 2018.

[38] H. Ruff, G. Calhoun, E. Frost, K. Behymer, and J. Bartik, "Comparison of adaptive, adaptable, and hybrid automation for surveillance task completion in a multi-task environment," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 155–159, SAGE Publications Sage CA: Los Angeles, CA, 2018.

[39] K. Stowers, N. Kasdaglis, M. A. Rupp, O. B. Newton, J. Y. Chen, and M. J. Barnes, "The IMPACT of agent transparency on human performance," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 3, pp. 245–253, 2020.

[40] R. W. Wohleber, G. L. Calhoun, G. J. Funke, H. Ruff, C.-Y. P. Chiu, J. Lin, and G. Matthews, "The impact of automation reliability and operator fatigue on performance and reliance," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 211–215, SAGE Publications Sage CA: Los Angeles, CA, 2016.

[41] R. W. Wohleber, G. Matthews, J. Lin, J. L. Szalma, G. L. Calhoun, G. J. Funke, C.-Y. P. Chiu, and R. Heath A, "Vigilance and automation dependence in operation of multiple unmanned aerial systems (UAS): a simulation study," *Human Factors*, vol. 61, no. 3, pp. 488–505, 2019.

[42] J. L. Wright, J. Y. C. Chen, and M. J. Barnes, "Human-automation interaction for multiple robot control: the effect of varying automation assistance and individual differences on operator performance," *Ergonomics*, vol. 61, no. 8, pp. 1033–1045, 2018.

[43] M. S. Jessee, T. Chiou, A. S. Krepps, and B. R. Prengaman, "A gaze based operator instrumentation approach for the command of multiple autonomous vehicles," in *2017 IEEE Conference on Control Technology and Applications (CCTA)*, pp. 1841–1846, 2017.

[44] S. L. Riggs and N. Sarter, "The development and evaluation of countermeasures to tactile change blindness," *Human Factors*, vol. 58, no. 3, pp. 482–495, 2016.

[45] M. Vered, P. Howe, T. Miller, L. Sonenberg, and E. Velloso, "Demand-driven transparency for monitoring intelligent agents," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 3, pp. 264–275, 2020.

[46] L. A. Breslow, D. Gartenberg, J. M. McCurry, and J. Gregory Trafton, "Dynamic operator overload: A model for predicting workload during supervisory control," *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 1, pp. 30–40, 2014.

[47] S. Chien, M. Lewis, K. Sycara, A. Kumru, and J. Liu, "Influence of culture, transparency, trust, and degree of automation on automation use," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 3, pp. 205–214, 2020.

[48] G. L. Calhoun, C. A. Miller, T. C. Hughes, and M. H. Draper, "UAS sense and avoid system interface design and evaluation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 21–25, SAGE Publications Sage CA: Los Angeles, CA, 2014.

[49] G. L. Calhoun, V. Ward, and H. A. Ruff, "Performance-based adaptive automation for supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 2059–2063, 2011.

[50] T. Chen, D. Campbell, L. F. Gonzalez, and G. Coppin, "Increasing autonomy transparency through capability communication in multiple heterogeneous UAV management," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 2434–2439, IEEE, 2015.

[51] J. M. Colombi and J. R. Ward, "Human systems integration: A discrete event simulation of operational utility for control of multiple small unmanned aerial systems," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 2145–2149, 2010.

[52] E. de Visser, T. Shaw, A. Mohamed-Ameen, and R. Parasuraman, "Modeling human-automation team performance in networked systems: Individual differences in working memory count," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 1087–1091, SAGE Publications, 2010.

[53] A. Hong, H. H. Bulthoff, and H. I. Son, "A visual and force feedback for multi-robot teleoperation in outdoor environments: A preliminary result," in *2013 IEEE International Conference on Robotics and Automation*, pp. 1471–1478, 2013.

[54] C. M. Humphrey and J. A. Adams, "General visualization abstraction algorithm for directable interfaces: Component performance and learning effects," *IEEE Transactions on Systems, Man and Cybernetics: Part A - Systems and Humans*, vol. 40, no. 6, pp. 1156–1167, 2010.

[55] M. Lewis, H. Wang, S. Y. Chien, P. Velagapudi, P. Scerri, and K. Sycara, "Process and performance in human-robot teams," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 2, pp. 186–208, 2011.

[56] J. E. Mercado, M. A. Rupp, J. Y. C. Chen, M. J. Barnes, D. Barber, and K. Procci, "Intelligent agent transparency in human-agent teaming for multi-UxV management," *Human Factors*, vol. 58, no. 3, pp. 401–415, 2016.

[57] E. Rovira, A. Cross, E. Leitch, and C. Bonaceto, "Displaying contextual information reduces the costs of imperfect decision automation in rapid retasking of ISR assets," *Human Factors*, vol. 56, no. 6, pp. 1036–1049, 2014.

[58] J. L. Wright, J. Y. Chen, M. J. Barnes, and P. A. Hancock, "Agent reasoning transparency's effect on operator workload," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 249–253, SAGE Publications Sage CA: Los Angeles, CA, 2016.

[59] T. Zhang and J. A. Adams, "Evaluation of a geospatial annotation tool for unmanned vehicle specialist interface," *International Journal of Human-Computer Interaction*, vol. 28, no. 6, pp. 361–372, 2012.

[60] G. Bales and Z. Kong, "Neurophysiological and behavioral studies of human-swarm interaction tasks," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 671–676, IEEE, 2017.

[61] J. Heard, R. Heald, C. E. Harriott, and J. A. Adams, "A diagnostic human workload assessment algorithm for collaborative and supervisory human-robot teams," *Journal of Human-Robot Interaction*, vol. 8, pp. 7–1–7–30, June 2019.

[62] J. Heard, J. Fortune, and J. A. Adams, "SAHRTA: A supervisory-based adaptive human-robot teaming architecture," in *IEEE International Conference on Cognitive and Computational Aspects of Situation Management*, IEEE, 2020.

[63] R. W. Wohleber, G. Matthews, L. E. Reinerman-Jones, A. R. Panganiban, and D. Scribner, "Individual differences in resilience and affective response during simulated UAV operations," in *Proceedings of the Human Factors and Ergonomics Society*

Annual Meeting, vol. 59, pp. 751–755, SAGE Publications Sage CA: Los Angeles, CA, 2015.

[64] J. Fortune, J. Heard, and J. A. Adams, "Real-time speech workload estimation for intelligent human-machine systems," in *Human Factors and Ergonomics Society Annual Meeting*, HFES, 2020.

[65] C. E. Harriott, G. L. Buford, J. A. Adams, and T. Zhang, "Mental workload and task performance in peer-based human-robot teams," *Journal of Human-Robot Interaction*, vol. 4, pp. 61–96, September 2015.

[66] C. E. Harriott, T. Zhang, and J. A. Adams, "Assessing physical workload for human-robot peer-based teams," *International Journal of Human-Computer Studies*, vol. 71, no. 7, pp. 821–837, 2013.

[67] C. E. Harriott and J. A. Adams, "Modeling human performance for human-robot systems," *Reviews of Human Factors and Ergonomics*, vol. 9, no. 1, pp. 94–130, 2013.

[68] J. Heard, C. E. Harriott, and J. A. Adams, "A survey of workload assessment algorithm," *Transactions on Human-Machine Systems*, vol. 48, no. 5, pp. 434–451, 2018.

[69] J. L. Wright, S. A. Quinn, J. Y. Chen, and M. J. Barnes, "Individual differences in human-agent teaming: An analysis of workload and situation awareness through eye movements," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 1410–1414, SAGE Publications Sage CA: Los Angeles, CA, 2014.

[70] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research," *Advances in Psychology*, vol. 52, 1988.

[71] N. Brooks, P. Scerri, K. Sycara, H. Wang, S.-Y. Chien, and M. Lewis, "Asynchronous control with ATR for large robot teams," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 444–448, 2011.

[72] J. Y. C. Chen, M. J. Barnes, S. A. Quinn, and W. Plew, "Effectiveness of RoboLeader for dynamic re-tasking in an urban environment," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, no. 1, pp. 1501–1505, 2011.

[73] E. de Visser, B. Kidwell, J. Payne, L. Lu, J. Parker, N. Brooks, T. Chabuk, S. Spriggs, A. Freedy, P. Scerri, and R. Parasuraman, "Best of both worlds: Design and evaluation of an adaptive delegation interface," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 57, no. 1, pp. 255–259, 2013.

[74] R. Ophir-Arbelle, T. Oron-Gilad, A. Borowsky, and Y. Parmet, "Is more information better? How dismounted soldiers use video feed from unmanned vehicles: Attention allocation and information extraction considerations," *Journal of Cognitive Engineering and Decision Making*, vol. 7, no. 1, pp. 26–48, 2013.

[75] T. Oron-Gilad and Y. Parmet, "Is more information better for dismounted soldiers? Display-layout considerations of multiple video feed from unmanned vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 345–349, SAGE Publications Sage CA: Los Angeles, CA, 2014.

[76] A. R. Panganiban and G. Matthews, "Executive functioning protects against stress in UAV simulation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 994–998, SAGE Publications, 2014.

[77] R. T. Stone, T. M. Schnieders, K. A. Push, S. Terry, M. Truong, I. Seshie, and K. Socha, "Human-robot interaction with drones and drone swarms in law enforcement clearing operations," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 63, pp. 1213–1217, 2019.

[78] H. Wang, A. Kolling, S. Abedin, P. Lee, S. Chien, M. Lewis, N. Brooks, S. Owens, P. Scerri, and K. Sycara, "Scalable target detection for large robot teams," in *2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, pp. 363–370, 2011.

[79] B. Kidwell, G. L. Calhoun, H. A. Ruff, and R. Parasuraman, "Adaptable and adaptive automation for supervisory control of multiple autonomous vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 428–432, 2012.

[80] A. A. Mkrtchyan, J. C. Macbeth, E. T. Solovey, J. C. Ryan, and M. L. Cummings, "Using variable-rate alerting to counter boredom in human supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 1441–1445, 2012.

[81] J.-Y. Jian, A. M. Bisantz, and C. G. Drury, "Foundations for an empirically determined scale of trust in automated systems," *International Journal of Cognitive Ergonomics*, vol. 4, no. 1, pp. 53–71, 2000.

[82] J. G. Boubin, C. F. Rusnock, and J. M. Bindewald, "Quantifying compliance and reliance trust behaviors to influence trust in human-automation teams," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, pp. 750–754, 2017.

[83] M. R. Endsley, "Measurement of situation awareness in dynamic systems," *Human Factors*, vol. 37, no. 1, pp. 65–84, 1995.

[84] R. Taylor, S. Selcon, and A. Swinden, "Measurement of situational awareness and performance: A unitary SART index predicts performance on a simulated ATC task," *Human factors in aviation operations*, pp. 275–280, 1995.

[85] J. Cacace, A. Finzi, V. Lippiello, M. Furci, N. Mimmo, and L. Marconi, "A control architecture for multiple drones operated via multimodal interaction in search & rescue mission," in *2016 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pp. 233–239, 2016.

[86] H. I. Son, L. L. Chuang, J. Kim, and H. H. Bulthoff, "Haptic feedback cues can improve human perceptual awareness in multi-robots teleoperation," in *11th International Conference on Control, Automation and Systems*, pp. 1323–1328, 2011.

[87] H. I. Son, A. Franchi, L. L. Chuang, J. Kim, H. H. Bulthoff, and P. Robuffo Giordano, "Human-centered design and evaluation of haptic cueing for teleoperation of multiple mobile robots," *IEEE Transactions on Cybernetics*, vol. 43, no. 2, pp. 597–609, 2013.

[88] G. Calhoun, M. Draper, C. Miller, H. Ruff, C. Breeden, and J. Hamell, "Adaptable automation interface for multi-unmanned aerial systems control: Preliminary usability evaluation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 57, pp. 26–30, 2013.

[89] F. Fortmann, H. Muller, A. Ludtke, and S. Boll, "Expert-based design and evaluation of an ambient light display to improve monitoring performance during multi-UAV supervisory control," in *IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA)*, pp. 28–34, 2015.

[90] S. L. Koh, K. Pfeil, and J. J. LaViola Jr, "Exploring the potential of full body and hand gesture teleoperation of robots inside heterogeneous human-robot teams," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 2008–2012, SAGE Publications Sage CA: Los Angeles, CA, 2018.

[91] "FAA Code of Federal Regulations (14 CFR) Part 107-Small Unmanned Aircraft System," 2016. https://www.ecfr.gov/cgi-bin/text-idx?node=pt14.2.107&rgn= div5.

[92] R. McKendrick, T. Shaw, H. Saqer, E. de Visser, and R. Parasuraman, "Team performance and communication within networked supervisory control human-machine systems," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 262–266, SAGE Publications Sage CA: Los Angeles, CA, 2011.

[93] R. Schaufele and M. Lukacs, "FAA aerospace forecast: Fiscal years 2019–2039," tech. rep., U.S Department of Transportation (DOT) Federal Aviation Adminis- tration (FAA), 2019. https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2019-39_FAA_Aerospace_Forecast.pdf.

[94] "U.S. Civil Airmen Statistics," 2019. https://www.faa.gov/data_research/aviation_data_statistics/civil_airmen_statistics/.

[95] M. W. Dye, C. S. Green, and D. Bavelier, "The development of attention skills in action video game players," *Neuropsychologia*, vol. 47, no. 8-9, pp. 1780–1789, 2009.

[96] A. E. Seiffert, S. T. Hayes, C. E. Harriott, and J. A. Adams, ""motion perception of biological swarms," in *Annual Cognitive Science Society*, pp. 2128–2133, 2015.

[97] R. A. McKinley, L. K. McIntire, and M. A. Funke, "Operator selection for unmanned aerial systems: comparing video game players and pilots," *Aviation, Space, and Environmental Medicine*, vol. 82, no. 6, pp. 635–642, 2011.

[98] I. Spence and J. Feng, "Video games and spatial cognition," *Review of General Psychology*, vol. 14, no. 2, pp. 92–104, 2010.

[99] M. L. Bolton and E. J. Bass, "Comparing perceptual judgment and subjective measures of spatial awareness," *Applied Ergonomics*, vol. 40, no. 4, pp. 597–607, 2009.

[100] R. B. Ekstrom, J. W. French, and H. H. Harman, *Kit of factor-referenced cognitive tests*. Educational Testing Service, Princeton, NJ, 1976.

[101] L. Gugerty and J. Brooks, "Reference-frame misalignment and cardinal direction judgments: group differences and strategies.," *Journal of Experimental Psychology: Applied*, vol. 10, no. 2, pp. 75–88, 2004.

[102] A. D. Baddeley and G. Hitch, "Working memory," in *The psychology of learning and motivation: Advances in research and theory* (G. H. Bower, ed.), vol. 8, pp. 47–89, Academic Press, 1974.

[103] R. W. Engle, "Working memory capacity as executive attention," *Current Directions in Psychological Science*, vol. 11, no. 1, pp. 19–23, 2002.

[104] A. R. Conway, M. J. Kane, M. F. Bunting, D. Z. Hambrick, O. Wilhelm, and R. W. Engle, "Working memory span tasks: A methodological review and user's guide," *Psychonomic Bulletin & Review*, vol. 12, no. 5, pp. 769–786, 2005.

[105] D. Derryberry and M. A. Reed, "Anxiety-related attentional biases and their regulation by attentional control.," *Journal of Abnormal Psychology*, vol. 111, no. 2, pp. 225–236, 2002.

[106] R. Farmer and N. D. Sundberg, "Boredom proneness: The development and correlates of a new scale," *Journal of Personality Assessment*, vol. 50, no. 1, pp. 4–17, 1986.

[107] C. Cameron, "Fatigue problems in modern industry," *Ergonomics*, vol. 14, no. 6, pp. 713–720, 1971.

[108] S. D. Manning, C. E. Rash, P. A. Leduc, R. K. Noback, and J. McKeon, "The role of human causal factors in US Army unmanned aerial vehicle accidents," tech. rep., Army Aeromedical Research Lab Fort Rucker AL, 2004.

[109] M. R. Rosekind, P. H. Gander, D. L. Miller, K. B. Gregory, R. M. Smith, K. J. Weldon, E. L. Co, K. L. Mcnally, and J. V. Lebacqz, "Fatigue in operational settings: examples from the aviation environment," *Human Factors*, vol. 36, no. 2, pp. 327–338, 1994.

[110] A. P. Tvaryanas and G. D. MacPherson, "Fatigue in pilots of remotely piloted aircraft before and after shift work adjustment," *Aviation, Space, and Environmental Medicine*, vol. 80, no. 5, pp. 454–461, 2009.

[111] C. Neubauer, G. Matthews, L. Langheim, and D. Saxby, "Fatigue and voluntary utilization of automation in simulated driving," *Human factors*, vol. 54, no. 5, pp. 734–746, 2012.

[112] S. R. Hursh, D. P. Redmond, M. L. Johnson, D. R. Thorne, G. Belenky, T. J. Balkin, W. F. Storm, J. C. Miller, and D. R. Eddy, "Fatigue models for applied research in warfighting," *Aviation, space, and environmental medicine*, vol. 75, no. 3, pp. A44–A53, 2004.

[113] N. D. Powel and K. A. Morgansen, "Multiserver queueing for supervisory control of autonomous vehicles," in *2012 American Control Conference (ACC)*, pp. 3179–3185, 2012.

[114] J. S. Warm, R. Parasuraman, and G. Matthews, "Vigilance requires hard mental work and is stressful," *Human Factors*, vol. 50, no. 3, pp. 433–441, 2008.

[115] E. J. Bass and A. R. Pritchett, "Human-automated judge learning: A methodology for examining human interaction with information analysis automation," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 38, no. 4, pp. 759–776, 2008.

[116] A. Wells, "A multi-dimensional measure of worry: Development and preliminary validation of the Anxious Thoughts Inventory," *Anxiety, Stress and Coping*, vol. 6, no. 4, pp. 289–299, 1994.

[117] W. Eberhard, *Guilt and Sin in Traditional China*. Berkeley: University of California Press, 1967.

[118] B. Torrence, B. Nelson, G. F. Thomas, B. L. Nesmith, and K. W. Williams, "Annotated Bibliography (1990-2019): Knowledge, Skills, and Tests for Unmanned Aircraft

Systems (UAS) Air Carrier Operations," tech. rep., Cherokee Nation 3-S and Federal Aviation Administration, n.d.

[119] "Remote Identification of Unmanned Aircraft, RIN 2120-AL31, Federal Regis- ter, Vol. 86, No. 10," January 2021. https://www.govinfo.gov/content/pkg/ FR-2021-01-15/pdf/2020-28948.pdf.

[120] "Operation of Small Unmanned Aircraft Systems Over People, RIN 2120-AK85, Federal Register, Vol. 86, No. 10," January 2021. https://www.govinfo.gov/content/pkg/FR-2021-01-15/pdf/2020-28947.pdf.

[121] M. L. Cummings, J. P. How, A. Whitten, and O. Toupet, "The impact of human-automation collaboration in decentralized multiple unmanned vehicle control," *Proceedings of the IEEE*, vol. 100, no. 3, pp. 660–671, 2012.

[122] A. Kopeikin, A. Clare, O. Toupet, J. How, and M. Cummings, "Flight testing a heterogeneous multi-UAV system with human supervision," in *AIAA Guidance, Navigation, and Control Conference*, pp. 1–18, 2012.

[123] P. T. Hu, B. Nelson, B. L. Nesmith, G. F. Thomas, and K. W. Williams, "Annotated Bibliography (1997-2019): Crew and Staffing Requirements of Unmanned Aircraft Systems in Air Carrier Operations ," tech. rep., Cherokee Nation 3-S and Federal Aviation Administration, n.d.

[124] E. T. Chancey, J. P. Bliss, Y. Yamani, and H. A. Handley, "Trust and the compliance-reliance paradigm: The effects of risk, error bias, and reliability on trust and dependence," *Human Factors*, vol. 59, no. 3, pp. 333–345, 2017.

[125] S. R. Dixon and C. D. Wickens, "Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload," *Human Factors*, vol. 48, no. 3, pp. 474–486, 2006.

[126] R. S. Gutzwiller, E. K. Chiou, S. D. Craig, C. M. Lewis, G. J. Lematta, and C.-P. Hsiung, "Positive bias in the 'Trust in Automated Systems Survey'? An examination of the Jian et al. (2000) scale," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 63, pp. 217–221, 2019.

[127] D. W. Lee, E. J. Bass, and C. Pankok Jr., "Developing operator-in-the-loop timeline requirements with a case study involving non-cooperative encounters with unmanned aircraft," in *2020 IEEE International Conference on Human-Machine Systems (ICHMS)*, pp. 1–6, 2020.

[128] J. D. Lee and N. Moray, "Trust, control strategies and allocation of function in human-machine systems," *Ergonomics*, vol. 35, no. 10, pp. 1243–1270, 1992.

[129] J. D. Lee and K. A. See, "Trust in automation: Designing for appropriate reliance," *Human Factors*, vol. 46, no. 1, pp. 50–80, 2004.

[130] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *Academy of Management Review*, vol. 20, no. 3, pp. 709–734, 1995.

[131] J. Meyer, "Effects of warning validity and proximity on responses to warnings," *Human Factors*, vol. 43, no. 4, pp. 563–572, 2001.

[132] L. Onnasch, "Crossing the boundaries of automation-function allocation and reliability," *International Journal of Human-Computer Studies*, vol. 76, pp. 12–21, 2015.

[133] R. Parasuraman and V. Riley, "Humans and automation: Use, misuse, disuse, abuse," *Human Factors*, vol. 39, no. 2, pp. 230–253, 1997.

[134] A. R. Pritchett, S. Y. Kim, and K. M. Feigh, "Measuring human-automation func- tion allocation," *Journal of Cognitive Engineering and Decision Making*, vol. 8, no. 1, pp. 52–77, 2014.

[135] A. Steinfeld, T. Fong, D. Kaber, M. Lewis, J. Scholtz, A. Schultz, and M. Goodrich, "Common metrics for human-robot interaction," in *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-robot Interaction*, pp. 33–40, 2006.

[136] E. J. Bass, L. A. Baumgart, and K. K. Shepley, "The effect of information analysis automation display content on human judgment performance in noisy environments," *Journal of Cognitive Engineering and Decision Making*, vol. 7, no. 1, pp. 49–65, 2013.

[137] J. M. Bradshaw, P. J. Feltovich, H. Jung, S. Kulkarni, W. Taysom, and A. Uszok, "Dimensions of adjustable autonomy and mixed-initiative interaction, AUTONOMY 2003. lecture notes in computer science," in *International Workshop on Computational Autonomy*, vol. 2969, Springer, 2003.

[138] J. Y. C. Chen, E. C. Haas, and M. J. Barnes, "Human performance issues and user interface design for teleoperated robots," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1231–1245, 2007.

[139] J. Y. C. Chen and M. J. Barnes, "Human-agent teaming for multirobot control: A review of human factors issues," *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 1, pp. 13–29, 2014.

[140] E. Edwards, "Automation in civil transport aircraft," *Applied Ergonomics*, vol. 8, no. 4, pp. 194–198, 1977.

[141] T. Fong and C. Thorpe, "Vehicle teleoperation interfaces," *Autonomous Robots*, vol. 11, no. 1, pp. 9–18, 2001.

[142] T. Fong, *Collaborative control: A robot-centric model for vehicle teleoperation*. PhD thesis, Carnegie Mellon University, 2001.

[143] E. Hollnagel and A. Bye, "Principles for modelling function allocation," *International Journal of Human-Computer Studies*, vol. 52, no. 2, pp. 253–265, 2000.

[144] D. W. Lee and E. J. Bass, "Simulating task sharing with delegation for autonomy and authority in air traffic control," in *2015 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 962–968, 2015.

[145] S. Loft, P. Sanderson, A. Neal, and M. Mooij, "Modeling and predicting mental workload in en route air traffic control: Critical review and broader implications," *Human Factors*, vol. 49, no. 3, pp. 376–399, 2007.

[146] P. Maes, "Agents that reduce work and information overload," *Communications of the ACM*, vol. 37, no. 7, pp. 30–40, 1994.

[147] C. A. Miller and V. Rlley, "Achieving the associate relationship; lessons learned from 10 years of research and design," in *Proceedings of the 3rd International Workshop on Human-Computer Teamwork*, pp. 174–180, 1995.

[148] V. Riley, *Automation and Human Performance: Theory and Applications*, ch. 3. Operator reliance on automation: Theory and data, pp. 19–35. Lawrence Erlbaum Associates, Inc., 1996.

[149] W. B. Rouse, "Adaptive aiding for human & computer control," *Human Factors*, vol. 30, no. 4, pp. 431–443, 1988.

[150] N. B. Sarter and D. D. Woods, "Pilot interaction with cockpit automation: Opera- tional experiences with the flight management system," *The International Journal of Aviation Psychology*, vol. 2, no. 4, pp. 303–321, 1992.

[151] N. B. Sarter and D. D. Woods, "How in the world did we ever get into that mode? mode error and awareness in supervisory control," *Human Factors*, vol. 37, no. 1, pp. 5–19, 1995.

[152] P. N. Squire and R. Parasuraman, "Effects of automation and task load on task switching during human supervision of multiple semi-autonomous robots in a dynamic environment," *Ergonomics*, vol. 53, no. 8, pp. 951–961, 2010.

[153] M. F. S. John and M. A. King, "The four-second supervisor: Multi-tasking supervision and its support," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, no. 4, pp. 468–472, 2010.

[154] C. D. Wickens, S. R. Dixon, and N. Johnson, "Imperfect diagnostic automation: An experimental examination of priorities and threshold setting," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, pp. 210–214, 2006.

[155] E. L. Wiener, "Cockpit automation," in *Human Factors in Aviation*, pp. 433–461, Elsevier, 1988.

[156] M. A. Goodrich and A. C. Schultz, "Human-robot interaction: A survey," *Foundations and Trends in Human-computer Interaction*, vol. 1, no. 3, pp. 203–275, 2007.

[157] C. J. Shannon, L. B. Johnson, K. F. Jackson, and J. P. How, "Adaptive mission planning for coupled human-robot teams," in *2016 American Control Conference (ACC)*, pp. 6164–6169, 2016.

[158] M. Lewis, H. Wang, S. Y. Chien, P. Velagapudi, P. Scerri, and K. Sycara, "Choosing autonomy modes for multirobot search," *Human Factors*, vol. 52, no. 2, pp. 225–233, 2010.

[159] G. Calhoun, H. Ruff, K. Behymer, and E. Frost, "Human-autonomy teaming inter- face design considerations for multi-unmanned vehicle control," *Theoretical Issues in Ergonomics Science*, vol. 19, no. 3, pp. 321–352, 2018.

[160] R. Oppermann, *Adaptive user support: ergonomic design of manually and automatically adaptable software*. CRC Press, 1994.

[161] C. A. Miller, H. Funk, R. Goldman, J. Meisner, and P. Wu, "Implications of adaptive vs. adaptable UIs on decision making: Why "automated adaptiveness" is not always the right answer," in *Proceedings of the 1st International Conference on Augmented Cognition*, pp. 22–27, 2005.

[162] C. A. Miller and R. Parasuraman, "Designing for flexible interaction between hu- mans and automation: Delegation interfaces for supervisory control," *Human Factors*, vol. 49, no. 1, pp. 57–75, 2007.

[163] R. Parasuraman, S. Galster, P. Squire, H. Furukawa, and C. Miller, "A flexible delegation-type interface enhances system performance in human supervision of multiple robots: Empirical studies with RoboFlag," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 35, no. 4, pp. 481–493, 2005.

[164] C. Pankok, Jr., E. J. Bass, P. J. Smith, J. Bridewell, I. Dolgov, J. Walker, E. An- derson, R. Concannon, P. Cline, and A. Spencer, "A7 - UAS Human Factors Control Station Design Standards (Plus Function Allocation, Training, and Visual Observer)," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), December 2017.

[165] C. Pankok, Jr., E. J. Bass, P. J. Smith, R. Storm, J. Walker, A. Shepherd, and A. Spencer, "A10 - Human Factors Considerations of Unmanned Aircraft System Procedures and Control Stations: Tasks CS-1 through CS-5," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), August 2017.

[166] Alan Hobbs and Beth Lyall, "Human Factors Guidelines for Unmanned Aircraft System Ground Control Stations: Preliminary Guidelines 1.0," tech. rep., NASA, 2015.

[167] RTCA Special Committee 228, "DO-365A Minimum Operational Performance Standards (MOPS) for Detect and Avoid (DAA) Systems," tech. rep., RTCA, Incorporated, Washington, DC, 2020.

[168] RTCA Special Committee 228, "DO-386 Vol I Minimum Operational Performance Standards for Airborne Collision Avoidance System Xu (ACAS Xu) (Vol I), and DO-386 Vol II Minimum Operational Performance Standards for Airborne Collision Avoidance System Xu (ACAS Xu) (Vol II: Algorithm Design," tech. rep., RTCA, Incorporated, Washington, DC, 2021.

[169] F. Friedman-Berg, J. Rein, and N. Racine, "Minimum visual information requirements for detect and avoid in unmanned aircraft systems," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 54–58, SAGE Publications, 2014.

[170] R. C. Rorie and L. Fern, "The impact of integrated maneuver guidance information on UAS pilots performing the detect and avoid task," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 55–59, SAGE Publications, 2015.

[171] R. C. Rorie, L. Fern, and R. J. Shively, "The impact of suggestive maneuver guidance on UAS pilots performing the detect and avoid function," *AIAA Infotech@ Aerospace*, p. 1002, 2016.

[172] K. W. Williams, "Minimum information requirements for an unmanned aircraft system detect-and-avoid traffic display under full-mission conditions, dot/faa/am- 20/06," tech. rep., Federal Aviation Administration, Office of Aerospace Medicine Civil Aerospace Medical Institute, 2019.

[173] K.-P. L. Vu, R. C. Rorie, L. Fern, and R. J. Shively, "Human factors contributions to the development of standards for displays of unmanned aircraft systems in support of detect-and-avoid," *Human factors*, vol. 62, no. 4, pp. 505–515, 2020.

[174] J. Y. C. Chen, S. G. Lakhmani, K. Stowers, A. R. Selkowitz, J. L. Wright, and M. Barnes, "Situation awareness-based agent transparency and human-autonomy

teaming effectiveness," *Theoretical Issues in Ergonomics Science*, vol. 19, no. 3, pp. 259–282, 2018.

[175] J. Chen, K. Procci, M. Boyce, J. Wright, A. Garcia, and M. Barnes, "Situation awareness-based agent transparency, ARL-TR-6905," tech. rep., Aberdeen Proving Ground (MD), US Army Research Laboratory, April 2014.

[176] J. Y. C. Chen, M. J. Barnes, A. R. Selkowitz, and K. Stowers, "Effects of agent transparency on human-autonomy teaming effectiveness," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 1838–1843, 2016.

[177] T. Helldin, U. Ohlander, G. Falkman, and M. Riveiro, "Transparency of automated combat classification," in *International Conference on Engineering Psychology and Cognitive Ergonomics*, pp. 22–33, Springer, 2014.

[178] D. Lee, A. Franchi, P. R. Giordano, H. I. Son, and H. H. Bulthoff, "Haptic teleoperation of multiple unmanned aerial vehicles over the internet," in *2011 IEEE International Conference on Robotics and Automation*, pp. 1341–1347, 2011.

[179] G. Jones, N. Berthouze, R. Bielski, and S. Julier, "Towards a situated, multimodal interface for multiple UAV control," in *2010 IEEE International Conference on Robotics and Automation*, pp. 1739–1744, 2010.

[180] F. Levillain, D. St-Onge, G. Beltrame, and E. Zibetti, "Towards situational awareness from robotic group motion," in *28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pp. 1–6, 2019.

[181] Y. Liu, J. M. Montenbruck, D. Zelazo, M. Odelga, S. Rajappa, H. H. Bulthoff, F. Allgower, and A. Zell, "A distributed control approach to formation balancing and maneuvering of multiple multirotor UAVs," *IEEE Transactions on Robotics*, vol. 34, no. 4, pp. 870–882, 2018.

[182] M. H. Draper, J. S. Pack, S. J. Darrah, S. N. Moulton, and G. L. Calhoun, "Human-machine interface development for common airborne sense and avoid program," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 44–48, SAGE Publications, 2014.

[183] L. Fern, R. C. Rorie, J. S. Pack, R. J. Shively, and M. H. Draper, "An evaluation of detect and avoid (DAA) displays for unmanned aircraft systems: The effect of information level and display location on pilot performance," in *Proceedings of 15th AIAA Aviation Technology, Integration, and Operations Conference*, 2015.

[184] K. Monk, R. J. Shively, L. Fern, and R. C. Rorie, "Effects of display location and information level on UAS pilot assessments of a detect and avoid system," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 50–54, SAGE Publications, 2015.

[185] J. S. Pack, M. H. Draper, S. J. Darrah, M. P. Squire, and A. Cooks, "Exploring performance differences between UAS sense-and-avoid displays," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 45–49, SAGE Publications, 2015.

[186] C. Santiago and E. Mueller, "Pilot evaluation of a UAS detect-and-avoid system's effectiveness in remaining well clear," in *Eleventh UAS/Europe Air Traffic Management Research and Development Seminar (ATM2015)*, 2015.

[187] D. J. Simons, "Current approaches to change blindness," *Visual Cognition*, vol. 7, no. 1-3, pp. 1–15, 2000.

[188] J. A. Adams, *Handbook of Unmanned Aerial Vehicles*, ch. 100 Cognitive task analysis for unmanned aerial system design, pp. 2425–2441. Springer Netherlands Dordrecht, 2015.

[189] J. A. Adams, C. M. Humphrey, M. A. Goodrich, J. L. Cooper, B. S. Morse, C. Engh, and N. Rasmussen, "Cognitive task analysis for developing unmanned aerial vehicle wilderness search support," *Journal of Cognitive Engineering and Decision Making*, vol. 3, no. 1, pp. 1–26, 2009.

[190] M. Askelson, H. Cathey, R. Marsh, Z. Waller, P. Snyder, G. Ullrich, C. Theisen, N. Kaabouch, W. Semke, M. Mullins, K. Foerster, R. Brothman, S. B. Hottman, K. Williamson, E. Johnson, A. VanHoudt, and Z. LaRue, "Small UAS Detect and Avoid Requirements necessary for Limited Beyond Visual Line of Sight (BVLOS) Operations," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), May 2017.

[191] P. W. Caro, "Aircraft simulators and pilot training," *Human Factors*, vol. 15, no. 6, pp. 502–509, 1973.

[192] R. M. Gagne, "Military training and principles of learning.," *American Psychologist*, vol. 17, no. 2, pp. 83–91, 1962.

[193] C. E. Nehme, J. W. Crandall, and M. Cummings, "An operator function taxonomy for unmanned aerial vehicle missions," in *12th International Command and Control Research and Technology Symposium*, pp. 19–21, 2007.

[194] C. Pankok Jr and E. J. Bass, "Information content requirements for remote pilot handover of control of unmanned aircraft systems in the National Airspace," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, pp. 81–85, SAGE Publications, 2018.

[195] T. B. Roby and J. T. Lanzetta, "Considerations in the analysis of group tasks.," *Psychological Bulletin*, vol. 55, no. 2, pp. 88–101, 1958.

[196] RTCA Inc., *Operational Services and Environmental Definition (OSED) for Unmanned Aircraft Systems (UAS)*. RTCA, Incorporated, 2010.

[197] T. L. Seamster and R. E. Redding, *Applied Cognitive Task Analysis in Aviation*. Routledge, 2017.

[198] J. Cerreta, T. Bruner, and P. Snyder, "A10-Human Factors Considerations of UAS Procedures and Control Stations: Tasks PC-1 through PC-3, Pilot and Crew (PC) subtask, Recommended Requirements and Operational Procedures," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), August 2017.

[199] A. Franchi, C. Secchi, M. Ryll, H. H. Bulthoff, and P. R. Giordano, "Shared control: Balancing autonomy and human assistance with a group of quadrotor UAVs," *IEEE Robotics Automation Magazine*, vol. 19, no. 3, pp. 57–68, 2012.

[200] S. Bruni, N. Schurr, N. Cooke, B. Riordan, and J. Freeman, "Designing a mixed-initiative decision-support system for multi-UAS mission planning," in *Proceedings of*

the Human Factors and Ergonomics Society Annual Meeting, vol. 55, pp. 21–25, SAGE Publications Sage CA: Los Angeles, CA, 2011.

[201] A. Castillejo-Calle, J. A. Millan-Romera, H. Perez-Leon, J. L. Andrade-Pineda,
I. Maza, and A. Ollero, "A multi-UAS system for the inspection of photovoltaic plants based on the ROS-MAGNA framework," in *2019 Workshop on Research, Education and Development of Unmanned Aerial Systems (RED UAS)*, pp. 266–270, 2019.

[202] G. Diehl and J. A. Adams, "Battery variability management for swarms," in *Interna- tional Symposium on Distributed Autonomous Robotic Systems*, 2021.

[203] P. Venero, A. Rowe, and J. Boyer, "Using augmented reality to help maintain persistent stare of a moving target in an urban environment," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 2575–2579, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[204] D. E. Kancler and D. A. Malek, "Using SMEs during initial development of small UAS concept of operations," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 2339–2343, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[205] C. M. Humphrey and J. A. Adams, "Human roles for robot augmented first response," in *Proceedings of the IEEE International Symposium on Safety, Security and Rescue Robotics*, 2015.

SUPPLEMENT 2: TASK 3 - HUMAN FACTORS LIMITATIONS FINAL REPORT

A26 A11L.UAS.74 Establish Pilot Proficiency Requirements: Multi-UAS Components
Task 3 Report

June 30, 2022

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16. Abstract
This research focuses on the human factors limitations to monitoring multiple UAS to include the identification of potential hazards, mitigations, and controls for the mitigations. The approach to identification of potential hazards, mitigations, and controls for the mitigations includes developing use cases and task analyses. Another component of this research is to review current methods for measurement of aptitude and the generation of a taxonomy to inform gaps with respect to multiple UAS control.

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A'	Area under the receiver operating characteristic curve (in signal detection theory)
d'	Index of sensitivity (in signal detection)

TABLE OF ACRONYMS

AOI	Area of Interest
ASSURE	Alliance for System Safety of UAS through Research Excellence
C^2	Command and control
ECG	Electrocardiogram
EEG	Electroencephalogram
FAA	Federal Aviation Administration
GPS	Global Positioning System
IPP	Integration Pilot Program
lbs.	pounds
LOA	Level of Automation or Level of Autonomy
LTE	Long-Term Evolution
MAT-B	Multi-Attribute Task Battery
max	Maximum
mUAS	Multi-Uncrewed Aircraft System
NASA	National Aeronautics and Space Administration
NASA-TLX	NASA Task Load Index
PSP	Partnership for Safety Plan
RF	Radio frequency
RTL	Return to Launch
SA	Situation Awareness
UAS	Uncrewed Aircraft System
UAV	Uncrewed Aerial Vehicle
UE	Unscheduled Events
UTA	Unit Trust Association
VTOL	Vertical Takeoff and Landing

EXECUTIVE SUMMARY

Commercial and public safety Uncrewed Aircraft Systems (UASs) are currently limited by the 14 Code of Federal Regulations (CFR) Part 107.205 prohibition on operating multiple aircraft by one person. The public as well as UAS commercial operations in applications such as package delivery and wildfire monitoring will benefit from modification to this prohibition. The Federal Aviation Administration (FAA) ASSURE study that this analysis supports will help to inform FAA regulations and industry standards addressing single supervisor and multiple UASs, or M:N Uncrewed Arial Vehicle (UAV) systems.

The ASSURE research team began to improve understanding human performance limitations by first considering loosely coupled tasks, where multiple vehicles conduct independent tasks (e.g., drone package delivery) and then tightly coupled tasks using an aerial ignition use case with two types of aircraft (surveillance and ignition). This effort provides a better understanding of the factors affecting a single supervisor's safe control of multiple UASs.

This analysis is designed to inform ASSURE researchers and FAA sponsors of human factors limitations to supervising multiple UAS to include the identification of potential hazards, mitigations, and controls for the mitigations. The approach includes the development of use cases and associated task analyses. For the loosely coupled task scenario, a task analysis developed with subject matter expert input identified that the majority of the complexity for multi-UAS control stems from tasks associated with unscheduled events such as return to launch or holding. However, the feasibility of a single supervisor monitoring multiple UAVs relies heavily on the usage of highly autonomous UAVs. In addition, task management strategies such as task prioritization and interruption need to be addressed for multi-UAS operations to be safe. For the tightly coupled task scenario, subject matter expert input highlighted the complexity related to managing multiple types of UAVs and their coupled missions.

For both scenarios, task analysis informed the identification of potential erroneous outcomes. Analysis of these hazards with respect to human performance limitations revealed that there are nine hazard mitigation classes that the FAA can enact: workspace design, control station design, display design, procedure design, training, UAV autonomy, decision support, organizational support, and personnel selection. The hazard analysis will guide subsequent computational modeling efforts investigating particular levels of UAV autonomy, decision support, and procedures. These latter analyses can support determining the types of human-in-the-loop studies needed to investigate M:N UAV systems.

A related analysis reviewed existing aptitude measurements. The research highlighted critical aptitudes, such as workload, situation awareness, and attention, but it is not clear which aptitudes play a critical role singly and/or in combination. There are no meta-analyses or other literature to support making claims about exactly which aptitudes are relevant to multi-UAS supervision.

The ASSURE research team established gaps in knowledge to support identifying the human factors limitations to supervising multiple UAS. It is expected that this project will generate even more questions that will need to be resolved before the FAA is able to institute substantial regulations and guidelines. However, researchers and the FAA will have a much clearer understanding of what further insight is needed to safely allow multiple UASs operations in the nation's airspace.

1 INTRODUCTION & BACKGROUND

This task focuses on the human factors limitations to supervising multiple UAS to include the identification of potential hazards, mitigations, and controls for the mitigations. The approach to the identification of potential hazards, mitigations, and mitigation controls is to first develop use cases and associated task analyses. This task leverages the literature review from Task 1. The next major section focuses on potential operational scenarios (use cases) that are validated by subject matter experts. The following section addresses associated human factors limitations to monitoring multiple UAS and associated potential hazards, mitigations, and controls. The subsequent section reviews existing aptitude measurements. A conclusion addresses gaps in knowledge to support identifying the human factors limitations to supervising multiple UAS.

2 DEVELOP OPERATIONAL SCENARIOS (USE CASES) AND TASK ANALYSIS THAT LEVERAGE PRIOR WORK (A7, A10) AND TASK 1 AND VALIDATE WITH SUBJECT MATTER EXPERTS.

This section presents the operational scenarios guiding this work. Two use cases were developed, a loosely coupled task and a tightly coupled task. A loosely coupled task exists when all UAVs in the system have independent goals that can be achieved without coordinating with other UAVs in the system. A tightly coupled task requires that UAVs in the system coordinate, to some level, to achieve the common mission goal, as well as the individual UAVs' goals. Ultimately, the decision to include both delivery and disaster response domains will allow the A26 project to provide insights about two different ends of the problem spectrum.

The loosely coupled scenario focuses on delivery drones and originated from interests expressed by the FAA. Utilization of UAVs in a delivery setting assumes the following: 1) UAVs will operate in populated areas in which the environment does not change frequently, 2) the weather is predictable, and 3) communication with other parties is reliable. The enroute flight phase for delivery drones was considered the primary scope for the task analysis based on FAA input. However, the other flight phases are discussed in the nominal use case for completeness.

The FAA expressed a preference for the tightly coupled task to focus on disaster response. After consulting with various subject matter experts, the team focused on the ridgeline aerial ignition scenario. The use of UAVs in this scenario assumes UAV operations occur in sparsely populated areas with minimal to no communication and potentially unpredictable weather. The tightly coupled scenario requires more coordination and supervisory attention than loosely coupled tasks. This scenario requires more autonomous cooperation between UAVs than is necessary to complete loosely coupled tasks.

2.1 Loosely Coupled Scenario

The loosely coupled delivery drone scenario was developed based on reviewing publicly available information. Interviews were conducted with a number of subject matter experts from various companies contributing toward developing delivery drones.

2.1.1 Identification of Delivery Domain Exemplars

The selection of the delivery domain prompted investigation about the current state of delivery UAVs in industry. The team conducted both internet searches and discussions with partner companies of the lead participants of the FAA Integration Pilot Program (IPP). The companies investigated may be found in Appendix A.

2.1.2 Delivery UAV Enabling Technology

The realistic use case for delivery UAVs was informed by collecting the following architectural and operations data: UAV Model, UAV maximum payload, target operation location, package loading/unloading strategy, UAV sensors, UAV actuators, and UAV communication method.

2.1.3 Descriptive Delivery Domain Narrative

The team developed the nominal use case by reviewing publicly available promotional videos and concept of operations documentation from Wing, Amazon, and others. The videos, concept of operations documentation, and most common exemplar characteristics were considered when developing the nominal use case. The use case narrative describes a single UAV delivery, including the actions of the UAVs, Supervisor, and other personnel. The narrative is divided by mission flight phases and the actions of involved actors, such as the UAVs, Supervisor, flight assistant, and recipient. The nominal use case was updated iteratively with feedback from A26 team members and industry partners. The nominal use case also contains assumptions related to delivery missions, UAV autonomy, UAV hardware, and the Supervisors.

2.1.4 Detailed Delivery UAV Nominal Use Case

A detailed nominal use case was developed to help visualize and organize the sequence of tasks expected for a nominal UAV delivery use case. The detailed use case contained the action of every expected involved actor.

2.1.5 Example Unexpected Events

Example potential unexpected events were developed collaboratively by A26 team members and validated through interviews with industrial partners. The example unexpected events were organized into the following categories: Supervisor failures, hardware failures, hardware damaging/inhibiting events, and flight path obstructions. Each example unexpected event was categorized to the responding agent (UAV autonomy or Supervisor monitoring the UAV). Ultimately, the objective of organizing the collection in this manner was to determine which example unexpected events occurred due to a failure in the UAV's onboard autonomy and required a response from the Supervisor. The example enroute flight phase-specific unexpected events were paired with the expected appropriate Supervisor response (i.e., unscheduled tasks). A task priority and interruptibility characteristic was included for each example unexpected event. A total of thirty-four example unexpected events were generated, as provided in Appendix B.

2.1.6 Example Distraction Events

Example potential Supervisor distraction events were developed collaboratively by A26 team members and validated through interviews with industrial partners. Ten example distractions were identified based on consideration of both internal and external distractions common in a shared workplace environment. The example distraction events were organized into categories based on their predicted impact on workload and task performance: high and low severity. The detailed example distractions are provided in Appendix B.

2.1.7 Results

2.1.7.1 Delivery UAV Enabling Technology

Twenty-three unique delivery UAV concepts were identified. Operation locations were mostly in rural and suburban areas. Two package loading/delivery methods were identified: an automated package procedure or manual hand load/unload. Two variations of the manual hand loading/unloading were demonstrated: one where the UAV must land and one where the UAV hovers and lowers a hook on a tether to which the package is attached. Concepts that use package drop techniques with and without a parachute and at varying distances from the ground also exist. The maximum payload across the twenty-three concepts ranged from 3.3 to 11 lbs. A variety of UAV sensors were identified, with visual cameras appearing most frequently. While most communication and navigation technologies appeared to use Long-Term Evolution (LTE) or Radio Frequency (RF), the available information for other UAV hardware was lacking. Appendix A documents the delivery UAV concept variations and Table 4 summarizes the findings.

Table 4. Summary of findings for Delivery UAV Concepts Exemplars.

Concept	**Description**
# of unique delivery concepts	23
Target operation location	Primarily rural and suburban
Most common method for package drop off	UAV hovers and lowers hooked package
Range of UAV maximum payload	3.3 lbs. - 11 lbs.
Package loading methods	Automated Package Loading Station Automated Package Loading Truck Manually by hand UAV hovers and loads package via hook and tether
Package drop off methods	Parachute drop Unloaded autonomously at Package Station UAV hovers and lowers package via hook and tether Lands and is unloaded by hand Low hover drop
UAV hardware	Visual camera Thermal imaging camera(s) Sonar imaging Global Positioning System (GPS)
UAV communication methods	4G LTE RF

2.1.7.2 Descriptive Narrative

The use case narrative addresses a single UAV package delivery, as found in Appendix B. The narrative is organized by the UAV's eight flight phases that occur during a delivery mission: pre-flight, take-off, ascend to cruising altitude, enroute, delivery, return, descend from cruising altitude, and landing. Assumptions were made to identify the appropriate tasks for involved actors at each flight phase.

2.1.7.3 Task Analysis

The use case identified eleven tasks that the human Supervisor is expected to perform during a shift, shown in Table 5 and Figure 1. Of these, four tasks are *scheduled* (i.e., routine) and occur during every shift. The scheduled tasks include accepting flights at the start of the shift, monitoring the enroute flights under the Supervisor's control, and handing off the flights still enroute at the end of the shift. The team assumes a generic "contact other party" task precedes the handoff tasks, but may not be necessary in practice depending on the workstation and communication architecture (i.e., contacting and either initiating or accepting a handoff may be one step). The role-specific tasks for scheduled events are provided in Appendix D.

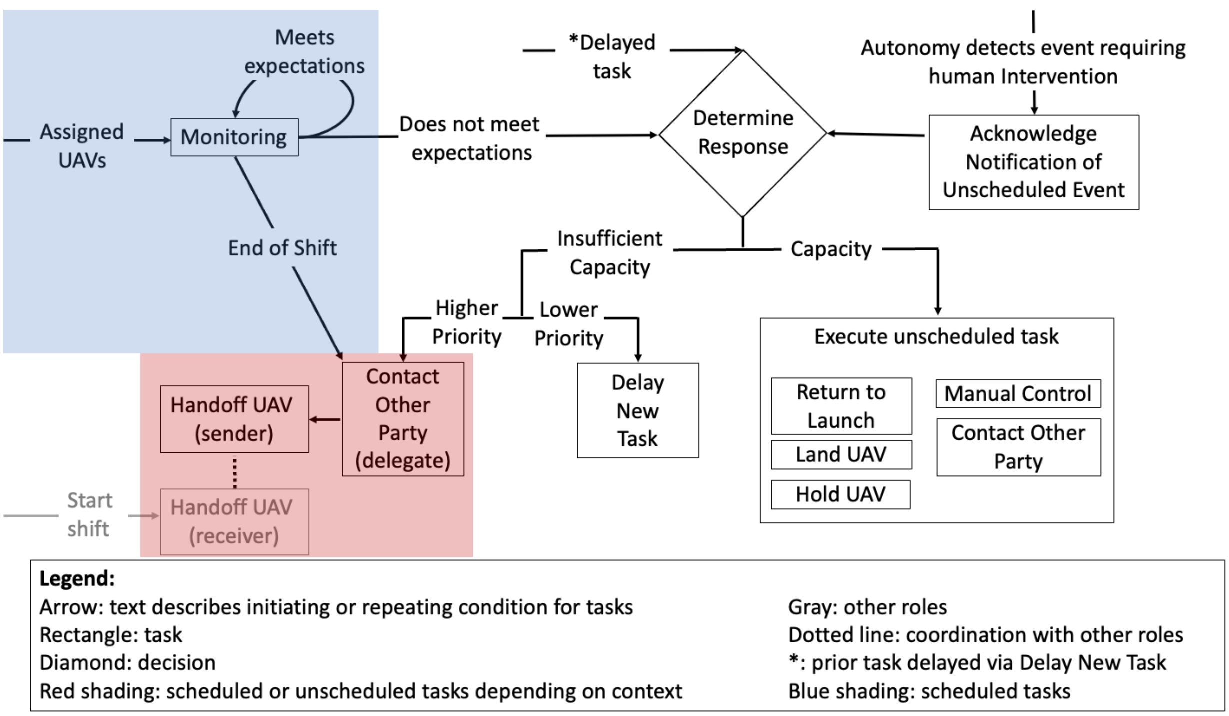

Figure 1. Nominal and unscheduled task analysis for Supervisor role in enroute phase. Nominal tasks are shown in the blue box. Tasks that may be either nominal or unscheduled depending on how they are initiated are shown in the red box. All other tasks are unscheduled.

Table 5. Supervisor Task Taxonomy for the Loosely Coupled Tasks Use Case.

Task	Description	Nominal Use	Task Category
Monitor flight(s)	Supervisor visually monitors the status of all UAVs under their control and detects problems	Scheduled	Monitoring
Contact other party	Supervisor needs to communicate with another party	Scheduled; Unscheduled	Communication
Handoff UAV (sender)	Supervisor passes command of the UAV to another	Scheduled; Unscheduled	Communication; discrete control
Handoff UAV (receiver)	Supervisor receives command of an UAV from another	Scheduled; Unscheduled	Communication; discrete control
Acknowledge notification of unscheduled event	Autonomy generates a notification for events that cannot be handled by the UAS, and the Supervisor must acknowledge and address issue	Unscheduled	Communication; discrete control
Delay task	Supervisor decides to delay a task until later	Unscheduled	Planning
Land UAV	Supervisor commands UAV to land immediately	Unscheduled	Discrete control
Return to Launch	Supervisor commands UAV to return to launch site	Unscheduled	Discrete control
Hold UAV	Supervisor commands UAV to enter holding pattern	Unscheduled	Discrete control
Manual Control (direct)	Supervisor navigates and aviates the UAV using direct control, power control	Unscheduled	Continuous control
Manual Control (autopilot)	Supervisor navigates the UAV using autopilot	Unscheduled	Discrete control

The remaining seven tasks are unscheduled in that they arise from an unexpected problem occurring during flight. The "contact other party" and handoff tasks may also be considered unscheduled if they are initiated in response to an unscheduled event. While the design of the interventions are outside the scope of this project, a majority of the unscheduled events, listed in Table 6, can be handled by the UAV's autonomy, as validated by interviews with Wing. The Supervisor will need to intervene when there is a system failure, such as with the UAV's autonomy. For example, if the UAV becomes unresponsive, then the Supervisor will need to contact other parties such as those who need to recover the UAV.

Table 6: Unscheduled events in the enroute phase.

Unscheduled event type	Unscheduled event	Supervisor Unscheduled Event Responses (Unscheduled Tasks)
Supervisor failure	Supervisor personal emergencies (e.g., Supervisor must step Away From C2 Workstation)	Hand off UAVs

Hardware failure	UAV overloaded and experience unexpected flight dynamics (measurement error / failure to measure in pre-flight step)	Command UAV to Return
	UAV unexpected Battery Depletion (UAV cannot reach delivery site/RTL)	Command UAV to Return/Land
	UAV landing due to UAV full/partial motor failure (UAV loses flight capabilities)	Contact Other Party
	UAV landing due to UAV GNSS (GPS) loss (Unusual)	Contact Other Party
	UAV communications loss (Unusual)	Contact Other Party
	UAV package actuator fails/ Premature release	Contact Other Party
	UAV delivery mechanism unable to be restored post-delivery (e.g. Wing hook and tether cannot be raised, Amazon Package Trapdoor cannot close)	Contact Other Party
Software failure	Adverse weather condition detected, UAVs do not return autonomously	Command UAV to Return
	Emergency in airspace and UAV is not responding	Contact Other Party
	UAV Fly Away (unexpected diversion from flight path; autonomy does not respond)	Command UAV to Return/Land; Manual Control
Hardware damaging/ inhibiting event	UAV Sensors Blinded by Man Made Airspace Condition (e.g., exhaust, steam plumes)	Command UAV to Return/Land
Flight path & mission obstructions	Supervisor receives external information about mission obstructions to which UAV autonomy does not have access	Command UAV to Return/Land/Hold
Collision	UAV crashes and unable to fly	Contact Other Party

The unscheduled tasks arise from two sources: the Supervisor having an unmet expectation during monitoring or a notification from the automation of a situation requiring human intervention. The Supervisor, aware of the unscheduled task, must react appropriately based on the unscheduled task's priority, shown in Table 7, and the Supervisor's current capacity, shown in Figure 1. The Supervisor can either execute, delay, or delegate the unscheduled task. The Supervisor will monitor executed tasks in order to verify that the UAV is correctly following the Supervisor's intentions, which adds to the Supervisor's monitoring load. The Supervisor is expected to execute an unscheduled task if they have available capacity. If they have insufficient capacity, the Supervisor will delay lower priority tasks and delegate higher priority tasks. Delayed tasks are executed at a later time (i.e., when the Supervisor has capacity). The Supervisor delegates a task by contacting another party (i.e., another human supervisor) and handing off the UAV experiencing the unexpected event.

Table 7. Supervisor's enroute task priority and interruptibility.

Task	Priority	Interruptible
Contact Other Party	Low	Yes
Return to launch	High	No
Hold UAV	Low	Yes
Land UAV	High	No
Manual Control	High	No

2.1.8 Discussion

The use case and task analysis development for the loosely coupled domain in the enroute phase provided insight into the feasibility of a single Supervisor monitoring multiple UAVs. The feasibility of a single Supervisor monitoring multiple UAVs in the loosely coupled domain relies heavily on the usage of highly autonomous UAVs. Subject matter experts validated that such automation is expected to be necessary to support package delivery. However, the large number of potential Supervisor Command and Control (C^2) interfaces and Supervisor work environments necessitated using generic assumptions for both. Explicitly constraining the use case and task analysis to specific examples may ultimately provide more detailed results in future studies.

Supervising multiple delivery UAVs during nominal use was determined to require relatively few tasks. The job becomes more complex when unscheduled events occur, and managing the associated unscheduled tasks creates more opportunities for potential human error. While some task management strategies can be addressed via a prioritization or interruption scheme, the details of task switching and the resumption of a restarted task are not addressed in Task 3.

2.2 Tightly Coupled Scenario

The tightly coupled multiple UAV ridgeline aerial ignition scenario was developed based on reviewing publicly available information (Detweiler et al. 2021, Glordan et al. 2018, NIFC 2020, NWCG multiple, Showrokski et al. 2016, Tidwell et al. 2016, US DOI 2010). Interviews were conducted with a number of wildland fire response subject matter experts, as well as Drone Amplified. DroneAmplified is the sole provider of aerial ignition UAVs in the United States; however, these systems are currently deployed within line of sight with a pilot in command at all times.

2.2.1 Descriptive Ridgeline Aerial Ignition Domain Narrative

The team developed the nominal use case by reviewing publicly available videos, the patent application, and other publicly available information. The use case narrative describes a small team of humans deploying 4-10 UAVs, including the actions of the UAVs, the Supervisor, and other personnel. The narrative is divided by a pre-deployment phase, the mission deployment phases and the actions of involved actors, such as the UAVs, Supervisor, Communication lead, and Logistics coordinator. The nominal use case was updated iteratively. The nominal use case also contains assumptions related to the ridgeline aerial ignition mission, UAV autonomy, UAV hardware, and the Supervisor.

2.2.2 Detailed Ridgeline Aerial Ignition Nominal Use Case

A detailed nominal use case was developed to help visualize and organize the sequence of tasks expected for a nominal multiple UAV ridgeline aerial ignition use case. The detailed use case contained the action of every expected involved actor.

2.2.3 Example Unexpected Events

Example potential unscheduled events were defined collaboratively by A26 team members. The example unscheduled events were organized into the following categories: mission related issues, Supervisor failures, hardware failures, software failures, and hardware damaging/inhibiting events. The unexpected events for this scenario only provide a high-level description, and are not as detailed as the loosely coupled scenario's unexpected events. A total of sixteen example unexpected events were generated, as provided in Appendix C.

2.2.4 Example Distraction Events

Example potential Supervisor distraction events were developed collaboratively by A26 team members. Seven example distractions were identified based on consideration of the deployment environmental conditions. A description is provided for each example distraction events and are provided in Appendix C.

2.2.5 Results

2.2.5.1 Descriptive Narrative

The use case narrative addresses multiple UAVs conducting a wildland fire ridgeline aerial ignition mission and can be found in Appendix C. The narrative assumes that pre-mission deployment preparation is completed before the small team departs for the actual mission deployment. Assumptions were made to identify the appropriate tasks for involved actors.

2.2.5.2 Task Analysis

The use case identified twenty tasks that the human Supervisor is expected to perform, shown in Table 8. While the loosely coupled tasks use case included communications, there is a greater need for communications in the tightly coupled tasks use case due to the greater coordination with the rest of the team. There are nine discrete control tasks (as opposed to three in the loosely coupled tasks use case) due to the greater range of activities associated with the two types (surveillance, ignition) of UAVs. There are also more monitoring and situation assessment tasks for the tightly coupled tasks use case due to the need to coordination with the other team members and to understand whether the surveillance and ignition UAVs are located and performing as intended.

Table 8. Supervisor Task Taxonomy for the Tightly Coupled Tasks Use Case.

Task	**Description**	**Nominal Use**	**Task Category**
Communicate with teammate (sender)	Supervisor verbally communicates with the Communication Lead and/or Logistics Coordinator.	Scheduled	Communications
Communicate with teammate (receiver)	Supervisor listens to the Communication Lead and/or Logistics Coordinator.	Scheduled	Communications
Launch mission plan	Supervisor executes the mission launch using their interface.	Scheduled	Discrete Control
Hold UAV	Supervisor commands one or more UAVs to hold.	Scheduled	Discrete Control
Initiate ignition sphere drop mission	Supervisor activates the ignition sphere drop phase of the mission using their interface.	Scheduled	Discrete Control
Modify ignition/ UAV parameters	Supervisor uses the interface to change a parameter that alters a UAV's behavior (e.g., sphere drop density, configuration threshold).	Scheduled	Discrete Control
Modify flight plan	Supervisor modifies a UAV's flight plan.	Scheduled	Discrete Control
Modify drop path	Supervisor uses waypoints to change the path along which an ignition UAV will drop spheres.	Scheduled	Discrete Control
Modify surveillance area	Supervisor designates a new area for a surveillance UAV to surveil.	Scheduled	Discrete Control
Modify surveillance flight pattern	Supervisor changes the flight pattern (e.g., stationary hover, lawn mower) used by a surveillance UAV to surveil its designated area.	Scheduled	Discrete Control
Return to launch	Supervisor commands one or more UAVs to return to launch.	Scheduled	Discrete Control
Evaluate dynamic checklist	Supervisor reviews the checklist and determines if any task is outstanding.	Scheduled	Monitoring and Situation Assessment
Evaluate ignition mission progress	Supervisor determines whether the mission's current progress is as intended.	Scheduled	Monitoring and Situation Assessment
Monitor flights	Supervisor visually monitors the status of all UAVs under their control and detects problems.	Scheduled	Monitoring and Situation Assessment

Task	Description	Nominal Use	Task Category
Monitor video feed	Supervisor visually monitors the video feed from a UAV's sensor(s).	Scheduled	Monitoring and Situation Assessment
Review flight plan	Supervisor reviews a new flight plan to determine if any further modifications are necessary.	Scheduled	Monitoring and Situation Assessment
Validate mission plan	Supervisor confirms that the mission plan created before arriving on site remains valid upon arrival to the mission location.	Scheduled	Monitoring and Situation Assessment
Validate team readiness	Supervisor verbally confirms that the other team members are ready to begin the mission.	Scheduled	Monitoring and Situation Assessment
Validate UAV position	Supervisor confirms that a UAV is in the correct location.	Scheduled	Monitoring and Situation Assessment
Verify locations within view of Surveillance UAV	Supervisor confirms that the area a surveillance UAV is currently monitoring is correct.	Scheduled	Monitoring and Situation Assessment

2.2.6 Discussion

The use case and task analysis development for the tightly coupled scenario highlighted the greater need for coordination with other team members, range of tasks due to the higher complexity of the mission, and the heterogeneity of the UAVs. Subject matter experts validated the need for greater automation, especially with regard to the surveillance and ignition goals. They also validated the need for greater support from performance aids such as dynamic checklists.

3 IDENTIFY POTENTIAL HAZARDS, MITIGATIONS, AND CONTROLS

Leveraging the Task 1 literature review and the use cases, this section identifies human factors limitations to monitoring multiple UAS, including potential hazards, mitigations, and mitigation controls.

3.1 Methods

3.1.1 Identifying Tasks of the Human Supervisor

3.1.1.1 Identifying Tasks of the Human Supervisor for the Loosely Coupled Tasks Scenario

For the loosely coupled tasks scenarios, Table 5 classifies the eleven Supervisor tasks by task category that help to further decompose tasks based on a model of human information processing (Parasuraman, Sheridan, & Wickens, 2000). Each Supervisor task is decomposed into up to four cognitive sub-tasks: information acquisition, assessment, decision, and execution, shown in Table

9. These sub-tasks reflect the fundamental perception, interpretation, judgment, and action stages of any activity.

Table 9. Task Decomposition of Supervisor Tasks for Loosely Coupled Tasks Scenario

			Cognitive Sub-tasks by Processing Stage			
Task	**Description**	**Task Category**	**Information Acquisition**	**Assessment**	**Decision**	**Execution**
Acknowledge notification of unscheduled event	Autonomy generates a notification for events that cannot be handled by the UAS; the Supervisor must acknowledge. Addressing the issue is a new task	Communication (receiver); discrete control	Attend to notification	Interpret notification	Decide to initiate abnormal/ emergency procedure	
Contact other party	Supervisor needs to communicate with another party	Communication	Perceive or recall contacts	Determine potential parties to contact	Decide who to contact	Initiate communication
Delay task	Supervisor decides to delay a task until later	Planning	Recall other tasks to complete	Determine priority	Decide when to schedule delayed task	Execute delayed task according to schedule
Handoff UAV (sender)	Supervisor passes command of the UAV to another human supervisor	Communication; discrete control	Perceive handoff request response from receiver	Determine receiver is ready to accept control	Decide to transfer control	Transfer control
Handoff UAV (receiver)	Supervisor receives command of an UAV from another human supervisor	Communication; discrete control	Perceive handoff request from sender	Determine if ready to accept control	Decide to accept handoff	Accept handoff
Land UAV	Supervisor commands UAV to land immediately	Discrete control	Perceive controls	Determine appropriate control	Confirm need to land	Execute land command
Monitor flight(s)	Supervisor visually monitors the status of all UAVs under their control and detects problems.	Monitoring	Perceive display; recall mission parameters	Compare system status to mission plan	Decide to initiate abnormal/ emergency procedure	
Return to launch	Supervisor commands UAV to return to launch site	Discrete control	Perceive controls	Determine appropriate control	Confirm need to return	Execute return command
Hold UAV	Supervisor commands UAV to enter hold	Discrete control	Perceive controls	Determine appropriate control	Confirm need to hold	Execute hold command
Manual Control (direct)	Supervisor navigates and aviates the UAV using direct control, power control	Continuous control	Perceive display	Determine error in flight path	Decide how to control aircraft	Exercise control

Task	Description	Task Category	Cognitive Sub-tasks by Processing Stage			
			Informa-tion Acquisition	Assess-ment	Decision	Execution
Manual Control (autopilot)	Supervisor navigates the UAV using autopilot	Discrete control	Perceive display	Determine flight plan	Decide on flight plan parameters	Program flight plan parameters

3.1.1.2 Identifying Tasks of the Human Supervisor for the Tightly Coupled Tasks Scenario

The tightly coupled tasks in Table 8 are broken down into cognitive sub-tasks for communication tasks in Table 10 and Table 11, for discrete control tasks in Table 12, and for monitoring and situation assessment tasks in Table 13.

Table 10. Task Decomposition of Supervisor Task for Tightly Coupled Tasks Scenario for Communications (Sender) Task

Task	Description	Cognitive Sub-tasks by Processing Stage		
		Generate	Transcribe	Transmit
Communicate with teammate	Supervisor verbally communicates with the Communication Lead and/or Logistics Coordinator.	Form intention	Transcribe message	Send message (speak)

Table 11. Task Decomposition of Supervisor Task for Tightly Coupled Tasks Scenario for Communications (Receiver) Task

Task	Description	Cognitive Sub-tasks by Processing Stage		
		Perception	Encoding	Interpretation
Communicate with teammate	Supervisor listens to the Communication Lead and/or Logistics Coordinator.	Perceive speaker	Encode message	Interpret meaning

Table 12. Task Decomposition of Supervisor Tasks for Tightly Coupled Tasks Scenario for Discrete Control Tasks

Task	Description	Cognitive Sub-tasks by Processing Stage			
		Information Acquisition	Assess-ment	Decision	Execution
Launch mission plan	Supervisor executes the mission launch using their interface.	Perceive controls	Determine appropriate control	Confirm readiness to launch	Execute the launch command

Task	Description	Cognitive Sub-tasks by Processing Stage			
		Information Acquisition	Assess-ment	Decision	Execution
Hold UAV	Supervisor commands one or more UAVs to hold.	Perceive controls	Determine appropriate control	Confirm need to hold	Execute the hold command
Initiate ignition sphere drop mission	Supervisor activates the ignition sphere drop phase of the mission using their interface.	Perceive controls	Determine appropriate control	Confirm readiness to drop	Execute the drop command
Modify ignition/ UAV parameters	Supervisor uses the interface to change a parameter that alters a UAV's behavior (e.g., sphere drop density, configuration threshold).	Perceive controls	Determine appropriate control	Confirm need to change parameter	Change the parameter
Modify flight plan	Supervisor modifies a UAV's flight plan.	Perceive display	Determine new flight path	Decide how to position waypoints	Program new flight plan
Modify drop path	Supervisor uses waypoints to change the path along which an ignition UAV will drop spheres.	Perceive display	Determine new drop path	Decide how to position waypoints	Program new drop path
Modify surveillance area	Supervisor designates a new area for a surveillance UAV to surveil.	Perceive display	Determine where surveillance is needed	Decide how to position new surveillance area	Program new surveillance area
Modify surveillance flight pattern	Supervisor changes the flight pattern (e.g., stationary hover, lawn mower) used by a surveillance UAV to surveil its designated area.	Perceive controls	Determine appropriate control	Confirm need to change flight pattern	Change the flight pattern
Return to launch	Supervisor commands one or more UAVs to return to launch.	Perceive controls	Determine appropriate control	Confirm need to return	Execute the return command

Table 13. Task Decomposition of Supervisor Tasks for Tightly Coupled Tasks Scenario for Monitoring and Situation Assessment Tasks

Task	Description	Cognitive Sub-tasks by Processing Stage		
		Information Acquisition	**Assessment**	**Decision**
Evaluate dynamic checklist	Supervisor reviews the checklist and determines if any task is outstanding.	Read checklist item	Determine status of checklist item	Decide what further action is necessary
Evaluate ignition mission progress	Supervisor determines whether the mission's current progress is as intended.	Perceive display; recall mission plan; discuss mission with team	Determine current mission effectiveness; compare current mission progress to mission plan	Decide whether current mission progress is satisfactory
Monitor flights	Supervisor visually monitors the status of all UAVs under their control and detects problems.	Perceive display; recall mission plan	Compare system status to mission plan	Decide to initiate abnormal/emergenc y procedure
Monitor video feed	Supervisor visually monitors the video feed from a UAV's sensor(s).	Perceive display; recall mission plan	Compare sensor information to mission plan	Decide whether further action is necessary
Review flight plan	Supervisor reviews a new flight plan to determine if any further modifications are necessary.	Perceive display	Determine if there are any issues with the flight plan	Decide whether flight plan is acceptable
Validate mission plan	Supervisor confirms that the mission plan created before arriving on site remains valid upon arrival to the mission location.	Perceive environment; recall mission plan	Determine feasibility of mission plan	Decide whether mission can proceed
Validate team readiness	Supervisor verbally confirms that the other team members are ready to begin the mission.	Verbally obtain other teammates' status	Determine each teammate's readiness	Decide team is ready
Validate UAV position	Supervisor confirms that a UAV is in the correct location.	Perceive display; recall mission plan	Compare UAV position to mission plan	Decide whether the UAV is in the correct position
Verify locations within view of Surveillance UAV	Supervisor confirms that the area a surveillance UAV is currently monitoring is correct.	Perceive display; recall mission plan	Compare current surveillance area to mission plan	Decide whether current surveillance area is appropriate

3.1.2 Determining Outcomes and Classification of Hazards

To identify hazards, the team determined the ways in which cognitive sub-tasks may succeed or fail. Successful outcomes indicate nominal performance and are therefore not hazardous. Failed outcomes indicate an error has occurred, causing a potential hazard to the mission. The team first detailed the analysis of each Supervisor task. Then the team addressed how tasks are selected and general procedural errors that may apply to any task. Then the team discussed the hazard taxonomy and how failed outcomes are classified as specific hazards.

The classes of outcomes that each cognitive sub-task may yield are enumerated for each Supervisor task based on a taxonomy of *commission* and *omission*. Commission refers to an outcome caused by the Supervisor's action, and omission refers to an outcome caused by the Supervisor's inaction. There is no wrong way to perform the simplest sub-tasks; therefore, the Supervisor's action (commission) or inaction (omission) directly determines whether the sub-task succeeds or fails. More complex sub-tasks may succeed and/or fail due to both commission and omission.

Table 14. Outcomes of the "Acknowledge Notification of Unscheduled Event" Task

Task	Processing Stage	Sub-task	Action	Outcome	Evaluation	Hazard(s)
Acknowledge notification of unscheduled event	Information Acquisition	Attend to notification	Commission	Notification is attended	Success	None
			Omission	Notification is not attended	Failure	Perception error
	Assessment	Interpret notification	Commission	Notification correctly interpreted	Success	None
			Commission	Notification incorrectly interpreted	Failure	Decision error
			Omission	Notification not understood	Failure	Knowledge error
	Decision	Decide to initiate abnormal/emergency procedure	Commission	Correctly decide to initiate procedure	Success	None
			Omission	Correctly decide not to initiate procedure	Success	None
			Commission	Incorrectly decide to initiate procedure	Failure	Decision error; Violation
			Omission	Incorrectly decide not to initiate procedure	Failure	Decision error; Violation

The "Acknowledge Notification of Unscheduled Event" task illustrates these degrees of complexity and can be seen in Table 14. The cognitive sub-task "Attend to Notification" may only succeed by commission (e.g., "Notification is attended") or fail by omission (e.g., "Notification is not attended"). The cognitive sub-task "Interpret Notification" is more complex: it may succeed only by commission (e.g., "Notification correctly interpreted"), but it may fail by either commission (e.g., "Notification incorrectly interpreted") or omission (e.g., "Notification not understood"). The cognitive sub-task "Decide to Initiate Abnormal/Emergency Procedure" is more complex, because the outcome depends on whether the decision conforms to the system state. The sub-task may succeed by commission if the Supervisor decides to initiate an emergency procedure, when the situation warrants it, or by omission if the Supervisor decides not to initiate an emergency procedure, when such a measure is unwarranted. The sub-task fails by omission if the Supervisor does not initiate a warranted emergency procedure, or by commission if the Supervisor initiates an emergency procedure in response to a false alarm. Note that at this stage in the analysis, the team is only concerned with the decision to initiate an emergency procedure or not. The choice of which procedure to initiate will be addressed in the next paragraph (procedural-level errors). When evaluating the outcomes of a particular cognitive sub-task, other cognitive sub-tasks are assumed to have been successful. For example, the analysis of the "Interpret Notification" sub-task assumes that there is a notification to be interpreted. If the notification was never attended and thus unavailable to be interpreted, the error is attributed to the "Attend to Notification" sub-task where the original failure occurred.

The nominal (i.e., successful) outcomes of all eleven Supervisor tasks for the loosely coupled tasks are provided in Table 15 and for the tightly coupled tasks in Table 16, Table 17, Table 18, and Table 19. Appendix E and extends this analysis to the non-nominal (i.e., unsuccessful) outcomes for the Supervisor tasks.

Table 15. Nominal Outcomes of the Supervisor Tasks and Sub-tasks for the Loosely Coupled Tasks Scenario.

Task	**Processing Stage**	**Sub-task**	**Outcome**
Acknowledge notification of unscheduled event	Information Acquisition	Attend to notification	Notification is attended
	Assessment	Interpret notification	Notification correctly interpreted
	Decision	Decide to initiate abnormal/ emergency procedure	Correctly decide to initiate procedure
			Correctly decide not to initiate procedure
Contact other party	Information Acquisition	Perceive contacts	All relevant information extracted accurately
		Recall contacts	Recall all relevant information correctly
	Assessment	Determine parties to contact	Applicable party identified
	Decision	Decide who to contact	Choose most appropriate contact
	Execution	Initiate communication	Effective communication
Delay new task	Information Acquisition	Recall other tasks to complete	Recall all relevant information correctly
	Assessment	Determine priority	Correctly assess priority of outstanding tasks
	Decision	Decide when to schedule delayed task	Schedule delayed task according to priority
	Execution	Execute delayed task according to schedule	Delayed task initiated when planned
Handoff UAV (receiver)	Information Acquisition	Perceive handoff request from sender	All relevant information extracted accurately
	Assessment		Correctly determine ready

Task	**Processing Stage**	**Sub-task**	**Outcome**
		Determine if ready to accept control	Correctly determine not ready
	Decision	Decide to accept handoff	Accept when ready
			Reject when not ready
	Execution	Accept handoff	Control taken
Handoff UAV (sender)	Information Acquisition	Perceive handoff request response from receiver	All relevant information extracted accurately
	Assessment	Determine receiver is ready to accept control	Correctly interpret the receiving Supervisor is ready
			Correctly interpret the receiving Supervisor is not ready
	Decision	Decide to transfer control	Decide to transfer when receiving Supervisor is ready
			Decide not to transfer when receiving Supervisor is not ready
	Execution	Transfer control	Control transferred
Hold UAV	Information Acquisition	Perceive controls	All relevant information extracted accurately
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to hold	Correctly choose hold
			Correctly reject hold
	Execution	Execute the hold command	Command executed
Land UAV	Information Acquisition	Perceive controls	All relevant information extracted accurately
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to land	Correctly choose land
			Correctly reject land
	Execution	Execute the land command	Command executed
Manual Control (direct)	Information Acquisition	Perceive flight information	All relevant information extracted accurately
	Assessment	Determine error in flight path	Error in flight path is estimated sufficiently
	Decision	Decide how to control aircraft	Sufficient control technique determined
	Execution	Exercise control	Appropriate control exercised
Manual Control (autopilot)	Information Acquisition	Perceive display	All relevant information accurately extracted
	Assessment	Determine flight plan	Appropriate flight planned
	Decision	Decide on flight plan parameters	All parameters chosen according to new flight plan

Task	Processing Stage	Sub-task	Outcome
	Execution	Program flight plan parameters	All parameters programmed as planned
Monitor flight(s)	Information Acquisition	Perceive display	All relevant information extracted accurately
		Recall mission parameters	Recall all relevant information correctly
	Assessment	Compare system status to mission plan	Correctly determine system status conforms to mission plan
			Correctly determine system status does not conform to mission plan
	Decision	Decide to initiate abnormal/emergency procedure	Correctly decide to initiate procedure
			Correctly decide not to initiate procedure
Return to Launch	Information Acquisition	Perceive controls	All relevant information extracted accurately
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to return	Correctly choose return
			Correctly reject return
	Execution	Execute the return command	Command executed

Table 16. Nominal Outcomes of the Communication (sender) Tasks and Sub-tasks for the Tightly Coupled Tasks Scenario.

Task	Processing Stage	Sub-task	Outcome
Communicate with teammate	Generate	Form intention	Pertinent intentions generated completely
	Transcribe	Transcribe message	Clearly transcribe complete intentions into words
	Transmit	Send message (speak)	Complete message spoken clearly

Table 17. Nominal Outcomes of the Communication (receiver) Tasks and Sub-tasks for the Tightly Coupled Tasks Scenario.

Task	Processing Stage	Sub-task	Outcome
Communicate with teammate	Perception	Perceive speaker	Complete message heard
	Encoding	Encode message	Correctly encode entire message
	Interpretation	Interpret meaning	Correctly interpret the speaker's intention

Table 18. Nominal Outcomes of the Discrete Control Tasks and Sub-tasks for the Tightly Coupled Tasks Scenario.

Task	Processing Stage	Sub-task	Outcome
Hold UAV	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to hold	Correctly choose to hold
			Correctly reject launch
	Execution	Execute the hold command	Command executed
Initiate ignition sphere drop mission	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm readiness to drop	Correctly choose to drop
			Correctly reject drop
	Execution	Execute the drop command	Command executed
Launch mission plan	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm readiness to launch	Correctly choose to launch
			Correctly reject launch
	Execution	Execute the launch command	Command executed
Modify drop path	Information Acquisition	Perceive display	All relevant information accurately extracted
	Assessment	Determine new drop path	Appropriate flight planned
	Decision	Decide how to position waypoints	All parameters chosen according to new flight plan
	Execution	Program new drop path	All parameters programmed as planned
Modify flight plan	Information Acquisition	Perceive display	All relevant information accurately extracted
	Assessment	Determine new flight path	Appropriate flight planned
	Decision	Decide how to position waypoints	All parameters chosen according to new flight plan
	Execution	Program new flight plan	All parameters programmed as planned
Modify ignition/UAV parameters	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to change parameter	Correctly choose to change parameter

			Correctly reject to change parameter
	Execution	Change the parameter	Command executed
Modify surveillance area	Information Acquisition	Perceive display	All relevant information accurately extracted
	Assessment	Determine where surveillance is needed	Correctly determine where surveillance is needed
	Decision	Decide how to position new surveillance area	Appropriate surveillance area selected
	Execution	Program new surveillance area	Correctly program new surveillance area
Modify surveillance flight pattern	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to change flight pattern	Correctly choose to change flight parameter
			Correctly reject to change flight parameter
	Execution	Change the flight pattern	Command executed
Return to launch	Information Acquisition	Perceive controls	All relevant information accurately extracted
	Assessment	Determine appropriate control	Correct control identified
	Decision	Confirm need to return	Correctly choose to return
			Correctly reject return
	Execution	Execute the return command	Command executed

Table 19. Nominal Outcomes of the Monitoring and Situation Assessment Tasks and Sub-tasks for the Tightly Coupled Tasks Scenario.

Task	**Processing Stage**	**Sub-task**	**Outcome**
Evaluate dynamic checklist	Information Acquisition	Read checklist item	Correctly read checklist item
	Assessment	Determine status of checklist item	Correctly determine that the item has been completed
			Correctly determine that the item has not been completed
	Decision	Decide what further action is necessary	Correctly check off item
			Correctly decide to initiate procedure
Evaluate ignition mission progress	Information Acquisition	Perceive Display	All relevant information accurately extracted
		Recall mission plan	Recall all relevant information correctly
		Discuss mission with team	All relevant information successfully communicated

	Assessment	Determine current mission effectiveness	Effectiveness sufficiently estimated
		Compare current mission progress to mission plan	Correctly determine that the current progress conforms to the mission plan
			Correctly determine that the current progress does not conform to the mission plan
	Decision	Decide whether current mission progress is satisfactory	Correctly decide that the current progress is satisfactory
			Correctly decide that the current progress is unsatisfactory
Monitor flights	Information Acquisition	Perceive display	All relevant information accurately extracted
	Information Acquisition	Recall mission plan	Recall all relevant information correctly
	Assessment	Compare system status to mission plan	Correctly determine system status conforms to mission plan
	Assessment	Compare system status to mission plan	Correctly determine system status does not conform to mission plan
	Decision	Decide to initiate abnormal/emergency procedure	Correctly decide to initiate procedure
	Decision	Decide to initiate abnormal/emergency procedure	Correctly decide not to initiate procedure
Monitor video feed	Information Acquisition	Perceive display	All relevant information accurately extracted
	Information Acquisition	Recall mission plan	Recall all relevant information correctly
	Assessment	Compare sensor information to mission plan	Correctly determine sensor information conforms to mission plan
	Assessment	Compare sensor information to mission plan	Correctly determine sensor information does not conform to mission plan
	Decision	Decide whether further action is necessary	Correctly decide further action is necessary
	Decision	Decide whether further action is necessary	Correctly decide further action is unnecessary
Review flight plan	Information Acquisition	Perceive Display	All relevant information accurately extracted
	Assessment	Determine if there are any issues with the flight plan	Correctly detect no issues with the flight plan
	Assessment	Determine if there are any issues with the flight plan	Correctly detect an issue with the flight plan
	Decision	Decide whether flight plan is acceptable	Correctly decide the flight plan is acceptable
	Decision	Decide whether flight plan is acceptable	Correctly decide the flight plan is unacceptable
Validate mission plan	Information Acquisition	Perceive environment	All relevant information accurately extracted

		Recall mission plan	Recall all relevant information correctly
	Assessment	Determine feasibility of mission plan	Correctly determine mission plan is feasible
			Correctly determine mission plan is not feasible
	Decision	Decide whether mission can proceed	Correctly approve mission plan
			Correctly disapprove mission plan
Validate team readiness	Information Acquisition	Verbally obtain other teammates' status	All relevant information accurately obtained
	Assessment	Determine each teammate's readiness	Correctly interpret teammate as ready
			Correctly interpret teammate as not ready
	Decision	Decide team is ready	Correctly decide team is ready
			Correctly decide team is not ready
Validate UAV position	Information Acquisition	Perceive display	All relevant information accurately extracted
		Recall mission plan	Recall all relevant information correctly
	Assessment	Compare UAV position to mission plan	Correctly determine UAV position conforms to mission plan
			Correctly determine UAV position does not conform to mission plan
	Decision	Decide whether the UAV is in the correct position	Correctly decide UAV is in the correct position
			Correctly decide UAV is in the incorrect position
Verify locations within view of Surveillance UAV	Information Acquisition	Perceive Display	All relevant information accurately extracted
		Recall mission plan	Recall all relevant information correctly
	Assessment	Compare current surveillance area to mission plan	Correctly determine surveillance area conforms to mission plan
			Correctly determine surveillance area does not conform to mission plan
	Decision	Decide whether current surveillance area is appropriate	Correctly decide the surveillance area is appropriate
			Correctly decide the surveillance area is not appropriate

Errors may also occur between Supervisor tasks. Figure 1 illustrates decision points in the workflow; therefore, a taxonomy of procedural-level errors applicable to all Supervisor tasks are incorporated. This taxonomy is based on the work of Hollnagel (1993; see also Bolton, Siminiceanu & Bass, 2011; Bolton, Bass & Siminiceanu, 2012; Bolton & Bass, 2013), who described the zero-order erroneous actions that may occur when executing a plan. Twelve such errors are identified in the analysis, shown in Table 20. These errors catalog failures in the tasks' pre- and post-conditions, describing how a task may fail to initiate, be selected to initiate inappropriately, or terminate prematurely. The procedural errors describe process errors between tasks or within tasks (i.e., between sub-tasks) through skips, repeats, omissions, and intrusions; which may be combined to describe sequential errors, such as performing a procedure's steps out of a prescribed order.

Table 20. Procedural-level Errors and Associated Hazards.

Procedural Error	**Description**	**Hazard(s)**
Activate wrong procedure	A task is initiated when it should not.	Decision error; Skill-based error
Fail to initiate task	A task that should be initiated is not.	Decision error; Perception error; Knowledge error; Violation
Premature Start	Initiating a task before the prescribed time.	Decision error; Violation
Late Start	Initiating a task after the prescribed time.	Decision error; Perceptual error; Violation
Execute intended action to wrong UAS	The correct procedure is selected, but applied to a different vehicle.	Skill-based hazard
Skip	Performing an action earlier than the prescribed order.	Decision error; Skill-based error; Knowledge error; Violation
Deferral	Performing an action later than the prescribed order.	Decision error; Skill-based error; Knowledge error; Violation
Repeat	Performing an already performed action.	Decision error; Skill-based error; Knowledge error; Violation
Task steps omitted	Not performing a prescribed action.	Decision error; Skill-based error; Knowledge error; Violation
Intrusion	Performing an unplanned action (often from a different procedure).	Decision error; Skill-based error; Perceptual error; Knowledge error
Premature Finish	Terminating a task earlier than prescribed.	Decision error; Skill-based error; Knowledge error; Violation
Late Finish	Terminating a task later than prescribed.	Decision error; Skill-based error; Knowledge error; Violation

The team defines all failed outcomes and procedural errors as *hazards* and uses a taxonomy based on the human factors analysis and classification system (HFACS; Shappell & Wiegmann, 2000) to categorize them. Shappell and Wiegmann defined five types of unsafe acts: decision errors, skill-based errors, perceptual errors, routine violations, and exceptional violations; to which we add knowledge errors (Table 21; see also "Definitions" (n.d.)). The hazards differentiate based on the Supervisor's intentions, such that decision errors, skill-based errors, perception errors, and knowledge errors reflect inadvertent mistakes in thinking, doing, sensing, and knowing, respectively, while violations describe the deliberate breaking of rules or established procedures. The team assigned hazards to each outcome based on the potential for the hazard's definition to apply to the outcome (see Table 20 and Appendix E). Note that the distinction between a routine violation and an exceptional violation may come down to the frequency with which the violation occurs, although there may be other differences. For example, routine violations become habits typically through condonation by management. Therefore, in order to maintain generalizability to a variety of operational scenarios, the team did not differentiate between the type of violation when assigning hazards to outcomes. The distinction was retained for the remaining analyses.

Table 21. Hazard Definitions.

Hazard	Definition	Examples
Decision error	"Conscious, goal-intended behavior that proceeds as designed, yet the plan proves inadequate or inappropriate for the situation." ("thinking" errors)	Poorly executed procedures, improper choices, or simply the misinterpretation and/or misuse of relevant information
Skill-based error	"Highly practiced behavior that occurs with little or no conscious thought, including the manner or technique with which one performs a task." ("doing" errors)	Visual scan patterns, inadvertent activation/deactivation of switches, forgotten intentions, and omitted items in checklists
Perceptual error	"These errors arise when sensory input is degraded as is often the case when flying at night, in poor weather, or in otherwise visually impoverished environments."	Misjudging distances, altitude, and decent rates, as well as responding incorrectly to a variety of visual/vestibular illusions.
Knowledge error	Occurs when the information needed to execute a procedure or otherwise is not available.	Forgetting, untrained procedures, other unknown information
Routine violation	"Tends to be habitual by nature and is often enabled by a system of supervision and management that tolerates such departures from the rules."	"Bending the rules"
Exceptional violation	"Isolated departures from authority, neither typical of the individual nor condoned by management."	

Note: With the exception of knowledge errors, the definitions for each hazard are taken from "Definitions" (n.d.)

3.1.3 Mapping Hazards to Mitigations

The team conducted a series of mappings to determine which mitigations may reduce the risk of the aforementioned hazards. The approach was to first map the hazards to their possible causes, followed by categorizing the causes to reduce the mapping space dimensionality. Next, the cause categories were mapped to mitigations. Finally, the mapping chains were traced and aggregated in order to reveal each hazards' possible mitigations.

Table 22. Out of Scope Causes for Hazards.

Personnel Factors	Organizational Influences
Physiological impairment	Human resources
Medical illness	Monetary/budget resources
Physiological incapacitation	Equipment/facility resources
Culture	Organizational structure
Personality	Organizational policies
Demographics	Organizational culture
	Organizational operations
	Organizational procedures
	Organizational oversight

The team surveyed the Task 1 literature review and the use case information for potential *causes* to hazards. 161 potential causes were identified. Fifteen causes were determined to be outside the scope of the hazard taxonomy, as shown in Table 22, as they generally describe personal illness and demographics, as well as organizational factors.

The team mapped hazards to their potential causes by iterating through the causes and for each hazard deciding whether the cause can reasonably be expected to give rise to the hazard. As part of this process, the team generated exemplars or selected excerpts from the hazard definitions to facilitate review. One analyst created the mappings, and another reviewed them. The complete mapping is in Appendix G.

To develop a complete mapping, many comparisons of possible causes to hazards are needed. To support this effort, researchers assigned each cause to a representative *cause category* taken from the enabling conditions taxonomy of HFACS (Shappell & Wiegmann, 2000). Definitions for each of the fifteen cause categories are provided in Table 23 (“Definitions” (n.d.)). The team used these definitions to categorize the causes, again generating exemplars or excerpts to facilitate review. Some examples of the cause categorization are provided in Table 24. The complete mapping is in Appendix H. .

Table 23. Cause Category Definitions.

Cause Category	**Definition**	**Examples**
Adverse mental state	Mental conditions that affect performance, including mental fatigue, personality traits, and attitudes	Situation awareness, task fixation, distraction, sleep loss, stressors, overconfidence, complacency, motivation
Adverse physiological state	Medical or physiological conditions	Visual illusions, spatial disorientation, physical fatigue, illness
Failure to account for mental limitations	Occurs when mission requirements exceed the mental capabilities of the individual	Rushed decisions, mental aptitude
Failure to account for physical limitations	Occurs when mission requirements exceed the individual’s physical capabilities	Night vision, physical size and strength constraints
Crew resource management	Communication, coordination, and teamwork among personnel	Crew introductions and briefings, checklists based on challenge-and-response concepts and methods for interruption and resumption, communication encouraging inquiry, advocacy, and assertion
Personal readiness	Occurs when individuals fail to prepare physically or mentally for duty	Crew rest requirements, alcohol/drug abuse, skipping meals
Technological Environment	The design of equipment and controls, display/interface characteristics, checklist layouts, task factors and automation	Mode annunciators
Physical Environment	The operational setting and the ambient environment	Weather, altitude, terrain, heat, vibration, lighting, toxins
Inadequate Supervision	Supervisor guidance and oversight	Guidance, training opportunities, leadership, motivation
Planned inappropriate operations	Unsafe management and assignment of work	Risk management, crew pairing, operational tempo
Failed to correct known problem	Instances when deficiencies among individuals, equipment, training or other related safety areas are “known” to the Supervisor, yet are allowed to continue unabated	Failure to consistently correct or discipline inappropriate behavior

Cause Category	Definition	Examples
Supervisory violations	Instances when existing rules and regulations are willfully disregarded by the human supervisors	Permitting individuals to operate an aircraft without current qualifications or license
Resource/acquisition management	Corporate-level decision making regarding the allocation and maintenance of organizational assets such as human resources (personnel), monetary assets, and equipment/facilities	Excessive cost-cutting, poorly maintained equipment and workspaces, and the failure to correct known design flaws in existing equipment
Organizational climate	The working atmosphere within the organization; the unofficial or unspoken rules, values, attitudes, beliefs, and customs of an organization.	Chain-of-command, delegation of authority and responsibility, communication channels, and formal accountability for actions
Organizational process	Corporate decisions and rules that govern the everyday activities within an organization; standardized operating procedures and oversight	Operational tempo, time pressures, incentive systems, and work schedules

Note: The definitions and examples for each cause category are taken from "Definitions" (n.d.)

Table 24. Classification of Causes to Hazards.

Enabling Condition	Cause Category	Example Cause(s)
Condition of the Operator	Adverse mental state	Channelized attention Complacency Mental fatigue
	Adverse physiological state	Medical illness Physiological incapacitation Physical fatigue
	Failure to account for mental limitations	Insufficient reaction time Incompatible intelligence/aptitude
	Failure to account for physical limitations	Visual limitation Incompatible physical capability
Personnel Factors	Crew resource management	Failed to back-up (crewmember) Failed to communicate/coordinate Failure of leadership
	Personal readiness	Excessive physical training Self-medicating Violation of crew rest requirement
Environmental Factors	Technological environment	Control mode Display flexibility Taskload
	Physical environment	Air traffic Disrupted flight performance Obstacles in environment
Unsafe Supervision	Inadequate supervision	Failed to provide oversight Failed to provide training Failed to track qualifications
	Planned inappropriate operations	Failed to provide adequate brief time Improper manning Mission not in accordance with rules/regulations

	Failed to correct known problem	Failed to correct document in error Failed to initiate corrective action Failed to report unsafe tendencies
	Supervisory violations	Authorized unnecessary hazard Failed to enforce rules and regulations Authorized unqualified crew for flight
Organizational Influences	Resource/acquisition management	Human resources Monetary/budget resources Equipment/facility resources
	Organizational climate	Organizational structure Organizational policies Organizational culture
	Organizational process	Organizational operations Organizational procedures Organizational oversight

Per FAA Order 8040.4B, the team does not distinguish between controls and mitigations, and because the team does not assume a specific design implementation, the team identified *mitigation classes* – categories of controls and mitigations – that may be employed to reduce the likelihood and/or severity of a hazard. There are nine hazard mitigation classes that the FAA can enact: workspace design, control station design, display design, procedure design, training, UAV autonomy, decision support, organizational support, and personnel selection. The team mapped the cause categories to the possible mitigations using a similar process to the prior mappings, generating exemplars or excerpts from the cause category definitions to facilitate review. The accumulated mitigations are provided in Table 25; the complete mapping matrix may be found in Appendix I. .

Table 25. Potential Mitigations to Causes of Hazards.

Cause Category	**Potential Mitigation(s)**
Adverse mental state	Workspace design, Control station design, Display design, Procedure design, Training, UAV autonomy, Decision support
Adverse physiological state	Workspace design, Control station design, Display design, Training
Failure to account for mental limitations	Display design, Procedure design, UAV autonomy, Decision support, Personnel selection
Failure to account for physical limitations	Workspace design, Control station design, Display design, UAV autonomy, Personnel selection
Crew resource management	Control station design, Procedure design, Training, UAV autonomy, Organizational support, Personnel selection
Personal readiness	Training, Personnel selection
Technological environment	Control station design, Display design, Procedure design, Training, UAV autonomy, Decision support, Organizational support
Physical environment	Workspace design, Training, UAV autonomy
Inadequate supervision	Training, UAV autonomy, Organizational support, Personnel selection
Planned inappropriate operations	Training, Organizational support, Personnel selection
Failed to correct known problem	Training, Organizational support, Personnel selection

Cause Category	Potential Mitigation(s)
Supervisory violations	Training, Personnel selection
Resource/acquisition management	Organizational support
Organizational climate	Organizational support
Organizational process	Organizational support

3.2 Results

3.2.1 Loosely-Coupled Scenario

Table 26 summarizes the hazards encountered during a particular information processing stage for the loosely coupled scenario. If a column sums to more than 100%, it indicates that some outcomes may be attributable to more than one type of hazard. For example, there were 25 hazardous outcomes in the information acquisition stage. None were attributable to decision errors or violations, whereas 13 (52%) may be caused by a skill-based error, 19 (76%) may be caused by a perceptual error, and 6 (24%) may be caused by a knowledge error. An example of a hazardous outcome being attributable to more than one type of hazard is recalling incorrect information. If the human has inaccurate knowledge because they were improperly trained then it is a knowledge error; however, if the human has accurate knowledge but the information is corrupted when retrieved from memory then it is a skill-based error.

Non-nominal outcomes during the information acquisition stage are perceptual errors, skill-based errors, and knowledge errors. Non-nominal outcomes during the assessment stage are decision errors, knowledge errors, and skill-based or perceptual errors. Non-nominal outcomes during the decision stage are almost entirely decision errors or violations, with some skill-based or knowledge errors also occurring. Non-nominal outcomes during the execution stage are largely skill-based errors or violations, with a few knowledge or decision errors also possible.

Inspecting Table 26 indicates that decision errors or violations are not expected to occur during the information acquisition stage, as this stage typically requires the perception or recall of information. Skill-based errors during information acquisition typically occur because of breakdowns in visual scan patterns, which are related to the prevalent theme of perception during this stage. Violations are not expected to occur during the assessment stage, as violations require an accurate understanding of the situation before the appropriate procedure for that situation can be willfully disregarded. The distribution of the other hazards during this stage reflects the fact that the typical function of assessment is to determine the state of the situation (i.e., a decision). The varying occurrence of knowledge, skill-based, and perceptual errors typically reflect omission errors (e.g., the state is unknown) or commission errors (e.g., flawed communication or perceptions of the current state). Perceptual errors are not expected to occur during the decision or execution stages because these stages typically concern what is done with the information after it has been acquired. Decision and skill-based errors during the decision and execution stages, respectively, are expected as they are fundamentally the "thinking" and "doing" hazards and stages. Violations are expected to co-occur with decision errors in the decision stage because an improper choice may be intentional or unintentional. Likewise, failures of execution may occur from either unintentional, skill-based errors or intentional violations.

Table 26. Non-nominal Outcomes and Frequency of Outcomes by Processing Stage (by column) for the Loosely Coupled Tasks Scenario.

Hazard	**Row Total**	**Processing Stage**			
		Information Acquisition	**Assessment**	**Decision**	**Execution**
Number of hazardous outcomes for processing stage	78	25	20	20	13
Decision Error	33	0/25 (0%)	14/20 (70%)	18/20 (90%)	1/13 (8%)
Skill-based Error	29	13/25 (52%)	3/20 (15%)	2/20 (10%)	11/13 (85%)
Perceptual Error	20	19/25 (76%)	1/20 (5%)	0/20 (0%)	0/13 (0%)
Knowledge Error	17	6/25 (24%)	8/20 (40%)	1/20 (5%)	2/13 (15%)
Violation	25	0/25 (0%)	0 (0%)	14/20 (70%)	11/13 (85%)

Note: A hazardous outcome can be associated with more than one hazard in a processing stage.

Table 27. Distribution of Hazards by Processing Stage.

Hazard	**Hazard Total**	**Information Acquisition**	**Assessment**	**Decision**	**Execution**
Decision Error	33	0/33 (0%)	14/33 (42%)	18/33 (55%)	1/33 (3%)
Skill-based Error	29	13/29 (45%)	3/29 (10%)	2/29 (7%)	11/29 (38%)
Perceptual Error	20	19/20 (95%)	1/20 (5%)	0/20 (0%)	0/20 (0%)
Knowledge Error	17	6/17 (35%)	8/17 (47%)	1/17 (6%)	2/17 (12)%
Violation	25	0/25 (0%)	0/25 (0%)	14/25 (56%)	11/25 (44)%

With respect to the distribution of hazards across processing stages shown in Table 27, 97% of decision errors appear during the assessment or decision stages, where the focus is on evaluation and judgment. 83% of skill-based errors appear during the information acquisition and execution stages (i.e., the perception and action stages). 95% of perceptual errors appear during the information acquisition stage as already described. 83% of knowledge errors appear in the information acquisition and assessment stages, where the declarative and procedural knowledge needed to inform decisions is recalled. Violations only appear during the decision and execution stages, with more hazardous outcomes in the decision stage than in the execution stage.

3.2.2 Tightly-Coupled Scenario

Table 28 summarizes the hazards encountered during a particular information processing stage for the Communication (sender) task category. Table 29 presents the distribution of hazards across processing stages. Here the majority of the hazards are related to the decision errors associated with generating the intended message and the skill-based errors that may occur in transcribing and transmitting the intended message.

Table 28. Non-nominal Outcomes and Frequency of Outcomes by Processing Stage (by column) for Communication (sender) Tasks.

Hazard	Row Total	Generate	Transcribe	Transmit
Number of hazardous outcomes for processing stage	7	2	2	3
Decision Error	2	2/2 (100%)	0/2 (0%)	0/3 (0%)
Skill-based Error	5	0/2 (0%)	2/2 (100%)	3/3 (100%)
Perceptual Error	0	0/2 (0%)	0/2 (0%)	0/3 (0%)
Knowledge Error	0	0/2 (0%)	0/2 (0%)	0/3 (0%)
Violation	3	2/2 (100%)	0/2 (0%)	1/3 (33%)

Note: A hazardous outcome can be associated with more than one hazard in a processing stage.

Table 29. Distribution of Hazards by Processing Stage During Communication (sender) Tasks.

Hazard	Hazard Total	Generate	Transcribe	Transmit
Decision Error	2	2/2 (100%)	0/2 (0%)	0/2 (0%)
Skill-based Error	5	0/5 (0%)	2/5 (40%)	3/5 (60%)
Perceptual Error	0	0/0 (0%)	0/0 (0%)	0/0 (0%)
Knowledge Error	0	0/0 (0%)	0/0 (0%)	0/0 (0%)
Violation	3	2/3 (67%)	0/3 (0%)	1/3 (33%)

Table 30 summarizes the hazards encountered during a particular information processing stage for the Communication (receiver) task category. Table 31 presents the distribution of hazards across processing stages. Here the majority of the hazards are related to the perceptual errors associated with not being able to acquire the intended message. Comparing the communication related hazards for senders and receivers, one can see that while receiving information incompletely has more opportunities to fail due to perceptual issues, disseminating information has more opportunities to fail due to skill-based errors.

Table 30. Non-nominal Outcomes and Frequency of Outcomes by Processing Stage (by column) for Communication (receiver) Tasks.

Hazard	Row Total	Perception	Encoding	Interpretation
Number of hazardous outcomes for processing stage	5	2	2	1
Decision Error	1	0/2 (0%)	0/2 (0%)	1/1 (100%)
Skill-based Error	3	0/2 (0%)	2/2 (100%)	1/1 (100%)

Perceptual Error	4	2/2 (100%)	2/2 (100%)	0/1 (0%)
Knowledge Error	1	0/2 (0%)	0/2 (0%)	1/1 (100%)
Violation	0	0/2 (0%)	0/2 (0%)	0/1 (0%)

Note: A hazardous outcome can be associated with more than one hazard in a processing stage.

Table 31. Distribution of Hazards by Processing Stage During Communication (receiver) Tasks.

Hazard	Hazard Total	Perception	Encoding	Interpretation
Decision Error	1	0/1 (0%)	0/1 (0%)	1/1 (100%)
Skill-based Error	3	0/3 (0%)	2/3 (67%)	1/3 (33%)
Perceptual Error	4	2/4 (50%)	2/4 (50%)	0/4 (0%)
Knowledge Error	1	0/1 (0%)	0/1 (0%)	1/1 (100%)
Violation	0	0/0 (0%)	0/0 (0%)	0/0 (0%)

Table 32 summarizes the hazards encountered during a particular information processing stage for the Discrete Control task category. Table 33 presents the distribution of hazards across processing stages. Applying the appropriate control for the appropriate situation can fail for many reasons from not acquiring the correct information to not identifying and selecting the correct control to failing to complete the execution of the tasks. In addition, there are many opportunities to "cut corners" or "bend the rules" when deciding what control to apply and apply it.

Table 32. Non-nominal Outcomes and Frequency of Outcomes by Processing Stage (by column) for Discrete Control Tasks.

Hazard	Row Total	Processing Stage			
		Information Acquisition	Assessment	Decision	Execution
Number of hazardous outcomes for processing stage	62	18	16	17	11
Decision Error	25	0/18 (0%)	10/16 (63%)	15/17 (88%)	0/11 (0%)
Skill-based Error	24	9/18 (50%)	2/16 (13%)	2/17 (12%)	11/11 (100%)
Perceptual Error	18	18/18 (100%)	0/16 (0%)	0/17 (0%)	0/11 (0%)
Knowledge Error	9	0/18 (0%)	7/16 (44%)	2/17 (12%)	0/11 (0%)
Violation	23	0/18 (0%)	0/16 (0%)	13/17 (76%)	10/11 (91%)

Note: A hazardous outcome can be associated with more than one hazard in a processing stage.

Table 33. Distribution of Hazards by Processing Stage During Discrete Control Tasks.

Hazard	Hazard Total	Information Acquisition	Assessment	Decision	Execution
Decision Error	25	0/25 (0%)	10/25 (40%)	15/25 (60%)	0/25 (0%)
Skill-based Error	24	9/24 (38%)	2/24 (8%)	2/24 (8%)	11/24 (46%)
Perceptual Error	18	18/18 (100%)	0/18 (0%)	0/18 (0%)	0/18 (0%)
Knowledge Error	9	0/9 (0%)	7/9 (78%)	2/9 (22%)	0/9 (0%)
Violation	23	0/23 (0%)	0/23 (0%)	13/23 (57%)	10/23 (43%)

Table 34 summarizes the hazards encountered during a particular information processing stage for the Monitoring and Situation Assessment task category. Table 35 presents the distribution of hazards across processing stages. Not surprisingly, there are more opportunities for failures due to information acquisition, with a majority from perceptual errors when sensory input may be degraded and skill-based errors such as failures in visual scan patterns or forgotten intentions.

Table 34. Non-nominal Outcomes and Frequency of Outcomes by Processing Stage (by column) for Monitoring and Situation Assessment Tasks.

Hazard	Row Total	Processing Stage		
		Information Acquisition	Assessment	Decision
Number of hazardous outcomes for processing stage	69	31	20	18
Decision Error	38	0/31 (0%)	20/20 (100%)	18/18 (100%)
Skill-based Error	36	17/31 (55%)	18/20 (90%)	1/18 (6%)
Perceptual Error	17	17/31 (55%)	0/20 (0%)	0/18 (0%)
Knowledge Error	17	12/31 (39%)	5/20 (25%)	0/18 (0%)
Violation	13	0/31 (0%)	0/20 (0%)	13/18 (72%)

Table 35. Distribution of Hazards by Processing Stage During Monitoring and Situation Assessment Tasks.

Hazard	Hazard Total	Information Acquisition	Assessment	Decision
Decision Error	38	0/38 (0%)	20/38 (53%)	18/38 (47%)
Skill-based Error	36	17/36 (47%)	18/36 (50%)	1/36 (3%)
Perceptual Error	17	17/17 (100%)	0/17 (0%)	0/17 (0%)
Knowledge Error	17	12/17 (71%)	5/17 (29%)	0/17 (0%)
Violation	13	0/13 (0%)	0/13 (0%)	13/13 (100%)

Monitoring and Situation Assessment tasks have greater opportunity for decision, knowledge, and skill-based errors than Discrete Control tasks due to their evaluative nature. Discrete Control tasks have greater opportunity for violations than Monitoring and Situation Assessment tasks because the former includes an execution stage where some physical action must be taken.
Table 36 compares the loosely coupled and tightly coupled scenarios. The tightly coupled scenario is more complex, requiring the Supervisor to complete nearly twice as many unique tasks with each task having slightly more potential outcomes, both nominal and non-nominal, and more potential hazards. In general, decision and skill-based errors are more prevalent than perception or knowledge errors for both scenarios. Skill-based errors (and to a lesser degree, decision errors) are substantially more possible in the tightly coupled scenario because of the higher levels of coordination needed to complete the ridgeline aerial ignition mission. These skill-based errors arise in the communication tasks required to coordinate actions among human teammates and in the many assessment and control tasks required to command multiple types of UAVs conducting different operations (e.g., ignition and surveillance) simultaneously.

Table 36. Comparison of Tasks, Outcomes, and Hazards Across Scenarios

	Loosely Coupled		Tightly Coupled		Percentage Change of Total
	Total	Average Per Task	Total	Average Per Task	
Tasks	11		19		72.7
Potential Outcomes	132	12.0	244	12.8	84.8
Nominal Outcomes	54	4.9	101	5.3	87
Non-nominal Outcomes	78	7.1	143	7.5	83.3
Potential Hazards	124	11.3	239	12.6	92.7
Decision Errors	33	3.0	66	3.5	100
Skill-based Errors	29	2.6	68	3.6	134.5
Perception Errors	20	1.8	39	2.1	95
Knowledge Errors	17	1.5	27	1.4	58.8
Violations	25	2.3	39	2.1	56

3.2.3 Mapping Hazards to Mitigations

The hazard-cause-mitigation mappings were traced in order to determine which mitigations are associated with which hazards. The results suggested that all nine mitigation strategies may be useful for controlling each of the six hazard classes. Although the researchers cannot recommend any particular mitigation strategy for a class of hazards based on this aggregate-level analysis, the approach can be used to inform a more specific analysis of individual hazard instances. Take the example of a decision error that occurs when interacting with the automation (e.g., during the Supervisor task "Acknowledge notification of unscheduled event"). The team identified 78 possible causes to decision errors, which may be mitigated by a wide variety of interventions; however, only 18 causes relate to interactions with automation specifically. Four of these 18 causes relate to hardware or software failures, while the remainder relate to human biases regarding automation, specifically trust or understanding of the automation. The mitigation to a hardware or software issue may be organizational support in the form of equipment repair or replacement, while biased decisions involving the automation may be better mitigated through training or a more transparent design of the decision aid.

3.3 Discussion

The researchers conducted a thorough analysis of the human factors limitations to monitoring multiple UAS. The team leveraged tasks of a human Supervisor. By applying information processing models to highlight the components of these tasks, the team diagnosed the non-nominal outcomes as hazards based on an established methodology (HFACS; Shappell & Wiegmann, 2000). Through a novel causal mapping process, the team was able to determine the root causes of these hazards and identify strategies the FAA can enact to mitigate the risks incurred by monitoring multiple UAS.

The methodology for identifying hazards by decomposing tasks into the various outcomes at each processing stage and then mapping the hazards to their corresponding mitigations via specific causes has potentially great value to human factors practitioners at large, and future work should investigate whether this procedure can be applied to other scenarios. The researchers have already demonstrated that the process can generalize in a limited fashion when it was first created for the loosely coupled scenario (i.e., package delivery) and then re-used it for the tightly coupled scenario (i.e., ridgeline aerial ignition). For this latter application, the team expanded the task taxonomy to include different categories of tasks and created prototypical processing stage templates for each category. In the future it may be possible to leverage the commonalities among tasks in a particular category to further refine these templates into a hierarchy of tasks, which would facilitate deeper analysis. With hundreds of potential outcomes, managing the mapping of outcomes to hazards, causes, and mitigations is effortful. It may be worthwhile to develop interactive tools and visualizations to improve the methodology's ease of use and the interpretability of its results.

The results suggest that there are more opportunities for hazards to arise from decision or skill-based errors than knowledge or perception errors. A caveat to this analysis is that the team did not consider the likelihood of particular hazards occurring; hence, one cannot conclude that decision or skill-based errors are expected to occur more often or to have greater severity. However, mitigations such as robust autonomy and decision aids may reduce the number of ways something could go wrong. Training of rote knowledge beyond what is needed to complete the Supervisor's tasks may be less important than training Supervisors to recognize and evaluate mission-critical situations.

The analysis was conducted at a sufficiently high level of abstraction to be generally applicable to a wide variety of operational domains and implementations. However, this high-level approach required many assumptions to be made regarding the capabilities of the automation available. Systems employing a lower Level of Autonomy (LOA) may encounter additional hazards as the human takes on duties that could be offloaded to a higher LOA. Analysis beyond the scope of this work will be required to determine implementation-specific interventions for more well-defined system designs. This approach provides constraints that may help guide such investigations.

This work was restricted to the human factors limitations of a single human operator supervising multiple UAS in the enroute phase for package delivery and ridgeline aerial ignition scenarios. For the package delivery scenario, future work beyond the scope of this project should consider other flight phases alternative human roles, such as a flight assistant or ground crew. The ridgeline aerial ignition case provided more task complexity. However in both cases, limited consideration was given to cooperation between multiple supervisors; the analysis focused primarily on handoffs and elementary communication such as team readiness. Future work, beyond the scope of this work, should address the human factors of coordinated teams of supervisors (i.e., M:N UAS control). Several potential causes to hazards that relate to organizational influences (e.g., policy and culture) and personnel factors (e.g., illness and demographics) were identified that are outside the scope of the chosen use case and hazard taxonomy.

4 APTITUDE MEASUREMENTS AND GAPS TAXONOMY

This section reviews existing aptitude measurements to inform the gaps with respect to multi-UAS control. It leverages the literature review from Task 1, where references to the included content may be found.

4.1 Methods

The measures identified in the literature review were categorized by the aptitude they measure, their measurement type (such as count or rating scale), whether the measure is objective or subjective, and if the measure is part of a larger construct. The team defines aptitude as any trait or skill that affects human competence. In its most direct interpretation, this definition includes traits like expertise and executive functioning, but the team also interprets it broadly to include influences like usability and workload, which are qualities of the human-machine system that affect the human's performance within that system. Measures that only measure performance without reference to the human operator or Supervisor were excluded from analysis.

4.2 Results

A list of the aptitudes appears in Table 37. Some aptitudes are listed as "perceived" to differentiate them from objective aptitudes with a similar label. Efficiency is included, although it may be considered a performance measurement as opposed to an aptitude. Taskload is included, although it is related to the task environment. Usability is also included, although it may be considered a design measure. Workload is commonly considered a multi-dimensional construct. Different researchers employ measures of one or more workload components. For example, the Workload Profile (Tsang & Velazquez, 1996) includes stages of processing (perceptual/central, response), code of processing (spatial, verbal), input (visual, auditory), and output (manual, speech) to measure workload. The Multiple Resource Questionnaire (Boles, et al. 2007) employs auditory, cognitive, physical, speech and visual components of workload.

Table 38 lists the measurement types by whether they are objective or subjective. The objective subjective, and composite measures organized by aptitude appear in Table 39, Table 40, and Table 41 respectively. So as not to list measures multiple times, individual measures that are part of the composite measures are listed with the composite (e.g. conscientiousness as a component of the Five Factor Model). Some studies measured aptitudes but the measurement details were missing so the measure is noted as unspecified.

Besides workload, the majority of objective measures address the allocation and control of attention, situation awareness, and efficiency (Table 39), which is not surprising given the complexity associated with monitoring and assessing the behaviors of multiple moving objects. The majority of the subjective measures involve different types of rating scales (Table 40).

The total number of individual aptitudes and measures highlight the complexity in addressing human limitations with respect to multi-UAS control. Further, the lack of a specific multi-tasking aptitude and associated measures means that any analysis will be multi-variate.

Table 37. Aptitudes summary.

Anxiety	Hardiness	Stress
Attention (allocation and control)	Knowledge	Taskload
Attention (allocation and control), Perceived	Multitasking	Trust in Automation
Automation bias	Performance (self), Perceived	Usability
Boredom proneness	Perseverance	Utilization
Busyness, perceived	Personality	Visual skills
Color vision	Planning	Working memory capacity
Communication	Response bias	Workload (Auditory)
Controllability	Responsibility (for accurate performance), Perceived	Workload (Cognitive)
Decision skills	Self-confidence	Workload (General)
Efficiency	Sensitivity	Workload (Physical)
Executive function	Situation awareness	Workload (Speech)
Expertise	Spatial ability	Workload (Visual)
Fatigue	Strategy, automation	Workload, Perceived

Table 38. Summary of measures measurement type by whether measure is objective or subjective.

Objective/ Subjective	**Type**
Objective	Concept map (concepts are correct or incorrect)
	Count
	Device-dependent
	Environmental (e.g., noise level)
	Multiple choice (choices are correct or incorrect)
	Neurophysiological
	Neurophysiological; task-dependent

Objective/ Subjective	Type
	Ocular
	Ocular; task-dependent
	Physiological
	Query (responses are correct or not)
	Query during task (responses are correct or not)
	Reading task (participant may not be able to read in color vision test)
	Self-report (i.e., frequent computer users)
	Task-dependent
	Tests (validated): Stop-Signal task, manual response version of the Stroop task, Number-letter task, local-global task, Letter Memory task, Keep Track task
	Vocal
Subjective	2-choice task
	Cognitive walk through
	Composite scale
	Decision tree
	Rank
	Rating scale
	Transcript coding
	Video coding

Table 39. Objective measures organized by aptitude.

Aptitude	Measure	Type
Anxiety	Electroencephalogram (EEG) "signals"	Neurophysiological
Attention (allocation and control)	Backtrack rate	Ocular
	Command Ratio	Task-dependent
	Convex hull area	Ocular
	Dwell time in Area Of Interest (AOI)	Ocular
	EEG signal classification	Neurophysiological
	Fixation Count	Ocular
	Fixation Count within AOI	Ocular
	Fixation Duration	Ocular
	Saccade Duration	Ocular
	Saccadic Amplitude	Ocular
	Scanpath length per second	Ocular
	Spatial density	Ocular
	Stationary entropy	Ocular

Aptitude	Measure	Type
	Task attended	Video coding
	Transition entropy	Ocular
	Transition rate	Ocular
	Transitions between AOIs	Ocular
Color vision	Ishihara color vision test	Reading task
Communication	Communication detail	Transcript coding
Controllability	Bandwidth of frequency response profile	Device-dependent
	H2 norm	Device-dependent
Efficiency	Area reconnoitered per unit time	Task-dependent
	Bomb Reaction Time	Task-dependent
	Camera Angle Error	Task-dependent
	Command Ratio	Task-dependent
	Decision Time	Task-dependent
	Fan Out	Task-dependent
	Idle Time (Vehicle/Robot)	Task-dependent
	Interaction time	Task-dependent
	Negative Stopped Neutral times	Task-dependent
	Neglect	Task-dependent
	Neglect time	Task-dependent
	Non-optimal play environment event performance time	Task-dependent
	Stopped Neutral Time	Task-dependent
	Task Completion Time	Task-dependent
	Time to position camera crosshairs on landmark	Task-dependent
	Time to respond to SA question	Task-dependent
Executive function	Executive functioning battery	Specific tests: stop-signal task, manual response version of the Stroop task, number-letter task, local-global task, letter memory task, keep track task
Expertise	Computer Experience	Self-report
	Pilot Experience	Self-report
	Professional Position	Self-report
	UAS experience	Self-report
	Video Game Experience	Self-report
Fatigue	Blink Frequency	Ocular
	EEG signals	Neurophysiological
	Skin Temperature	Physiological

Aptitude	**Measure**	**Type**
Knowledge	Team Performance Laboratory- Knowledge Analysis Test Suite —Concept Map	Concept map
Multitasking	Multitasking Throughput (MT)	Task-dependent
Planning	Interface interactions	Task-dependent
Response bias	Beta	Task-dependent
Sensitivity	A'	Task-dependent
	D'	Task-dependent
	Just-Noticeable-Difference	Task-dependent
Situation awareness	Glance ratio (percent of time glances are within AOI)	Ocular
	SA queries percentage correct	Query
	Situation Awareness Global Assessment Technique	Queries during task
	Teleoperation actions	Task-dependent
Spatial ability	Cube comparison test	Multiple choice
	Spatial Orientation Test	Multiple choice
Stress	Cerebral Blood Flow Velocity (CBFV; Transcranial Doppler Sonography (TCD))	Neurophysiological
	Electroencephalogram (EEG) Spectral Power (alpha, beta, gamma, theta bands)	Neurophysiological
	Heart Rate Variability (HRV; Electrocardiogram (ECG))	Physiological
	Inter-Beat-Interval (IBI; Electrocardiogram (ECG))	Physiological
Taskload	Task Density	Task-dependent
	Task switches or interruptions count	Task-dependent
Trust in Automation	Compliance (acceptance of automation's recommendation)	Task-dependent
	Proper Use (correct acceptance and correct rejection of automation’s recommendations)	Task-dependent
	Reliance (acceptance of automation's non-action)	Task-dependent
Usability	Interaction or keystrokes, mouse clicks	Count
Utilization	Ratio of "busy" time to total mission time	Task-dependent
	Unique agents used count	Task-dependent
Visual skills	Multiple object tracking capacity	Task-dependent
	Visual Search Time	Task-dependent
Working memory capacity	Automated operation span task	Task-dependent
	Secondary task failure rate	Task-dependent

Aptitude	**Measure**	**Type**
Workload (General)	Span-of-control	Task-dependent
Workload (Auditory)	Noise level	Environmental
	Speech Response Time	Vocal
Workload (Cognitive)	Blink duration	Ocular
	Blink Frequency	Ocular
	Blink Latency	Ocular
	Cognitive load per targets reached	Neurophysiological; task-dependent
	EEG event-related potential	Neurophysiological
	EEG signal classification	Neurophysiological
	EEG Spectral Power Density (alpha and theta bands)	Neurophysiological
	False Starts Count	Vocal
	Fragments Count	Vocal
	Filler Utterances	Vocal
	Fixation Count	Ocular
	Fixation Duration	Ocular
	Fixation Rate	Ocular
	Functional Near-Infrared Spectroscopy with regional oxygen saturation index	Neurophysiological
	Galvanic skin response	Physiological
	Heart rate	Physiological
	Heart Rate Variability	Physiological
	Noise Level	Environmental
	Pupil Dilation	Ocular
	Saccade Duration	Ocular
	Saccades per targets reached count	Ocular; task-dependent
	Saccadic Amplitude	Ocular
	Skin Temperature	Physiological
	Speech Rate	Vocal
	Speech Response Time	Vocal
	Syntax Errors Count	Vocal
	Utterance Length	Vocal
	Utterance Repetitions	Vocal
Workload (Physical)	Galvanic skin response	Physiological
	Heart rate	Physiological
	Postural Load	Task-dependent
	Respiration rate	Physiological

Aptitude	Measure	Type
	Skin Temperature	Physiological
	Variance in Posture	Task-dependent
	Vector Magnitude	Task-dependent
Workload (Speech)	False starts count	Vocal
	Filler Utterances	Vocal
	Fragments Count	Vocal
	Syntax Errors Count	Vocal
	Respiration rate	Physiological
	Speech Rate	Vocal
	Speech Response Time	Vocal
	Utterance Length	Vocal
	Utterance Repetitions	Vocal
Workload (Visual)	Blink duration	Ocular
	Blink Frequency	Ocular
	Blink Latency	Ocular

Table 40. Subjective measures organized by aptitude.

Aptitude	Measure	Type
Attention (allocation and control), Perceived	Attentional Control Survey	Rating scale
Automation bias	Implicit Association Test	2-choice task
Boredom proneness	Boredom Proneness Survey (BPS)	Rating scale
Busyness, perceived	Unspecified	Rating scale
Decision skills	Decision Process	Cognitive walk through
Hardiness	Dispositional Resilience Scale	Rating scale
Performance (self), Perceived	Unspecified	Rating scale
Perseverance	Grit	Rating scale
Responsibility (for accurate performance), Perceived	Unspecified	Rating scale
Self-confidence	Decision Confidence	Rating scale
	Trust And Self-Confidence Measure	Rating scale
	Unspecified	Rating scale
Situation awareness	Knowledge of UAS and mission state and ability to anticipate/accommodate trends	Rating scale
	Situational Awareness Rating Technique	Rating scale
	Unspecified	Rating scale

Aptitude	Measure	Type
Strategy, automation	Unspecified	Rating scale
Stress	Coping Strategy	Rating scale
Trust in Automation	Expectations of how well the system should be performing	Rating scale
	Predictability	Rating scale
	Trust And Self-Confidence Measure	Rating scale
	Trust In Automated Systems	Rating scale
	Trust In Human-Robot Interaction	Rating scale
	Trust Questionnaire	Rating scale
	Unspecified	Rating scale
	Universal Trust in Automation Trust Questionnaire (Performance, Purpose, and Process Dimensions of Trust)	Rating scale
Usability	Comfort	Rating scale
	Computer System Usability Questionnaire	Rating scale
	Ease of use or Perceived Usability	Rating scale
	Icon usefulness for speed and accuracy	Rating scale
	Icon usefulness per prompt type	Rating scale
	Perceived impact of interface on performance	Rating scale
	Perceived potential effectiveness (of automation)	Rating scale
	Perceived Speed	Rating scale
	Perceived Understanding	Rating scale
	Preference (Automation control or LOA)	Rating scale
	Preference (Interface)	Rank
	Preference (Interface)	Rating scale
	Usability and Trust Survey	Rating scale
	Usefulness	Rating scale
Workload (General)	Cooper-Harper Scale	Decision tree
	Verbal in situ ratings	Rating scale
Workload (Cognitive)	Modified Cooper-Harper Scale	Decision tree
	Subjective Workload Assessment Technique	Rating scale
Workload, Perceived	Unspecified	Composite scale

Table 41. Composite subjective measures organized by aptitude.

Aptitude	**Composite Scale**	**Factors**
Personality	Five Factor Model ("Big Five") (Norman, 1963)	Agreeableness Conscientiousness Extraversion Neuroticism Openness
Stress	Dundee Stress State Question (Matthews et al., 1999)	Distress Engagement Worry
Trust in Automation	Human-Computer Trust Scale (Madsen and Gregor, 2000)	Faith Perceived Reliability Perceived Technical Competence Perceived Understandability Personal Attachment
Workload, Perceived	Multiple Resource Questionnaire (Boles and Adair, 2001)	Auditory emotional process Auditory linguistic process Facial figural process Facial motive process Manual process Short term memory process Spatial attentive process Spatial categorical process Spatial concentrative process Spatial emergent process Spatial positional process Spatial quantitative process Tactile figural process Visual lexical process Visual phonetic process Visual temporal process Vocal process
	National Aeronautics and Space Administration (NASA) Task Load Index (NASA-TLX) (Hart and Staveland, 1988)	Effort Frustration Mental Demand Performance Physical Demand Temporal Demand
	Workload Profile (Tsang and Velazquez, 1996)	Stage of Processing: Perceptual/Central, Response Code of Processing: Spatial, Verbal Input: Auditory, Visual Output: Manual, Speech

5 CONCLUSION

Task 3 addressed human factors limitations to supervising multiple UAS and the identification of potential hazards, mitigations, and controls for the mitigations. The work focused on a loosely coupled task, specifically the enroute flight phase of package delivery and a tightly coupled task based on investigation of tasks supporting wildland fires. A prior literature review and use cases validated by subject matter experts were used to guide the work. Another focus of the work addressed existing aptitude measurements. Note that this work focused on operations. Aptitudes based on other factors such as organizational and personnel ones are out of scope.

This section highlights gaps based on the scope and results of this work and the state of the art:

1. For the loosely coupled scenario, the task analysis and the focus on scheduled tasks highlight that monitoring, vigilance, and boredom may directly influence human performance. A gap includes the lack of studies focused on the specific effects of vigilance and boredom in multi-UAS package delivery contexts.
2. The input from the subject matter experts may be very unique compared to what may have been collected from those using other multi-UAS logistics models. As such, for the loosely coupled task scenario, the developed use case is a notional use case that does not represent any specific company's drone logistics model. Similarly, for the tightly coupled scenario, the developed use case is an abstracted exemplar with respect to ridgeline aerial ignition and the use of surveillance and ignition drones. A gap is the lack of validated use cases for a wider range of loosely and tightly coupled tasks.
3. There are no data about how frequently the unscheduled events may occur in practice. There is a gap in understanding the necessary levels of training and expertise required for addressing the unscheduled tasks when supervising multiple UAS.
4. The tasks associated with the unscheduled events were at a high level. For example, there may be a range of landing tasks (e.g., land immediately vs. first identifying landing location that may be further away, fly to it and landing). For holding, there also may be a range of methods and some may be specific to aircraft type. A fixed wing aircraft may execute a predefined holding pattern while a multi-rotor will hover. Some can do both hover and fly like a fixed wing and may not prefer to hover due to power needs. Thus, a gap is identifying the full range of methods for addressing each unscheduled event and completing the analysis for each method.
5. The tightly coupled tasks scenario not only added the dimension of coupled tasks but also two types of UAVs (surveillance and ignition). While the resulting analyses addressed the different task and team work associated with the different types, this work did not systematically address the complexity from supervising different UAV types with different missions and performance capability. Thus, a gap is analyzing the potential interaction of task types, aircraft types, and types of missions (e.g., surveillance and ignition) with respect to human performance.
6. Table 37 highlights a range of aptitudes. The research highlighted critical aptitudes, such as workload, situation awareness, and attention, but it is not clear which aptitudes play a critical role singly and/or in combination. Aptitude measures developed under specific experimental paradigms and using laboratory tasks such as Multi-Attribute Task Battery (MAT-B) (Comstock & Arnegard, 1992) may not easily translate to applied scenarios, like multi-UAS control. General measurements such as those collected by self-reports may not be relevant in

a field study. There are no meta-analyses or other literature to support making claims about exactly which aptitudes are relevant to multi-UAS supervision. Thus, there is a gap in understanding what combination of aptitudes are the most important with respect to supervising multiple UAS.

7. With respect to multi-tasking specifically, validated measures for multi-UAS operations are not available. Fox, Haupt and Tsang (2021) published the results of an approach to estimate which cognitive processes are degraded or enhanced when multiple tasks are simultaneously completed. They demonstrated its utility for dual- and triple-task combinations of the MAT-B (Comstock & Arnegard, 1992). The measure introduced by Fox et al. is limited to the analysis of response times and does not account for other measures or integrated measures such as weighted combinations (i.e., tradeoffs) of speed and accuracy. Thus, a gap is that there is no single aptitude or single validated measure that can capture all the human performance limitations related to multitasking with respect to supervising multiple UAS.
8. Some aptitude measures may be difficult to obtain during real-time operations. Measures that yield results in real- or near real-time allow for interventions that support the operation as it is unfolding (e.g., adaptive automation; Chen & Barnes, 2014). Developing methods and measures that can be used in real-world operations is a gap.
9. Teamwork may be an important skill for Supervisors and other roles. For example, Supervisors may need to delegate work to others when overloaded. There is limited research on what type of coordination abilities may be important. Thus, a gap is determining the exact role for the human Supervisor for delegation.
10. Some aptitudes may be very sensitive to the task. Thus, collecting accurate data will require specific design/implementation assumptions, including the level of autonomy and flight phase. Specific implementations will define clear Supervisor roles and support. Thus, one gap is validating what specific autonomy will be available for each task and tasks in combination. A related gap is a lack of detailed timing information for human performance of various tasks.
11. The type of task management strategies (e.g., detailed task switching, resuming delayed tasks) have not been defined for domains such as package delivery. Thus, it is difficult to predict operator overload. In addition, different types of autonomy such as a system managing a task queue with the ability to reschedule tasks automatically could support task management. A gap is the definition of such capability.

6 REFERENCES

Boles, D. B., & Adair, L. P. (2001). The multiple resources questionnaire (MRQ). In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 45, No. 25, pp. 1790-1794). Sage CA: Los Angeles, CA: SAGE Publications.

Bolton, M. L., & Bass, E. J. (2013). Generating erroneous human behavior from strategic knowledge in task models and evaluating its impact on system safety with model checking. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *43*(6), 1314-1327.

Bolton, M. L., Bass, E. J., & Siminiceanu, R. I. (2012). Generating phenotypical erroneous human behavior to evaluate human–automation interaction using model checking. *International Journal of Human-Computer Studies*, *70*(11), 888-906.

Bolton, M. L., Siminiceanu, R. I., & Bass, E. J. (2011). A systematic approach to model checking human–automation interaction using task analytic models. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *41*(5), 961-976.

Boles, D. B., Bursk, J. H., Phillips, J. B., & Perdelwitz, J. R. (2007). Predicting dual-task performance with the Multiple Resources Questionnaire (MRQ). *Human Factors, 49(1)*, 32-45.

Chen, J. Y. C., & Barnes, M. J. (2014). Human-agent teaming for multirobot control: A review of human factors issues. *IEEE Transactions on Human-Machine Systems*, *44*(1), 13-29.

Comstock, J. R., & Arnegard, R. J. (1992). *The multi-attribute task battery for human operator workload and strategic behavior research (NASA TM-104174):* NASA Langley Research Center.

Detweiler, C., S. Elbaum, J. Higgins, C. Laney, C. Allen, D. Twidwell, and E. M. Beachly (2021) Fire Suppression and ignition with Unmanned Aerial Vehicles, United States Patent Application # US 2021/0322805 A1.

Diehl, G. and J. A. Adams (2021) Battery Variability Management for Swarms, *International Symposium on Distributed Autonomous Robotic Systems*.

Drone Amplified, https://droneamplified.com/?v=7516fd43adaa.

Fox, E. L., Houpt, J. W., &. Tsang, P. S. (2021). Derivation and demonstration of a new metric for multitasking performance. *Human Factors, 63(5)*, 833-853.

Giles, D. (2020) Forest Service Standards for UAS Operations, US Department of Agriculture, Forest Service.

Glordan, D., Y. Hayakawa, F. Nex, F. Remondino, and P. Tarolli (2018) Review article: The use of Remotely Piloted Aircraft Systems (RPAs) for natural Hazards Monitoring and Management, *Natural Hazards Earth System Sciences*, 18: 1079-1096.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in Psychology* (Vol. 52, pp. 139-183). North-Holland.

HFACS, Inc. (n.d.). *Definitions*. The HFACS Framework. https://www.hfacs.com/definitions.html

Hollnagel, E. (1993). The phenotype of erroneous actions. *International Journal of Man-Machine Studies*, *39*(1), 1-32.

Johnston, K., British Columbia Forest Service, Forest Protection, S-235 (BC) Ignition Operations, Student Manual.

Madsen, M., & Gregor, S. (2000). Measuring human-computer trust. In 11th Australasian conference on information systems (Vol. 53, pp. 6-8). Brisbane, Australia: Australasian Association for Information Systems.

Matthews, G., Joyner, L., Gilliland, K., Campbell, S.E., & Huggins, J., & Falconer, S. (1999) Validation of a comprehensive stress state questionnaire: Towards a state 'Big Three'? In I. Mervielde, I.J. Deary, F. De Fruyt, & F. Ostendorf (Eds.), *Personality Psychology in Europe* (Vol. 7), pp. 335-350. Tilburg: Tilburg University Press.

(NIFC) National Interagency Fire Center (2020) Interagency Standards for Fire and Fire Aviation Operations (NFES 2724), U.S. Department of the Interior and Department of Agriculture.

(NWCG) National Wildfire Coordinating Group, Communicator's Guide for Wildland Fire Management: Fire Education, Prevention and Mitigation Practices.

National Wildfire Coordinating Group, Instructor Guide, S-190 Unit 4: Topology.

National Wildfire Coordinating Group (2013) Wildland Fire Incident Management Field Guide, PMS 210.

Norman, W. T. (1963). Toward an adequate taxonomy of personality attributes: Replicated factor structure in peer nomination personality ratings. *Journal of Abnormal and Social Psychology, 66,* 574–583.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *30*(3), 286-297.

Shappell, S. A., & Wiegmann, D. A. (2000). The human factors analysis and classification system--HFACS. Retrieved from https://commons.erau.edu/publication/737

Showronski, N. S., S. Haag, J. Trimble, K. L. Clark, M. R. Gallagher, and R. G. Lathrop (2016) Structure-Level Fuel Load Assessment in the Wildland-Urban Interface: A Fusion of Airborne Laser Scanning and Spectral Remote-Sensing Methodologies, *International Journal of Wildland Fire*, 25: 547-557.

Tidwell, D., C. R. Allen, C. Detweiler, J. Higgins, C. Laney, and S. Elbaum (2016) Smokey Comes of Age: Unmanned Aerial Systems for Fire Management, *Frontiers in Ecology and the Environment*, 14(6): 333-339.

Tsang, P. S., & Velazquez, V. L. (1996). Diagnosticity and multidimensional subjective workload ratings. *Ergonomics, 39(3),* 358-381.

(US DOI) U.S. Department of the Interior (2010) Reclamation Managing Water in the West, Wildland Fire Management Guidelines, Bureau of Reclamation.

APPENDIX A. DELIVERY UAV CONCEPTS EXEMPLARS.

This appendix includes the delivery UAV concept exemplars. Blank cells indicate no information was found.

Primary – Corp., Org., University	Delivery UAV Provider Partner	Primary - Deli. By UAV Part 135 Exemption	Primary in IPP?	Delivery UAV Provider in IPP?	Primary - Part 107 Waivers	Country & Type of Operation	UAV Model	UAV Max Payload (lbs.)	Year Concept Revealed	Primary - Target Operation Location
MatterNet	MatterNet	No	Yes	Yes	107.29, 107.31, 107.33, 107.39	Switzerland - Trials USA - Experimental (WakeMed Hospitals)	M2	4.4	2020	Suburb, Urban
Zipline	Zipline	No	Yes	Yes	107.29, 107.31, 107.33(b), 107.33(c), 107.35	Rwanda - Commercial USA - Experimental (Walmart)	Sparrow	3.9	2018	Rural, Suburb
Flytrex	Flytrex	No	Yes	Yes	107.29	Iceland - Experimental USA - Experimental	Flytrex UAV	6.6	2020	Rural, Suburb
Flirtey	Flirtey	No	Yes	Yes	107.29, 107.31, 107.35	USA - Experimental	Eagle		2019	Suburb
Walmart	Flytrex	No	No	Yes	None	USA-Experimental	DJI Matrice 600 Pro	6.6	2020	Suburb
Walmart	Zipline	No	No	Yes	None	USA-Experimental	Zipline Sparrow	3.9	2020	Rural, Suburb

Primary – Corp., Org., University	Delivery UAV Provider Partner	Primary - Deli. By UAV Part 135 Exemption	Primary in IPP?	Delivery UAV Provider in IPP?	Primary - Part 107 Waivers	Country & Type of Operation	UAV Model	UAV Max Payload (lbs.)	Year Concept Revealed	Primary - Target Operation Location
UPS - Flight Forward	MatterNet	Yes - IPP	Yes	Yes	107.39	USA - Trials	M2	4.4	2020	Suburb
UPS - Flight Forward	Wingcopter	Yes - IPP	Yes	No	107.39	USA-Experimental	Wingcopter 178 Heavy Lift	13.2	2020	Rural
UPS - Flight Forward	Workhorse	Yes - IPP	Yes	No	107.39	USA-Experimental	HorseFly		2017	Rural
Wing	Wing	Yes - IPP	Yes	Yes	107.29, 107.31, 107.33(b), 107.33(c)(2), 107.35, 107.39, 107.51(c), 107.51(d)	Australia - Commercial Finland - Commercial USA - Trials	Hummingbird V2-7000	3.3	2020	Rural, Suburb
Amazon	Amazon Prime Air	Yes - PSP	No	No	None	USA - Trials	MK27	5	2019	Rural, Suburb
Amazon	Amazon Prime Air	Yes - PSP	No	No	None	USA-Experimental			2015	Rural, Suburb
UberEats	Uber Elevate	No	Yes	Yes	None	USA - Trials			2019	

Primary – Corp., Org., University	Delivery UAV Provider Partner	Primary - Deli. By UAV Part 135 Exemption	Primary in IPP?	Delivery UAV Provider in IPP?	Primary - Part 107 Waivers	Country & Type of Operation	UAV Model	UAV Max Payload (lbs.)	Year Concept Revealed	Primary - Target Operation Location
UberEats	Uber & ModalAI	No	Yes	Yes	None	USA - Trials			2019	Urban
FedEx	Wing	No	Yes	Yes	FedEx Express 107.29	USA - Trials (Wing has DBD Part 135 Exemption)	Hummingbird V2-7000	3.3	2020	Rural, Suburb
Airbus	Airbus	No	Yes	Yes	(Airbus Aerial) 107.29,107.31, 107.33(b) and (c)(2), 107.39	Singapore - Experimental	Airbus SN1 C1S Variant	8.8	2018	Urban
Airbus	Airbus	No	Yes	Yes	(Airbus Aerial) 107.29,107.31, 107.33(b) and (c)(2), 107.39	Singapore - Experimental	Airbus SN1 C1S Variant	8.8	2019	Urban, Ocean
University of Hawaii	Skyfront	No	Yes	No	None	USA - Experimental	Skyfront Perimeter	8.8	2019	Ocean
Bell Flight	Bell Flight	No	Yes	Yes	None	USA - Experimental	UAV Delivery Canada APT 70	70	2020	
UAV Delivery Canada	UAV Delivery Canada	No	No	No	None	Canada - Experimental	Sparrow	9.9	2020	Rural, Suburb

Primary – Corp., Org., University	Delivery UAV Provider Partner	Primary - Deli. By UAV Part 135 Exemption	Primary in IPP?	Delivery UAV Provider in IPP?	Primary - Part 107 Waivers	Country & Type of Operation	UAV Model	UAV Max Payload (lbs.)	Year Concept Revealed	Primary - Target Operation Location
DHL	EHang	No	No	No	None	Taiwan - Commercial or Trials	Ehang Falcon	11	2019	Urban
DHL	DHL	No	No	No	None	Germany - Experimental	Parcelcopter 3.0	4.4	2016	Rural
DHL	Wingcopter	No	No	No	None	Tanzania - Experimental	Parcelcopter 4.0 (Wingcopter 178 Heavy Lift)	9.7	2018	Rural
BLKTATU	BLKTATU	No	No	No	None	Australia - Experimental			2015	Urban

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
MatterNet	MatterNet	Medical package is placed in Quadcopter UAV's station outside of the business. Station opens and the UAV takes off and travels to its destination. The UAV lands in the station at its delivery location, the package is separated by the station's automation process and the customer picks up the package.	Station	Lands in Package Station						MatterNet Cloud Platform

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
Zipline	Zipline	Plane UAV (not quad) sling shot into air. Drops package via parachute Plane flies back and is caught mid-flight	Hand Loaded	Para-chute Drop	GPS			Package Drop Door		
Flytrex	Flytrex	Quad lifts from store, delivers to home via lowering wire with bag attached	Hand Loaded	Hovers; Lowers package via hook & tether.				Hook & Tether Motor		FlyTrex Control Center
Flirtey	Flirtey	Business has Flirtey station at their location. The UAV is launched with package from the business's loc. and the UAV goes and drops off the package.	Auto-mated at business location, Station	Hovers; Lowers package via hook & tether.	GPS	Camera for QR Code		Hook & Tether Motor		

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
Walmart	Flytrex	Quad lifts from store, delivers to home via lowering wire with bag attached	Hand Loaded	Hovers; Lowers package via hook & tether.				Hook & Tether Motor		FlyTrex Control Center
Walmart	Zipline	Plane UAV (not quad) sling shot into air. Drops package via parachute Plane flies back and is caught mid flight	Hand Loaded	Para-chute Drop	GPS			Package Drop Door		
UPS - Flight Forward	MatterNet	Hand loaded quad-copter UAV outside of business. It travels to the customer home and delivers the package via tether & hook.	Hand Loaded	Hovers; Lowers package via hook & tether.				Hook & Tether Motor		MatterNet Cloud Platform

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
UPS - Flight Forward	Wing-copter	Electric Vertical Takeoff and Landing (VTOL) UAV	Hand Loaded	Hovers; Lowers package via hook & tether.	GPS		LTE Iridium, RF	Hook & Tether Motor		
UPS - Flight Forward	Workhorse	Take Off: UAV comes from truck Delivery: Drops at home while delivery worker drops another package	Truck Driver places package under-neath UAV	Hovers; Lowers package via hook & tether.	GPS	RF Beacons	LTE	Hook & Tether Motor		Work-Horse Aeres Delivery App
Wing	Wing	UAV/Plane lowers hook for package Lowers hook with package for delivery	Hovers; Loads package via hook & tether	Hovers; Lowers package via hook & tether.	GPS			Hook & Tether Motor		Wing Un-crewed Traffic Manage-ment (UTM) Wing App
Amazon	Amazon Prime Air	VTOL UAV, Leaves Amazon Warehouse Lowers and Drops package(does not land)			GPS	Camera for QR Mat, Sonar, Thermal Camera				

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
Amazon	Amazon Prime Air	VTOL UAV, Leaves Amazon Warehouse Lowers and Drops package(does not land)	Automated at business location	Low Drop	GPS	Camera for QR Mat		Package Drop Door		
UberEats	Uber Elevate	UAV picks up package from restaurant. UAV navigates to pre-determined location and awaits for deliveryman to pick up package and deliver the package to the customer's home. Once the package is removed from the UAV, it fly back to the restaurant.	Hand Loaded	Lands in pre-deter-mined location and awaits last mile delivery man					Autonomous	Uber Elevate Cloud Systems

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
UberEats	Uber & ModalAI	Uber order is made. Order is placed in package. Package is handloaded under UAV. UAV lifts off and travels to predetermined drop off location. UAV lands and releases package. Package is taken by last-mile deliveryman. UAV returns to starting location.	Hand Loaded	Lands in pre-deter-mined location and awaits last mile delivery man	GPS LTE	Camera	LTE	Package Drop Release	Autonomous	Uber Elevate Cloud Systems
FedEx	Wing	UAV/Plane lowers hook for package Lowers hook with package for delivery	Hovers; Loads package via hook & tether	Hovers; Lowers package via hook & tether.	GPS			Hook & Tether Motor		

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
Airbus	Airbus	Package is placed in package station and an automated system loads the package onto the UAV. The UAV uses "aerial corridors" to drop off package at a parcel station designated by customer.	Auto-mated at Package Station	Lands in Package Station						AirBus Operation Center, UTM

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
Airbus	Airbus	UAV is handloaded at the Port. It travels to the customer Ship via 'aerial corridors'. The UAV arrives at the ship for delivery and lands have the package removed. Once the package is removed the UAV returns the Port.	Hand Loaded	Lands						AirBus Operation Center, UTM

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
University of Hawaii	Skyfront	UAV leaves the shore with handloaded package. Flies to submarine and lowers package. Package is secured by Submarine crewmates and the UAV returns to the shore.		Hovers, Lowers package via hook & tether						
Bell Flight	Bell Flight	APT 70 pod is attached to the APT 70 UAV. UAV takes off from the ground and travels to drop off location. APT 70 lands and pod contents are retrieved. APT 70 UAV returns to launch location.	Hand Loaded Pod	Lands						

Primary - Corporation, Organization, University	**Delivery UAV Provider Partner**	**Description of Delivery Concept**	**Package Loading Method**	**Drop Off Method**	**UAV Navigation Sensors**	**UAV Sensors**	**Communication**	**UAV Actuators**	**Type of UAV Control**	**Primary - Software/ Networks**
UAV Delivery Canada	UAV Delivery Canada	UAV takes off from location in "UAVSpot" Lands in another "UAVSpot"	Automated at business location, Hand Loaded	Lands in Package Station	GPS-Based	Camera for QR Code				FLYTE Flight Management software
DHL	EHang	Package is placed within "Intelligent Cabinet" (Package Station). UAV has package attached autonomously. UAV takes off from the station. UAV Lands at receiving package station. Package is unloaded autonomously.	Automated at Package Station	Lands in Package Station	GPS	Camera for "visual identification"	"real-time network connection"	None	Autonomous	
DHL	DHL	Lift off and drop off on DHL Package Station	Automated at business location, Station	Lands in Package Station				None	Autonomous	

Primary - Corporation, Organiza-tion, University	Delivery UAV Provider Partner	Description of Delivery Concept	Package Loading Method	Drop Off Method	UAV Naviga-tion Sensors	UAV Sensors	Communica-tion	UAV Actuators	Type of UAV Control	Primary - Software/ Networks
DHL	Wing-copter	EVTOL UAV is handloaded. Lifts off and travels to its destination. Upon arrival the UAV lands to have the package removed manually by the customer. UAV returns home.	Hand Loaded	Lands	GPS		LTE Iridium, RF	Package Drop Servo Release	Autonomous	
BLKTATU	BLKTATU	UAVs drop packages off into nets attached to side of apartment balconies.		Low Drop into Nets		Camera for QR Code			Autonomous	

APPENDIX B. LOOSELY COUPLED USE CASE: DELIVERY UAVS.

12. B.1. NOMINAL USE CASE

B.1.1 Taxonomy

- **Supervisor**: Human operator monitoring the UAVs controlled by the UAV autonomy (Pilot-Flying)
- **Pilot-Flying (PF)**: The autonomy controlling the UAV during a delivery mission
- **Flight Assistant**: Worker at the Delivery UAV warehouse in charge of supervising the automatic UAV selection, package loading, and positioning for Take-Off.
- **C^2**: Command and Control
- **Mission-Flight-Info**:
    - Regional Weather: (wind speeds, precipitation)
    - Generated Flight Path
    - Delivery Related Information (estimated delivery duration, UAV battery levels, delivery delay buffer time)
    - Energy Parameters (battery levels)
    - Propulsion Parameters
    - Flight and Navigation information (airspeed, altitude, location)
    - C^2 Workstation and UAV communication link signal strength, quality, or status
- **Available Capacity**: Value reflective of the current workload of a Supervisor.
- **Centralized Missions System**: System responsible for generating delivery missions from delivery requests, keeping track of delivery mission statuses, package delivery status, and other delivery mission information. The Supervisor's C^2 Workstation pulls its information from this system.
- **Automated Landing Site Coordinator**: A subcomponent of the Centralized Mission Systems responsible for managing the availability of landing sites for returning UAVs.
- **Route Planner**: A subcomponent of the Centralized Missions System, in charge of generating UAV flight paths.
- **Supervisor Selector**: A subcomponent of the Centralized Missions System, in charge of selecting an appropriate Supervisor for an incoming delivery mission.
- **UTM**: Uncrewed Aircraft System Traffic Management
- **VTOL**: Vertical Take-off and Landing
- **Ramp Up**: The period at the start of the Supervisor's shift, or the start of a work period after a break, during which the maximum number of en-route UAVs are assigned to the Supervisor.

- **Ramp Down**: The period at the end of the Supervisor's shift, or at the end of a work period just before a break, during which the UAV's assigned to the Supervisor land and are not replaced, resulting in the Supervisor being responsible for zero UAVs at the shift, or work period end.

B.1.2 Assumptions

A number of assumptions inform the nominal use case assumptions, as presented in Table 42. These assumptions were formed based on interviews with industrial subject matter experts or were basic assumptions associated with the research proposal.

Table 42 En-route nominal use case modeling assumptions.

Proposal Assumptions:
Day, Visual Meteorological Conditions operations only, with potential for night visual meteorological condition operations enabled by new standards and rules.
UAV operations will be conducted from the surface to 500' AGL, with additional evaluation of the potential for operations up to 1,200'AGL.
UAV operations will be conducted over other than densely populated areas, unless all UAV comply with potential criteria or standard that demonstrates safe flights over populated areas.
UAV will not be operated close to airports or heliports. 'Close' is initially defined as greater than 3 miles from an airport unless permission is granted from air traffic control or airport authority. A distance of greater than 5 miles will be examined if needed to support an appropriate level of safety.
Small UAV are potentially designed to an Industry Consensus Standard and issued an FAA Airworthiness Certificate or other FAA approval.
The multiple UAV may be operating in scenarios that include *n* UAV that have *n* unique paths distributed over an area of operation.
Subject Matter Expert-Based Assumptions:
A human Supervisor sits at a Command-and-Control (C^2) station that permits monitoring and modifying UAV operations as needed.
The Supervisor has been trained, but may only have a high school diploma or equivalent.
The Supervisor's shift includes mandatory breaks.
Upon shift start or return from break, there is a Ramp up period during which UAV launch and are assigned to the Supervisor until the maximum number permitted is reached.
When approaching shift end or break period, no new UAV are assigned to the Supervisor within the window that the UAV will not complete their delivery before the Supervisor's shift end or break commences.
Each Supervisor has a maximum limit of UAVs to supervise simultaneously.
Each Supervisor is responsible for a sector of the operational area that is deconflicted from other Supervisors.

The UAVs are highly autonomous, and the Supervisor is generally monitoring progress with very little interaction.
Loosely Coupled Scenario Specific Assumptions
Each UAV is assigned a separate and independent goal location and the locations do not overlap.
Situation awareness is generally related to what is transpiring with the overall system, meaning all monitored UAVs are healthy and completing their task without issue.
The C^2 interface is not specifically designed or defined.
At a minimum, a portion of the C^2 interface display contains a map of the Supervisor's area of responsibility that includes individual glyphs for each deployed UAV for which the Supervisor is responsible.
At a minimum, a portion of the C^2 interface display will provide the Supervisor with critical deployed UAV specifical mission information (i.e., mission status, vehicle health status, time to delivery completion, airspeed, navigation path, communication connectivity).
At a minimum, the C^2 interface provides ability access relevant mission information (i.e., delivery location, package weight).

B.1.3 Nominal Use Case Detail

This appendix provides the overview of the nominal loosely coupled, deliver drone scenario. The use case is divided by flight phase.

Flight Phase: Pre-Flight

A UAV delivery for a product from Company-A is requested by Customer-Q who lives in a suburban town. Company-A's Centralized Mission System creates a delivery mission for the request (Delivery-$) and the Route Planner generates an optimized flight path for Delivery-$**,** which is deconflicted using the UTM.

Meanwhile, at Company-A's Delivery UAV Warehouse, UAV-1 is selected for Delivery-$ by an automated UAV selection system and Flight Assistant-IX performs a preflight inspection to ensure UAV-1's airworthiness. Flight-Assistant-IX supervises UAV-1 as it is autonomously loaded with the package. Once the package is loaded, the UAV verifies the package weight and adjusts its own flight control parameters appropriately to the expected change in flight dynamics based on the package weight. Next, Flight-Assistant-IX verifies whether the mission flight path conforms to operations/airspace restrictions. Delivery-$'s mission data is uploaded into UAV-1.

An automated UAV positioning system moves UAV-1 to a take-off site. UAV-1 is set in a standby state.

Customer-Q's location is provided with the delivery order to Company-A's dispatchers who allocate Delivery-$ to a specific group of Company-A Supervisors who supervise UAV deliveries for the region in which the order originated. The Supervisor Selector selects an available Supervisor from the group with an *available capacity of N*.

The selected Supervisor's (Supervisor-X) command and control *(C^2)* workstation receives the notification of and details for Delivery-$. Supervisor-X acknowledges the assignment.

Delivery-$'s mission information (e.g., flight path, UAV status) are automatically displayed on the C^2 workstation display alongside all other deliveries being monitored.

Supervisor-X will monitor all current UAVs' Mission-Flight-Info. Supervisor-X is alerted via a notification on the C^2 workstation if any assigned UAV is involved in an Unscheduled Event the onboard autonomy (PF) cannot resolve. A task would then be queued for Supervisor-X to respond accordingly to the Unscheduled Event.

Flight Phase: Take off

UAV-1 will attempt to complete Delivery-$ autonomously. UAV-1 begins an autonomous take-off procedure. UAV-1's flight phase status is automatically updated on Supervisor-X's C^2 workstation at the start of seven flight phases: Take-off, Ascent to Cruising Altitude, Enroute, Delivery, Return, Descent from Cruising Altitude, Landing. Supervisor-X monitors all assigned UAVs which now includes UAV-1.

Flight Phase: Ascent to Cruising Altitude

UAV-1 ascends to the designated cruise altitude, assuming VTOL capabilities. During ascent, the UAV adheres to the UTM's deconfliction requirements. UAV-1's flight phase status is updated on Supervisor-X's C^2 workstation. Supervisor-X continues to monitor all assigned UAVs.

Flight Phase: Enroute

Once at cruise altitude, UAV-1 continues following Delivery-$'s generated flight path and adheres to the UTM's deconfliction requirements to Customer-Q's package delivery site. UAV-1's flight phase status is updated on Supervisor-X's C^2 workstation. Supervisor-X continues to monitor all assigned UAVs.

Flight Phase: Delivery

UAV-1 arrives at the Customer-Q's package delivery site. Delivery-$'s status is updated on Supervisor-X's C^2 workstation. UAV-1 begins an autonomous Package Drop Off procedure. First, UAV-1 searches for an acceptable landing site. Upon identifying a landing site, UAV-1 begins descending to drop the package. While descending UAV-1 constantly scans its surroundings. Once the UAV reaches an acceptable drop-off altitude, UAV-1 releases the package. After package release, UAV-1begins its ascent to flying altitude. UAV-1's delivery status is updated on Supervisor-X's C^2 workstation. Supervisor-X continues to monitor all assigned UAVs.

Flight Phase: Return

Once at flying altitude, UAV-1 begins following Delivery-$'s UTM generated flight path back to Company-A's Delivery UAV Warehouse. UAV-1's flight phase status is updated on Supervisor-X's C^2 workstation. Supervisor-X continues to monitor all assigned UAVs.

Flight Phase: Descent from Cruising Altitude

UAV-1 descends from cruising altitude as it approaches the Delivery UAV Warehouse following Delivery-$'s generated flight path. The UAV continues adhering to the UTM's deconfliction requirements. UAV-1's flight phase status is updated on Supervisor-X's C^2 workstation. Supervisor-X continues to monitor all assigned UAVs.

Flight Phase: Landing

UAV-1 arrives at the UAV Delivery Warehouse and travels to the pre-allocated landing site chosen by the Automated Landing Site Coordinator. UAV-1's flight phase status is updated on Supervisor-X's C^2 workstation.

UAV-1 begins an autonomous landing procedure. First, UAV-1 searches for an acceptable area to land on the landing site. Upon finding a suitable spot, UAV-1 begins descending to the landing site. While descending, UAV-1 constantly scans its surroundings. UAV-1 lands and Delivery-$'s mission status is updated to "Complete" on Supervisor-X's C^2 workstation. Delivery-$ is now complete. Supervisor-X continues to monitor remaining active assigned UAVs.

13. B.2. UNEXPECTED EVENT USE CASE

Potential example Unscheduled Events (UE) were developed collaboratively by A26 team members and validated through interviews with various industrial partners; however, it is noted that a complete and detailed analysis of all unexpected events for the loosely coupled scenario are not within the scope of this project. A number of assumptions, based on the industrial partner's feedback, were derived, as listed in Table 43. The unscheduled events were organized into the following categories: Supervisor failures, hardware failures, hardware damaging/inhibiting events, and flight path obstructions. Each unscheduled event was categorized to the responding agent (UAV autonomy or monitoring Supervisor). Ultimately, the objective of organizing the collection in this manner was to determine which unscheduled events occurred due to a failure in the UAV's onboard autonomy and required a response from the Supervisor. The en-route flight phase-specific unscheduled events were paired with the expected appropriate Supervisor response (i.e., unscheduled tasks). A task priority and interruptibility characteristic were included for each unscheduled task.

Table 43. Unexpected event use case modeling assumptions.

Subject Matter Expert-Based Assumptions:
The UAV's autonomy will handle a majority of UEs and not require Supervisor intervention.
UEs requiring Supervisor attention will occur approximately once per week per UAV.
The human Supervisor generally does not need to be notified of UEs that are common (e.g., avoiding collisions with stationary or moving obstacles).
It is assumed that the system design is sufficiently mature so that safety critical UEs across the entire operation in which neither the system nor the human can reduce or prevent harm will be extremely rare.
The uncrewed aircraft traffic management system will handle UAV deconfliction. If the UAV is not to collide with an obstacle, then obstacle detection and avoid automation will handle the situation. Detection and avoidance technology will be used for crewed aircraft.

There exists an Unexpected Event Supervisor who is dedicated to handling any type of UE across the system and assumes responsibility for a UAV experiencing such an event.
All UEs are applicable to multiple UAVs.
The UAV autonomy is aware of UEs and for classifying the specific type of UE, but the system requirements to support this awareness are beyond the scope of this project.

Based on industrial subject matter feedback, many UEs will be handled by the UAV's on-board autonomy and; thus, will not add to the Supervisor's workload. When asked about the frequency of UEs, the subject matter experts from different organizations indicated one (1) or fewer UEs are anticipated per week of operations per vehicle. Generally, as the number of delivery drones deployed in the national airspace increases, the overall total number of UEs will also increase. The research team developed the notion of an *Unexpected Event Supervisor*, one or more individuals who are solely dedicated to handling UEs that the primary Supervisors are unable to handle (e.g., an emergency in the airspace, mid-air collision), while maintaining adequate awareness and supervision for the rest of their fleet. UE Supervisors have a dedicated C2 station and are required to be ready to respond to any assigned UE immediately. UEs that will be handled by this specialized UE Supervisor are modeled as being handed-off to that individual. The UE Supervisor is not modeled as part of A26 and is considered beyond the scope of the current project.

Thirty-four example UEs were developed and were categorized via a taxonomy. Some of these example UEs have a common high-level event, but represent unique variants that impact human performance and may do so differently depending on the Supervisor's required response. As well, a single UE may affect multiple UAVs simultaneously, or multiple different UEs can occur for either a single UAV or multiple UAVs simultaneously. The example UEs were categorized into a hierarchy, shown in Figure 2, as requiring the UAVs' autonomy to respond to the event (red nodes), or a human Supervisor being responsible for the response (blue nodes). The example UEs are organized into seven categories (the light grey nodes): Intentional Interference, Mission Changes, Hardware Failure and Difficulties, Flight Path and Mission Obstruction, Software Failure, Collisions and UAV Damage, and Supervisor Failures.

Each leaf node's and associated graph edge's color in Figure 2 indicates who is responsible for responding to the UE. If the leaf node is Blue, the Supervisor is responsible for responding to the UE. For example, the "Emergency in the Airspace" UE may require either the UAVs' autonomy to be aware and respond, or the UAVs' autonomy may be unaware and a human response is required, shown as the two leaves associated with the Emergency in the Airspace white parent node. The grayish red leaf nodes indicate that the UAVs' Autonomy responds, but the human Supervisor is not immediately notified. For example, a "Package Delivery Cancellation" within the Mission Changes UE category. Further, each UE has an associated severity level, represented via the number in the leaf node [1 (low), 10 (high)].

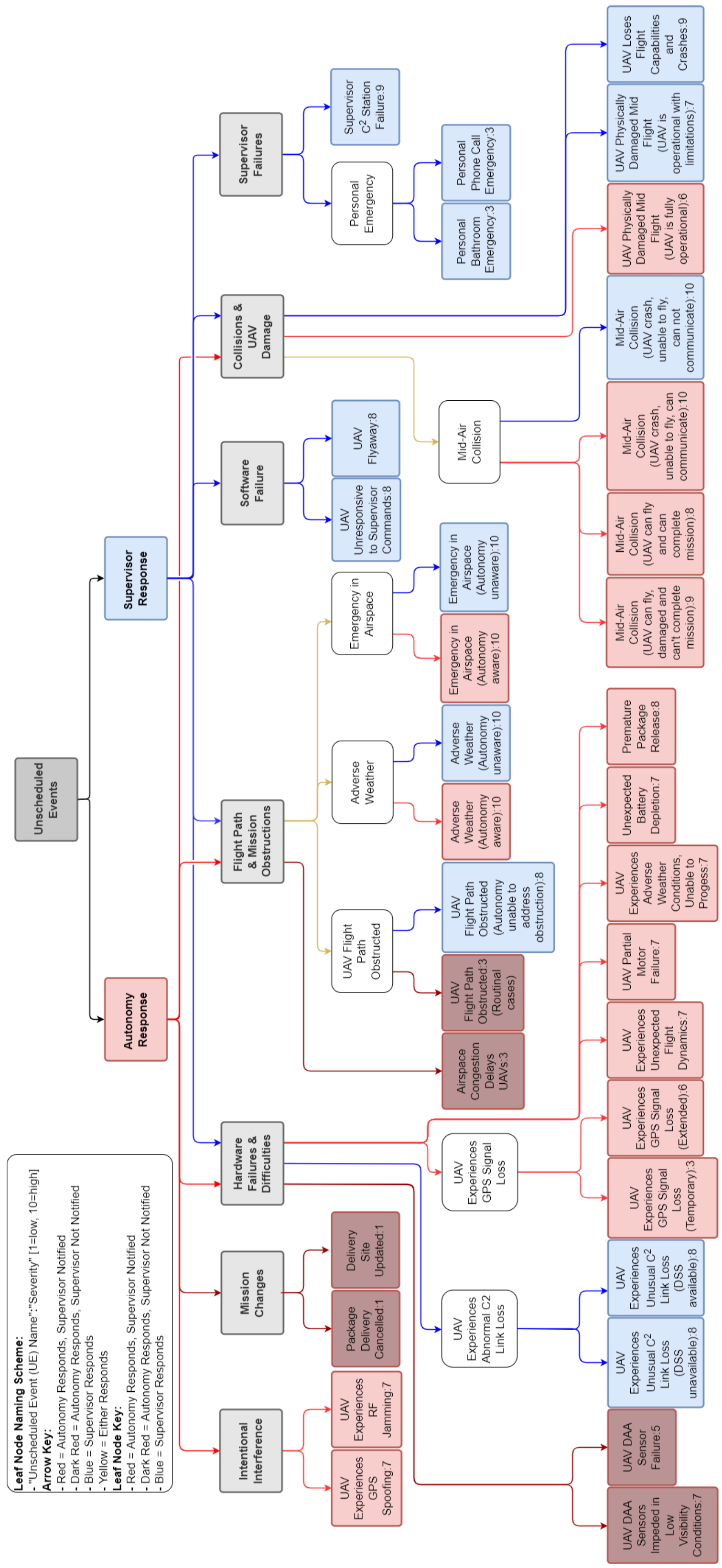

Figure 2. Unexpected Event Taxonomy Hierarchy.

Each UE was analyzed within the taxonomy and was described using the same format. Prior to providing the format, it is important to define terms that are used throughout each UE description:

- *Nominal Monitoring*: Supervision of UAV(s) that are not experiencing issues completing the assigned delivery mission.
- *Post-Response Monitoring:* Continuous supervision of UAV(s) after the UAV(s) have been given a command in response to a UE.
- *Periodic Check-ins:* Supervision of UAV(s) for multiple short durations after the UAV(s) have been given a command in response to a UE.
- *Direct Monitoring:* Direct supervision of a specific UAV with less focus on other UAVs.
- *Affected UAV(s):* The UAV(s) that experienced the UE.

Each UE description includes the following fields:

- *Description:* A brief statement describing what the particular UE represents.
- *Event Severity:* The UE's potential danger or damage to the UAV, civilians or property [1 (low), 10 (high)].
- *Supervisor Notification Need:* Describes how crucial it is to have the Supervisor notified about the UE [1 (low), 10 (high)].
- *Supervisor Response Need:* Describes how crucial it is to have the Supervisor respond to the UE [1 (low), 10 (high)]
- *Autonomy Aware:* Describes whether the UAV's Autonomy is cognizant of the UE's occurrence [Yes, No].
- *Responder:* Describes the party responsible for initially and directly addressing the UE, typically the UAV itself or the Supervisor, although others may also respond.
- *Supervisor Aware:* Describes whether the Supervisor is cognizant of the UE's occurrence.
- *Supervisor Notified:* Describes whether the Supervisor is made cognizant of the UE's occurrence by either being notified by the C^2 station, or an external communication source.
- *Additional Supervisor Monitoring Required:* Describes whether the autonomy's or Supervisor's response to the UE requires the Supervisor to either post response monitor, direct monitor, or periodically check in on affected UAV(s).
- *Supervisor Perception Possibilities:* Lists potential methods, without focusing on specific user interface designs, by which the Supervisor can be notified of and made cognizant of the UE's occurrence.
- *Notes:* Contains general comments about the UE and details on the expected autonomy or Supervisor response to the UE.
- *Modeling Notes:* Details on the implementation of the autonomy's or Supervisor's response within the IMPRINT Pro model.

B.2.1 Supervisor Failures

B.2.1.1 Supervisor C^2 Station Failure

Description: The Supervisor's C^2 station crashes, freezes, is affected by communication outages, or experiences input or output device failure.
Event Severity: 10
Supervisor Notification Need: 1

Supervisor Response Need: 10
Autonomy Aware: Yes
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Self
Notes: Supervisor Responses to Variations of C^2 Station Failures

- C^2 Crash or Freeze
  - A centralized C^2 Station Management system recognizes the Supervisor C^2 Station is unresponsive due to a system crash or freeze. The C^2 Station Management system communicates with the UAV Management system to have the Supervisor's UAVs reassigned to a new Supervisor. Meanwhile, the Supervisor will attempt to restart the C^2 station.
  - If the C^2 station does not restart the Supervisor will contact the Command Center's IT team to assist.
  - The Supervisor will contact Command Center personnel to confirm whether the Supervisor's assigned UAVs were reassigned automatically and if not, to have them reassigned.
- Output Device Failure (i.e., Monitor failure) or Input Device Failure (i.e., Mouse, Keyboard failure)
  - The Supervisor will first troubleshoot the issue themselves.
  - If unable to successfully troubleshoot the output/input device the Supervisor will contact the Command Center's IT team to assist with the issue.
  - If the situation lasts longer than a few minutes the Supervisor must contact Command Center personnel capable of reassigning all of the Supervisor's UAVs to other Supervisors.
  - Additionally, the UAVs are automatically reassigned to another Supervisor if the C^2 Station Management system recognizes the Supervisor's C^2 station has not had input after several minutes.
- Communication Outages:
  - A centralized cloud-based C^2 Station Management system recognizes the Supervisor C^2 Station is offline. The C^2 Station Management system communicates with a cloud-based UAV Management system to have the Supervisor's UAVs reassigned to new Supervisors of command centers in other regions not affected by the communications outage.
  - The Supervisor will attempt to contact personnel associated with the cloud-based C^2 Station Management system over non-affected communication lines i.e., telephone. Next, the Supervisor confirms with the personnel whether their assigned UAVs were resigned automatically, and if not, to have them reassigned.

Modeling Notes: Not to be modeled.

B.2.2 Mission Changes

B.2.2.1 Package Delivery Canceled

Description: The customer cancels the package delivery while the UAV is en-route.
Event Severity: 1

Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Can be made aware. The Supervisor can make themselves aware of the UE if they look into the delivery mission details via the C^2 station.
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: The Supervisor is not explicitly notified about the package delivery cancellation, but information about the UE is accessible for the Supervisor via the C^2 station within the UAV's mission details.
Notes:

- The Autonomy will update the affected UAV's flight plan and it will return to the launch site (RTL).
- The Supervisor does not stop Nominally Monitoring the UAV after the UE occurs. The Supervisor will continue monitoring the UAV until RTL is completed.

Modeling Notes: This UE will not be modeled, because it does not involve the Supervisor directly. Further, the Supervisor's workload will be based on the ability to interrogate the UAV's representation to gain access to the information and the implementation of such actions can dramatically differ, impacting workload differently.

B.2.2.2 Delivery Site Updated

Description: The customer changes the delivery site while the UAV is en-route.
Event Severity: 1
Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Can be made aware. The Supervisor can make themselves aware of the UE if they look into the delivery mission details.
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: The Supervisor is not explicitly notified about the delivery order location update, but information about the UE is accessible for the Supervisor via the C^2 station within the UAV's mission details.
Notes: Different conditions elicit different responses from the Autonomy:

- The UAV has enough fuel to deliver the package to the updated delivery site. Therefore, the Autonomy updates the UAV's flight plan, and the Supervisor continues to Nominally Monitor the UAV.
- The UAV does not have enough fuel to deliver to the updated delivery site. Therefore, the Autonomy commands the UAV to RTL. The Supervisor continues Nominally Monitoring the UAV until it RTLs.
- The updated delivery site is outside of the Supervisor's sector, but the UAV has enough fuel to make the delivery. Therefore, the Autonomy unassigns the UAV from the Supervisor and reassigns the UAV to an available Supervisor overseeing UAVs in the sector in which the updated delivery site resides.

Modeling Notes: This UE will not be modeled, because it does not evoke an action from the Supervisor. Further, the Supervisor's workload will be based on the ability to interrogate the UAV's representation to gain access to the information and the implementation of such actions can dramatically differ, impacting workload differently.

B.2.3 Intentional Interference

B.2.3.1 UAV Experiences Global Position System (GPS) Spoofing

Description: The UAV is GPS spoofed by a malicious actor, and the Supervisor is notified of the GPS inconsistencies reported by the UAV.
Event Severity: 7
Supervisor Notification Need: 5
Supervisor Response Need: 3
Autonomy Aware: Yes. Although the specifics are beyond the scope of the current effort, the Autonomy can become aware of inconsistencies with GPS data, but not that it is being spoofed. The UAV's Autonomy can become aware of the GPS inconsistencies using the following methods:

- Comparing the UAV's current reported spoofed position with locations on the originally planned route.
- Comparing observed environmental landmarks with known landmarks (i.e., buildings, bridges) distinct to the area in which the UAV is currently.

Responder: Supervisor
Supervisor Aware: Yes. Aware of GPS inconsistency.
Supervisor Notified: Yes. Notified about GPS inconsistencies.
Additional Supervisor Monitoring Required: Yes, as Periodic Check-ins
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/o Audible Alert
- Text Log w/ Audible Alert
- Glyph Change w/ Audible Alert
- Glyph Change w/o Audible Alert

Notes: Sequence of events:

- Multiple UAVs can experience spoofing simultaneously.
-
- The Autonomy becomes aware of the inconsistencies with its GPS data.
- The Supervisor acknowledges the notification about the GPS inconsistencies.
- The Supervisor periodically checks in to see if the UAV GPS issue has been resolved.
- At any point, if the severity of GPS inconsistencies surpasses a threshold:
  - The Autonomy commands the UAV to attempt to RTL, attempt to land at a secondary landing site, or land in place. The UAV cannot be permitted to continue to fly its planned path if it is believed to be controlled via GPS spoofing.
  - The Supervisor is notified about the Autonomy's commands and PR Monitors the affected UAV.
  - The Autonomy contacts the UAV retrieval team to recover the UAV if the UAV was commanded to land at a secondary location or land in place.

Modeling Notes: Sequence of events in model:

- The Supervisor first completes the "Acknowledge Notification" task of ___ secs and ____ workload.

- The Supervisor engages in a "Periodic Check-in" task that occurs N times. Each check-in lasts __ secs with a workload of __ and occurs at a spaced interval of ____ secs.
  - The "Periodic Check-in" task is completed in parallel with the Nominal Monitoring of N-1 unaffected UAVs.
- At any point, if the severity of GPS inconsistencies surpasses a threshold:
  - Supervisor engages in the "Acknowledgement of Notification" task for __ secs with a workload of __.
  - The Supervisor PR Monitors the affected UAV for __ secs with a workload of __ as it reacts to the commands of the Autonomy.

B.2.3.2 UAV Experiences Radio Frequency (RF) Jamming

Description: The UAV is subjected to RF jamming, mid-flight, by a malicious actor.
Event Severity: 7
Supervisor Notification Need: 3
Supervisor Response Need: 3
Autonomy Aware: Possibly. UAVs may have the capacity to surmise that it is being RF jammed.
Responder: Autonomy
Supervisor Aware: Possibly. The Supervisor will only be able to know about the UE if the UAV reestablishes the C^2 link and the UAV's Autonomy notifies the Supervisor. Otherwise, the Supervisor will perceive the RF jamming of the UAV as a C^2 link loss.
Supervisor Notified: Yes. The Supervisor is notified about the C^2 link loss of the UAV by the C^2 station and not notified about RF jamming.
Additional Supervisor Monitoring Required: Yes, as Periodic Check-ins
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/ Audible Alert
- Visual Glyph Change w/ Audible Alert

Notes:

- Multiple UAVs can experience jamming simultaneously.
- Technologies capable of RF Jamming UAVs are illegal in the United States.
- Sequence of events:
  - UAV's Autonomy perceives the RF jamming.
  - Autonomy determines if UAV is capable of continuing the mission:
    - If the UAV is capable of continuing the delivery mission while being jammed, then the UAV continues and reports back to the Supervisor when possible.
    - If the UAV is incapable of continuing the delivery mission due to jamming, the Autonomy either commands the UAV to land in place or RTL.
  - Meanwhile, the C^2 station notices a drop in communication with the affected UAV but is only able to perceive the event as a C^2 link loss and not RF jamming.
  - The Supervisor receives a notification from the C^2 station about the C^2 link loss between the C^2 station and UAV.
  - Next, the Supervisor periodically checks in on the UAV to see if communication has been reestablished between the UAV and the Supervisor's C^2 station.
    - If the UAV does not reestablish communication with the Supervisor's C^2 station by the time the UAV was supposed to have finished its mission, the "UAV Experiences Unusual C^2 Link Loss" UE is considered.

*Modeling Notes: S*equence of events in model:

- The Supervisor first completes the "Acknowledge Notification" task of __ secs and __workload.
- Next, the "Periodic Check-in" task occurs N times with a duration of __ secs and workload of __. Each check-in occurs at a spaced interval of ____ secs.
- The "Periodic Check-in" task is completed in parallel Nominal Monitoring of N-1 UAVs.
    - If the UAV does not reestablish communication with the Supervisor by the initially estimated end time of the delivery mission, the Supervisor will follow the logic and tasks laid out in the "UAV Experiences Unusual C^2 Link Loss" UE.

B.2.4 Hardware Failures and Difficulties

B.2.4.1 UAV Experiences Extended GPS Signal Loss

Description: UAV experiences severe GPS signal loss for an extended period of time making it impossible for the UAV to safely continue with the mission.
Event Severity: 6
Supervisor Notification Need: 6
Supervisor Response Need: Varies
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Visual Glyph Change without Audible Alert

Notes: Sequence of events:

- Upon sensing the GPS signal loss, the Autonomy commands the UAV to either: Return to location of last GPS connection.
    - UAV arrives at the location of the last GPS location. If the GPS dead zone is on the en-route path, the Autonomy reroutes to avoid the dead zone:
        - If the UAV has rerouted multiple times and is still unable to find a path with an adequate GPS signal, the UAV is commanded to return to launch. The Supervisor is notified after the first reroute attempt.
        - The Supervisor Post-Response Monitors the UAV as it attempts to reroute.
        - The Supervisor returns to Nominally Monitoring the UAV if it is capable of finding a path with an adequate GPS signal.
        - After rerouting X number of times or after Y seconds, the Supervisor is notified. The Supervisor decides whether the UAV continues or aborts the mission.
    - UAV arrives at the location of the last GPS location, GPS dead zone is near the delivery site:
        - The Autonomy chooses to either find a different delivery location or RTL without delivering the package. The Supervisor is not notified about this even.
- Upon sensing the GPS signal loss, the Autonomy commands the UAV to either: Land in Place
    - The Supervisor is notified about the UE and Autonomy's command and then post-Response monitors the UAV while it lands.
    - After the UAV lands, the Autonomy contacts the UAV retrieval team.

- The UAV is unassigned from the Supervisor.
- The maintenance crew is responsible for analyzing the fight logs to determine the cause of the unexpected flight dynamics and making any necessary repairs prior to the UAV being redeployed.

Modeling Notes: This UE can impact multiple UAVs simultaneously. Sequence of events in model:

- Autonomy commands the UAV to either:
  - Return to location of last GPS connection:
    - If the GPS dead zone is on the en-route path:
      - The Autonomy reroutes to avoid the dead zone.
      - The Supervisor is notified after the first reroute attempt. Supervisor engages in "Acknowledge Notification" task for __ secs with a workload of ___.
      - The Supervisor begins to Post-Response Monitor the UAV with a workload of __.
    - If GPS dead zone is near the delivery site:
      - The Autonomy chooses to either find a different delivery location or RTL without delivering the package.
      - The Supervisor is not notified about this and remains Nominally Monitoring the affected UAV.
  - Land in place:
    - The Supervisor is notified of the Autonomy's action. Supervisor engages in "Acknowledge Notification" task for __ secs with a workload of ___.
    - The Supervisor Post-Response Monitors the affected UAV with a workload of __ until it lands. After the UAV lands the UAV is unassigned from the Supervisor.

B.2.4.2 UAV Experiences Temporary GPS Signal Loss

Description: UAV experiences short GPS signal loss during the mission. The UAV is still capable of making mission progress despite occasional GPS loss.
Event Severity: 3
Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No
Additional Supervisor Monitoring Required: No, the Supervisor will be unaware of the UE because temporary GPS signal loss is an expected occurrence for the UAV's Autonomy to handle. The Supervisor will not stop Nominally Monitoring the UAV.
Supervisor Perception Possibilities: Not Notified
Notes: This UE can impact multiple UAVs simultaneously.
The affected UAV experiencing temporary GPS loss will attempt to navigate by other means without GPS. If a GPS link is reestablished the event will be logged and the UAV will continue with the delivery mission. The Supervisor is never notified of the event but capable of seeing its occurrence in the log.
Modeling Notes: This UE will not be modeled because it does not involve the Supervisor.

B.2.4.3 UAV Experiences Unusual C^2 Link Loss (DSS Available)

Description: A UAV's Autonomy has not communicated with the Supervisor's C^2 station for an extended period of time; the Supervisor is unsure about the whereabouts of the UAV or its mission status. The C^2 station has a DSS implemented to assist with information gathering and analysis.
Event Severity: 8
Supervisor Notification: 8
Supervisor Response Need: 8
Autonomy Aware: Yes
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No. The Supervisor will be Nominally Monitoring the UAV and does not engage in any other form of monitoring.
Supervisor Perception Possibilities: Notified by C^2 station

- Visual Glyph Change w/ Audible Alert
  - Glyph saliency increased

Notes: This UE can impact multiple UAVs simultaneously. Sequence of events:

- The affected UAV enters an out of communication state. After a short period of time (1 min), the UAV glyph is changed (i.e., color change) to represent the UAV's prolonged out of communications state. After X mins the UAV passes the notification threshold and the Supervisor is formally notified to investigate.
- The Supervisor contacts the UAV's Launch Site's UAV Management Team to determine if the UAV has returned.
  - If Yes: The Supervisor can remove the UAV's assignment.
  - If No: The Supervisor interacts with the DSS, inputting information about the affected UAV. The DSS predicts the potential current locations of the UAV. Then, the DSS communicates its analysis, about the UAV's predicted current location, to the UAV Retrieval team. The UAV Retrieval team is now responsible for retrieving the UAV.
- The UAV is unassigned from the Supervisor.

Modeling Notes:

- This UE will occur due to the UAV needing to descend to drop off a package, or because the UAV is navigating through a built environment and line of site is lost with the communications technology. The descent for package delivery is outside the scope of the current research effort. As well, the possibility of a system wide communications outage can occur.
- This UE can occur for a single UAV, or multiple UAVs simultaneously.
- Implementing this UE in the model will require the affected UAV to be in an out of communications state for a period of time before the Supervisor begins contacting the Launch Sites UAV Management Team to determine the UAV's whereabouts.
- While in the out of communications state the UAV is no longer Nominally Monitored by the Supervisor but is still considered one of the Supervisor's N-assigned UAVs.
- Sequence of events in model:
  - The C^2 link loss experienced by the affected UAV surpasses the notification threshold, a notification is sent to the Supervisor.

- The Supervisor engages in the "Acknowledge Notification" task for __ secs with a workload of __.
- The Supervisor completes the "Contacts UAV Management Team" task for __ secs a with a workload of __.
  - UAV return confirmed by UAV Management Team: The affected UAV is unassigned from the Supervisor.
- UAV return not confirmed by UAV Management Team:
  - The Supervisor engages in the "Gather UAV Information for DSS" task for __ secs with a workload of __.
  - The Supervisor completes the "Interact with DSS" task for __ secs with a workload of __.
  - The affected UAV is unassigned from the Supervisor.

B.2.4.4 C^2 Link Loss (decision support system is unavailable)

Description: A UAV's Autonomy has not communicated with the Supervisor's C^2 for an extended period of time; the Supervisor is unsure about the whereabouts of the UAV or its mission status. The C^2 station does not have a decision support system implemented to assist the Supervisor with information gathering and analysis.
Event Severity: 8
Supervisor Notification: 8
Supervisor Response Need: 8
Autonomy Aware: Yes
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No. The Supervisor will continue Nominally Monitoring the UAV and does not engage in any other form of monitoring.
Supervisor Perception Possibilities: Notified by C^2 station

- Visual Glyph Change w/ Audible Alert
  - Glyph saliency increased

Notes:

- This UE will occur due to the UAV needing to descend to drop off a package, or because the UAV is navigating through a built environment and line of site is lost with the communications technology. The descent for package delivery is outside the scope of the current research effort. As well, the possibility of a system wide communications outage can occur.
- This UE can occur for a single UAV, or multiple UAVs simultaneously.
- Sequence of Events Overview:
  - The affected UAV enters an out of communication state. After a short period of time (1 min), a visual change occurs (i.e., UAV glyph color change) to represent the UAV's prolonged out of communications state. After 7 mins the UAV passes a notification threshold and the Supervisor is formally notified to investigate.
  - Before addressing the event, the Supervisor first decides if they will assume full responsibility of addressing the event or if they will hand-off the affected UAV to a dedicated UE Supervisor.

- The Supervisor manually gathers information about the affected UAV, such as the UAV's last known location, how long it has been out of communication, last known speed and direction, and last known flight phase. An analysis of the gathered data results in a prediction of the UAV's current whereabouts as well as the UAV's expected RTL time.
- If the expected RTL time arrives and the UAV has not reestablished contact, the Supervisor proceeds to contact the UAV's Launch Site's UAV Management Team to determine if the UAV has returned.
  - If Yes: The Supervisor requests the removal of the UAV's assignment.
  - If No: The Supervisor communicates their analysis of the situation to the UAV Retrieval Team. The UAV Retrieval Team becomes responsible for retrieving the UAV.
- The UAV is ultimately unassigned from the Supervisor.

Modeling Notes:

- Implementing this UE requires the affected UAV to be out of communications for an extended time period before the Supervisor is officially notified of the Extended C^2 Link Loss UE. Prior to notification, the Supervisor may interpret visual UAV glyph changes that indicate the increasing communications loss duration. The Supervisor is officially alerted through the C^2 station about the UE at seven minutes.
- The affected UAV is nominally monitored, while in the initial out of communications event.
- The Supervisor, when notified of the Extended C^2 Link Loss UE, completes tasks required to respond to the event, which interrupts the Supervisor's nominal monitoring task.
- The Supervisor can hand-off the affected UAV to the dedicated UE Supervisor. Upon hand-off completion, the Supervisor is no longer responsible for the UAV.
- A waiting period simulates the Supervisor waiting to determine if the UAV can reestablish communications as it nears or lands at the launch site. During this waiting period, the Supervisor returns to Nominally Monitoring the other UAVs. Once the waiting period completes, the Supervisor switches back to addressing the UE.

B.2.4.5 Unexpected Battery Depletion

Description: A UAV loses charge faster than expected mid-delivery mission.
Event Severity: 7
Supervisor Notification Need: 3
Supervisor Response Need: 3
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/o Audible Alert
- Text Log w/ Audible Alert
- Visual Glyph Change w/ Audible Alert

- Visual Glyph Change w/o Audible Alert

Notes: Sequence of events:

- The Supervisor receives and acknowledges a notification about the un expected event.
- The Autonomy is capable of commanding the UAV to land in place, to RTL, or to land at a secondary landing site.
  - Commanding to land in place will require the Autonomy to communicate with the UAV Retrieval Team to provide the UAV's location once it lands.

The Supervisor is notified of Autonomy's actions after the Autonomy's commands have been received by the UAV.

Modeling Notes: Sequence of events in model:

- The Supervisor will engage in the "Acknowledge Notification" task for ___ secs with a workload of ____.
- Next, depending on the Autonomy's response, the Supervisor will continue monitoring the affected UAV for different durations of time:
  - If the Autonomy Response is: Command UAV to Land in Place
    - The UAV will have its flight plan updated and land. Then the UAV will be unassigned from the Supervisor.
  - If the Autonomy Response is: Command UAV to RTL or land at a secondary landing site.
    - The UAV will have its flight plan updated and reroute accordingly.
- The Supervisor will Nominally Monitor the UAV throughout this process.

B.2.4.6 UAV Detect and Avoid (DAA) Sensor Failure

Description: A UAV's DAA sensors stop functioning mid-flight.
Event Severity: 5
Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Not Notified
Notes:

- Sequence of events:
  - The Autonomy chooses to either RTL or land at a secondary landing site known to be clear of obstructions.
  - The Supervisor will remain unaware of the UE's occurrence and Nominally Monitor the UAV regardless of the Autonomy's response.
- The Supervisor can look within the UAV's mission details to identify information about the UE's occurrence.

Modeling Notes:

- This UE will not be modeled because it does not involve the Supervisor.

- Sequence of events in model:
  - Based on the Autonomy's response to the UE, the UAV in the model updates its flight plan to either RTL or land at a nearby secondary location.
  - The Supervisor will remain unaware of the UE and Nominally Monitor the UAV as its flight path changes due to the Autonomy's response.

B.2.4.7 Premature Package Release

Description: The delivery package is unintentionally released from the UAV mid-flight due to hardware or software failures.
Event Severity: 8. A falling package has a high potential of causing damage to property or harm to humans.
Supervisor Notification Need: 7
Supervisor Response Need: 7
Autonomy Aware: Yes
Responder: Autonomy, and the Supervisor.
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Notified by C^2

- Visual Glyph Change w/ Audible Alert
  - Glyph saliency increased

Notes: Sequence of events:

- The Autonomy contacts the package retrieval team and sends the package's predicted drop location. The package retrieval team is responsible for making sure the package is retrieved and also responsible for assessing any damage caused by the package at the drop site.
- The Autonomy commands the UAV to either RTL. The Supervisor is notified of the UE. The occurrence of this UE over traffic or populated areas will require the Supervisor to report the incident to first responders or air traffic control.

Modeling Notes: Sequence of events in model:

- The Autonomy commands the UAV to RTL site upon detecting loss of payload. Based on the UAV's location when the event occurred the UAV will fly for __ secs.
- The Supervisor engages in the "Acknowledge Notification" task for __ secs with a workload of __.
  - If the UE occurred over traffic or a populated area:
    - Supervisor engages in the "Report Incident to First Responder and Airspace Personnel" task.
    - The Supervisor begins Direct Monitoring the UAV with a workload of __ from the end of the "Acknowledge Notification" task to the end of the "Report Incident to First Responder and Airspace Personnel" task.
    - The Supervisor returns to Nominally Monitoring the affected UAV.
  - If the UE occurred over a non-populated area:
    - The Supervisor returns to Nominally Monitoring the affected UAV.

B.2.4.8 UAV Partial Motor Failure

Description: A UAV experiences partial motor failure but is still capable of flying.
Event Severity: 7
Supervisor Notification: 7
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Notified by C^2

- Text Log w/ Audible Alert
- Visual Glyph Change w/ Audible Alert
    - Saliency increased

Notes: Sequence of events:

- The Autonomy becomes aware of the partial motor failure,
- the Autonomy commands the UAV to RTL or land at a secondary landing site or land in place.
- The Supervisor is notified about the UE through the C^2 station and acknowledges a notification of the UE's occurrence.
- The Supervisor continues to Nominally Monitor the UAV as it RTLs or lands at a secondary landing site.

Modeling Notes: Sequence of events in model:

- The UAV's flight plan is updated, and depending on the selected command, will either RTL or fly to land at a secondary landing site for __ secs.
- The Supervisor engages in the "Acknowledgment of Notification" task for ___ secs with a workload of ___.
- The Supervisor completes the "Assess the Situation" task of __ workload for __ secs.
    - The Supervisor has not stopped Nominally Monitoring the UAV.
- The Supervisor continues to Nominally Monitor the UAV as it either RTL or lands at a secondary landing site.

B.2.4.9 UAV Experiences Unexpected Flight Dynamics

Description: UAV suddenly experiences difficulty maintaining stability and control of pitch, yaw, or roll.
Event Severity: 7
Supervisor Notification Need: 5
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/ or w/o Audible Alert

- Visual Glyph Change with or without Audible Alert
- Popup attached to Glyph

Notes:

- This UE can impact multiple UAVs simultaneously.
- The instant the Autonomy becomes aware of the continual unusual flight dynamics, the UAV's goal is changed to land in place, RTL, or land at the secondary landing site.
- After the Autonomy makes a response, the Supervisor is notified and acknowledges the Autonomy's actions.

Modeling Notes:

- The moment the Autonomy becomes aware of the unusual flight dynamics it will decide between land in place, RTL, or land at a secondary landing site.
- The Supervisor will engage in the "Acknowledge Notification" task for __ secs with a workload of __.
- If the autonomy decides Land in Place the Supervisor will Nominally Monitor the UAV as it lands in place.
- Otherwise, the Supervisor will Nominally Monitor the UAV as it RTLs or lands at a secondary landing site for ___ secs.

B.2.4.10 UAV Experiences Adverse Wind Conditions and Unable to Progress

Description: UAV experiences strong constant winds, turbulent winds, propeller vortices, or wind shear and is unable to progress safely.
Event Severity: 7
Supervisor Notification Need: 6
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional *Supervisor Monitoring Required*: Yes
Supervisor Perception Possibilities: Yes

- Text w/ Audible Alert
- Visual Glyph Change w/ Audible Alert
  - Glyph highlighted or circled
  - Glyph color change

Notes: This UE can impact multiple UAVs simultaneously.
Initially, the Autonomy will focus on keeping the UAV stable while progressing, but if the UAV continuously experiences adverse wind conditions and is unable to safely make progress, the Autonomy decides to either have the UAV reroute, RTL, land in a secondary landing site, or land in place.

  - Land in place or landing in a secondary site triggers a notification for the Supervisor.

    - The Autonomy contacts the "UAV retrieval team" to pick up the UAV after it has landed.
- Reroutes or RTL do not trigger notifications for the Supervisor.
    - Information about the UE and Autonomy's commands are logged in the mission details and are accessible by the Supervisor if necessary.

Modeling Notes:

- If the Autonomy commanded the UAV to land in place, or land in a secondary site, a notification is sent to the Supervisor.
    - The Supervisor engages in the "Acknowledge Notification" task for __ secs with a workload of __.
    - Then, the Supervisor Post-Response Monitors the affected UAVs for _ secs with a workload of __.
    - The Supervisor returns to Nominally Monitoring the UAV.
- If the Autonomy commanded the UAVs to, reroute or RTL, the Supervisor does not receive a notification and therefore continues to Nominally Monitor the UAVs.

B.2.4.11 UAV DAA Sensors impeded in Low Visibility Conditions

Description: UAV is unable to utilize on-board detect and avoid sensors that are impeded by low visibility conditions caused by: heavy rain, fog, smoke, snowfall, falling leaves, exhaust plumes, steam plumes, lights, lasers, searchlights, fireworks, etc.
Event Severity: 7
Supervisor Notification: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Not Notified
Notes: This UE can impact multiple UAVs simultaneously.
The Autonomy will command the UAV to reroute (i.e., raise or lower in altitude) to try and regain vision.
Modeling Notes: This UE will not be modeled because it does not require Supervisor involvement.

B.2.5 UAV Software Failure

B.2.5.1 UAV Flyaway

Description: UAV has significantly diverged from its flight path and is not attempting to correct back to the planned course.
Event Severity: 7
Supervisor Notification Need: 10
Supervisor Response Need: 10
Autonomy Aware: No
Responder: Supervisor

Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities:

- Notified by C^2 station
    - Visual glyph change
    - Visual popup attached to glyph
    - A notification window appears in the center of the C^2 station interface.

Supervisor Interprets Flyaway from UAV glyph and Mission Information

- The Supervisor visually perceives UAV deviating from the flight path.

Notes:

- This UE can impact multiple UAVs simultaneously.
- If the Supervisor was notified by the C^2 station, the Supervisor first acknowledges the C^2 station's notification.
- Upon UE perception, the Supervisor will send a command and monitor if the UAV responds to the command. The command can either be land in place, RTL, or land at a secondary landing location.
    - If the UAV is commanded to Land in Place and is responsive, the Supervisor will Post-Response Monitor the UAV as it lands.
    - If the UAV is commanded to RTL or land at a secondary landing site then the Supervisor will Post-Response Monitor the UAV for a portion of the return flight. The Supervisor will return to Nominal Monitoring until the UAV Lands.
    - If the UAV is not responsive to either command, the Supervisor will have to communicate with the UAV Retrieval Party.
        - Possible Outcome 1: The Supervisor will hand-off the UAV to the UAV retrieval team and will no longer be responsible for the UAV at all. The UAV's glyph disappears from the Supervisor's C^2 station interface.
        - Possible Outcome 2: The Supervisor will communicate the current location and heading of the UAV and stay in periodic communication with the retrieval team as the retrieval team tracks and attempts to retrieve the UAV. The Supervisor will Direct Monitor the UAV until the UAV ultimately crashes or the retrieval team lowers and captures the UAV.

Modeling Notes:

- If the C^2 station notified the Supervisor, the Supervisor must complete the "Acknowledge Notification" task for __ secs with a workload of __.
- The Supervisor sends a land in place, RTL, or land at a secondary landing location command for __ secs with a workload of __.
- Assuming the Supervisor's command is received by the UAV, the Supervisor will Post-Response Monitor the UAV for ___ secs as it either lands in place, RTL, or lands at a secondary landing site.

- If the command is not received by the UAV, the Supervisor will contact the UAV retrieval team and will Direct Monitor the affected UAV while still simultaneously Nominally Monitoring the other N-1 UAVs.

B.2.5.2 UAV Unresponsive During Unexpected Event

Description: UAV is unresponsive to Supervisor's commands intended to address an ongoing unscheduled event affecting the UAV.
Event Severity: 8
Supervisor Notification Need: Notification not possible. The C^2 is assumed to be unable of determining whether the UAVs are correctly responding to the Supervisor's command; therefore, the C^2 is unable to notify the Supervisor about the occurrence of this UE.
Supervisor Response Need: 10
Autonomy Aware: No
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: No
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Perceived during Post-Response Monitoring
Notes:

- This UE is more of a UE "extension" than a standalone UE. For example, a Supervisor commanded UAVs to RTL because of an Emergency in the Airspace and some of the UAV's are not reacting to the command.
- This UE may occur after any instance of a Supervisor Response.
- This UE has been included for the sake of completeness.

Modeling Notes:

- This UE can be modeled; however, it will come in the form of additional Supervisor tasks once the Supervisor realizes the UAV experiencing a UE is not reacting to the Supervisor's Response command.

B.2.6 Flight Path and Mission Obstructions

B.2.6.1 Emergency in Airspace (UAV unaware)

Description: Primary Supervisor is aware of the emergency and all aircraft in the designated airspace need to exit the designated airspace. The autonomy is unaware of the emergency.
Event Severity: 10
Supervisor Notification Need: 10
Supervisor Response Need: 10
Autonomy Aware: No
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by Outside Source

- Audibly

    - Informed by Co-worker in person
    - Informed by Co-worker over Phone
    - Emergency Broadcast Notification System on C^2 station or in the command center
- Text
    - Informed by Co-worker over C^2 station
    - Informed by Co-worker over Phone
    - Emergency Broadcast Notification System on C^2 station
- Audibly and Text
    - Emergency Broadcast Notification System on C^2 station

Notes: This UE can impact multiple UAVs simultaneously.
Upon perception, the Supervisor has several options:

- Hand-off to the UE Supervisor
- Command UAV(s) into Holding Pattern
- Command UAV(s) to Return to Launch
- Command UAV(s) to Land at Secondary Landing Site
- Reroute UAV(s)
- Do Nothing, continue the mission

Modeling Notes:

- The UE Supervisor's tasks are not modeled, rather the model focuses on the main Supervisor.
- Different Supervisor Responses will trigger different actions by the UAVs:
    - Command UAV(s) to RTL or Secondary Landing Site
        - All affected UAV(s) are no longer “Nominally Monitored” and are instead Post-Response Monitored for ___ secs with a workload of ____. While Post-Response Monitors the affected UAVs, the Supervisor Nominally Monitors the non-affected UAVs in parallel. The Supervisor returns to Nominally Monitoring the affected UAVs once Post-Response Monitoring is completed.
    - Command UAV(s) into Holding Pattern
        - The affected UAV(s) hold their position and are Post-Response Monitored until a few outcomes occur:
            - The Supervisor is notified about the end of the airspace emergency and, therefore commands the UAVs to continue with the Delivery Mission delivery, battery levels permitting. The affected UAV(s) return to being Nominally monitored.
            - UAV Battery Levels are getting low and the UAV must RTL.
    - Command UAV(s) to RTL or Secondary Landing Site
        - The affected UAV(s) are Post-Response Monitored for the first ____ secs, with a workload of ____, as they RTL or land at a secondary landing site. Then, the Supervisor returns to Nominally Monitoring the affected UAVs.
    - Reroute UAV(s)
        - The affected UAV(s) are rerouted for ___ secs with a workload of ____. All UAVs are rerouted simultaneously for the sake of model simplicity,

- The affected UAV(s) are Post-Response Monitored for the first ____ secs as they follow their new flight paths. Then, the Supervisor returned to Nominally Monitoring the affected UAV(s).

B.2.6.2 Emergency in Airspace, Autonomy Aware

Description: UAV(s) Autonomy is aware of an emergency in the airspace and is responsible for clearing the affected airspace of UAV.
Event Severity: 10
Supervisor Notification Need: 8
Supervisor Response Need: 1
Autonomy Aware: No
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 Station

- Affected areas of operations are made visually salient on the interface's sector map. An audible alert is played and the glyphs of affected UAVs are made visually salient. A notification window, describing the emergency, appears in the center of the affected area.

Notes:

- This UE can impact multiple UAVs simultaneously.
- The Autonomy is aware of the Emergency in Airspace and is capable of responding. After the Autonomy commands the affected UAV(s), the Supervisor is notified to acknowledge and assess the Autonomy's action.
- Next, the Supervisor Post-Response Monitors the affected UAVs to ensure they are reacting accordingly to the Autonomy's command.
- *Modeling Notes:*
- The Supervisor completes the "Acknowledgment of Notification and Assessment of Autonomy Response" task for ___ secs and workload of __.
- Next, the Supervisor Post-Response Monitors the affected UAVs for ___ secs with a workload of ___. Meanwhile, the Supervisor also Nominally Monitors the unaffected UAVs.

B.2.6.3 UAV Flight Path Obstructed

Description: The UAV is unable to temporarily progress in the mission because its flight path is being obstructed by objects like other UAV, stationary obstacles (e.g., buildings, vegetation, utility poles), crewed aircraft, or wildlife.
Event Severity: 3 (advisory [Williams et al, 2021])
Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No

Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Not Notified
Notes:

- Regardless of the type of obstruction encountered, the Autonomy will command the UAV to either reroute, adjust its velocity, or hold in place.
- The Autonomy logs the UE occurrence and the Autonomy's actions within the mission flight log. The information is retrievable by the Supervisor if necessary; however, the Supervisor is not notified of the UE's occurrence.

Modeling Notes: This UE is something the Autonomy will need to be able to handle entirely on its own; therefore, Supervisor involvement is not necessary, making this UE not required to model.

B.2.6.4 UAV Path Obstructed (Autonomy Unable to Address Obstruction)

Description: UAV's planned path is obstructed for an extended time period and UAV is unable to make mission progress.
Event Severity: 4 (caution [Williams et al, 2021])
Supervisor Notification Need: 1
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Not Notified
Notes:

- The Autonomy will need to handle this UE entirely on its own; therefore, a Supervisor involvement is not necessary. This UE is not modeled.
- Possible UAV responses to this UE include landing in place or returning to launch.

B.2.6.5 Adverse Weather, Autonomy Aware

Description: The Autonomy is aware that the UAV's ability to fly safely is at risk due to imminent adverse weather conditions (i.e., thunderstorms, low visibility conditions, or hail).
Event Severity: 10
Supervisor Notification Need: 5
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 Station

- Affected areas of operations are made visually salient on the interface's sector map. An audible alert is played and the glyphs of affected UAVs are made visually salient. A notification window, describing the adverse weather, appears in the center of the affected area.

Notes: This UE can impact multiple UAVs simultaneously.

This instance assumes adverse weather information is digitized and available to the Autonomy. The Autonomy is capable of taking appropriate actions. The Supervisor is notified of Autonomy's actions and acknowledges the Autonomy's action.

Modeling Notes:

- The "Acknowledgment of Notification" task is completed in parallel with the "Nominal Monitoring" task.
- The "Acknowledgment of Notification" task lasts ____ seconds and has a workload of ____.

B.2.6.6 Adverse Weather, Autonomy Unaware

Description: The Autonomy is unaware that the UAV's ability to fly safely is at risk due to imminent adverse weather conditions (i.e., thunderstorms, low visibility conditions, or hail).
Event Severity: 10
Supervisor Notification Need: 10
Supervisor Response Need: 10
Autonomy Aware: No
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified from Outside Source

- Audibly
  - Informed by Co-worker in person
  - Informed by Co-worker over Phone Call
- Text
  - Informed by Co-worker over C^2 station
  - Informed by Co-worker over Phone Text Messages
  - Weather Broadcast Notification System on C^2 station

Audibly and Text

- Weather Broadcast Notification System on C^2 station

Notes:

- This UE can impact multiple UAVs simultaneously.
- Adverse Weather and "Emergency in Airspace" share a lot in common. The same Supervisor responses for an "Emergency in the Airspace" can be used for "Adverse Weather".
- Upon perception of the UE, the Supervisor has several response options:
  - Command UAV(s) to Holding Pattern
  - Command UAV(s) to Return to Launch
  - Command UAV(s) to Land at Secondary Landing Site
  - Reroute UAV(s)
  - Do Nothing

Modeling Notes:

- Regardless of the manner the Supervisor perceives the UE, the Supervisor's subsequent tasks are the "Acknowledge/Receive Notification" task and then the appropriate UAV command task.
- Possible Supervisor Response:
  - Command UAV(s) to Return
    - All commanded UAV(s) are no longer Nominally Monitored and instead Post-Response Monitored _ secs with a workload of _. The Supervisor returns to Nominally Monitoring the affected UAVs after Post-Response Monitoring.
    - The affected UAV(s) all independently RTL or land at a secondary landing site for ____ secs.
  - Command UAV(s) into Holding Pattern
    - The affected UAV(s) hold their position and are Post-Response Monitored until a few outcomes occur:
    - The Supervisor is notified about the end of the adverse weather event and therefore commands the UAVs to continue with the Delivery Mission delivery, battery levels permitting. The affected UAV(s) return to being Nominally monitored.
    - UAV Battery Levels are getting low and either the Autonomy or Supervisor commands the UAV(s) to RTL or land at a secondary landing site.
  - Command UAV(s) to RTL or Land at a Secondary Landing Site
    - The affected UAV(s) are Post-Response Monitored for the first ____ secs, with a workload of ____, as they RTL or land at a secondary landing site. The Supervisor returns to Nominally Monitoring the affected UAVs after having Post-Response Monitored them.
  - Reroute UAV(s)
    - The affected UAV(s) are rerouted for ___ secs with a workload of ____. All UAVs are rerouted simultaneously for the sake of model simplicity.
    - The affected UAV(s) are Post-Response Monitored for the first ____ secs as they follow their new flight paths. Then, the Supervisor returned to Nominally Monitoring the affected UAV(s).

B.2.6.7 Airspace Congestion Delays UAV

Description: UAV is unable to make mission progress due to continual airspace congestion with other aircraft.
Event Severity: 3
Supervisor Notification Need: 3
Supervisor Response Need: 3
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: No
Supervisor Notified: No
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Not Notified

Notes: This UE can impact multiple UAVs simultaneously.
While in heavy airspace congestion conditions, the UAV will continuously adjust its speed and reroute to prevent collision with other UAV's flying nearby.
Modeling Notes: This UE will not be modeled, because it does not involve the Supervisor.

B.2.7 Collisions

B.2.7.1 Mid-Air Collision (Crash), Autonomy Online

Description: UAV has crashed and is unable to fly, but the UAV's Autonomy is still capable of communicating with Supervisor.
Event Severity: 10 (warning [Williams et al, 2021])
Supervisor Notification Need: 10
Supervisor Response Need: 1
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/ Audible Alert
- Visual Glyph Change w/ Audible Alert
    - Glyph highlighted or circled
    - Glyph changes color

Visual Popup

- Popup graphic attached to affected UAV's glyph appears
- A notification window appears in the center of the C^2 station interface.

Notes:

- This instance of the UE assumes the Autonomy is capable of communicating with the UAV retrieval team without Supervisor's involvement.
- The Supervisor receives a notification about the UE and as well as information about what was communicated between the Autonomy and UAV retrieval team.
- The Supervisor periodically check-ins on the affected UAV in parallel with Nominally Monitoring the *N*-1 unaffected UAVs.
- After the UAV retrieval team arrives at the crash site and assesses the UAV in person, the Supervisor is relieved of their assignment to the UAV.
- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.

Modeling Notes:

- The Supervisor engages in a "Notification Acknowledgement" task of ___ workload for ___ secs. This occurs in parallel with the Nominal Monitoring of the other *N*-1 UAVs.

- Next, the Supervisor engages in a "Periodic Check-in" task that occurs N times. Each check-in lasts __ secs with a workload of __ and occurs at a spaced interval of ____ secs.
  - The "Periodic Check-in" task is completed in parallel with the Nominal Monitoring of *N*-1 unaffected UAVs.
- The affected UAV is unassigned from the Supervisor.

B.2.7.2 Mid Air Collision (Crash), Autonomy Offline

Description: UAV has crashed, is unable to fly, and the UAV's Autonomy is offline or incapable of communicating with the Supervisor due to the sustained damage.
Event Severity: 10 (warning [Williams et al, 2021])
Supervisor Notification Need: 10
Supervisor Response Need: 10
Autonomy Aware: Yes
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log w/ Audible Alert
  - Visual Glyph Change with Audible Alert
  - Glyph highlighted or circled
  - Glyph changes color
- Visual Popup
  - Popup graphic attached to affected UAV's glyph appears
  - A notification window appears in the center of the C^2 station interface.

Notes: This instance of the UE assumes the Autonomy is incapable_of communicating with the UAV retrieval team; therefore, the Supervisor is responsible for communication.

- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.

Modeling Notes:

- The Supervisor engages in a "Notification Acknowledgement" task of ___ workload for ___ secs. This occurs in parallel with the Nominal Monitoring of the other *N*-1 UAVs.
- Next, the Supervisor completes the "Contact UAV Retrieval Team" task that incurs ____ workload for ___ seconds". The UAV is presumably handed-off in this conversation; therefore, the UAV is removed from the Supervisor's supervision.
- The "Contact UAV Retrieval Team" task will occur in parallel with the Supervisor's "Nominal Monitoring" task of the other *N*-1 UAVs.
- The affected UAV is unassigned from the Supervisor.

B.2.7.3 Mid Air Collision
Description: UAV collided with an object while flying and is still airworthy and capable of completing the mission.
Event Severity: 8 (warning [Williams et al, 2021])
Supervisor Notification Need: 5
Supervisor Response Need: 5
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Text Log with Audible Alert
- Visual Glyph Change with Audible Alert
- Visual Glyph Change without Audible Alert

Notes: The Supervisor is notified of the UAV's collision. Autonomy has commanded the UAV to continue flying. The Supervisor Post-Response Monitors the UAV for _____ secs until the Supervisor considers the UAV to be functioning normally. The Supervisor then returns to Nominally Monitoring the UAV.

- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.

Modeling Notes:

- The Supervisor engages in an "Acknowledge Notification" task with a workload of ___ for __ seconds.
- Next, the Supervisor engages in the "Post-Response Monitor" task for the affected UAV for ____ secs with a workload of ___.
    - o The "Acknowledge Notification" task and "Post-Response Monitoring" task both occur in parallel with the "Nominal Monitoring" task of the *N*-1 unaffected UAVs.
- The Supervisor returns to Nominally Monitoring the affected UAV as it continues with its mission.
- The UAV is unassigned from the Supervisor once it lands.

B.2.7.3 Mid-Air Collision (UAV can fly, but damaged. Cannot complete the mission)
Description: UAV sustains damage from a collision with an object while airborne, maintains flight capabilities, but loses airworthiness.
Event Severity: 9 (warning [Williams et al, 2021])
Supervisor Notification Need: 5
Supervisor Response Need: 5
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes

Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Text Log with Audible Alert
- Visual Glyph Change with Audible Alert
- Visual Glyph Change without Audible Alert

Notes:

- The autonomy acts as the primary responder and attempts to address the event by commanding the UAV to RTL, or have it land at a secondary landing site. Meanwhile, the Supervisor is notified of the UE and proceeds to gather relevant information related to the event in order to report the incident to airspace officials. If the Supervisor is unable to address the situation, the UAV is handed-off to a dedicated UE Supervisor.
- Once all options for grounding the UAV have been exhausted, the Supervisor becomes responsible for landing the UAV. The Supervisor is alerted and begins identifying a method to ground the UAV. After addressing the UE, the Supervisor returns to nominal monitoring of the unaffected UAVs.
- The recording and safe guarding of the event, data, etc. logs will be the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.

Modeling Notes:

- The UE Supervisor's tasks are not modeled, rather the model focuses on the primary Supervisor.
- Logic was included to have the Supervisor switch tasks in the event a more important task arises. For example, the Supervisor is working on reporting the incident, but is suddenly notified the Autonomy needs assistance in grounding the UAV.
- The UAV is unassigned from the Supervisor if it landed or handed-off.

B.2.7.4 UAV Losses Flight Capabilities and Crashes

(i.e., Full Motor Failure, Lightning Strike, Affected by Adverse Weather Conditions)
Description: UAV experiences a full loss of flight and crashes into the ground due to adverse weather conditions, or hardware failure; the Autonomy is incapable of communicating with the UAV retrieval team on its own.
Event Severity: 9
Supervisor Notification Need: 5
Supervisor Response Need: 5
Autonomy Aware: Yes
Responder: Supervisor
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: No
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Text Log with Audible Alert

- Visual Glyph Change with Audible Alert
- Visual Glyph Change without Audible Alert

Notes:

- This UE covers all the possible instances where a UAV crashes into the ground not due to a mid-air collision.
- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.
- Sequence of events:
    - The Supervisor is notified about the crashed UAV.
    - The Supervisor contacts the UAV Retrieval Team to communicate the location of the crash.

Modeling Notes: Sequence of events in model:

- The Supervisor engages in the "Acknowledgement of Notification" task for __ secs with a workload of __.
- The Supervisor completes the "Contact UAV Retrieval Team" task that incurs __ workload for __ seconds". The UAV is presumably handed-off in this conversation; therefore, the UAV is removed from the Supervisor's supervision.
    - The "Contact UAV Retrieval Team" task will occur in parallel with the Supervisor's "Nominal Monitoring" task of the other *N*-1 UAVs.

B.2.7.5 UAV Physically Damaged Mid Flight and Maintains Flight

Description: UAV sustains damage while flying, not due to a collision (i.e., hit by a projectile), and remains operational.
Event Severity: 6 (warning [Williams et al, 2021])
Supervisor Notification Need: Varies
Supervisor Response Need: Varies
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Text Log with Audible Alert
- Glyph Change with Audible Alert
- Glyph Change without Audible Alert

Notes: If operational, then the Autonomy commands the UAV to continue with the Mission and the Supervisor acknowledges the notification about the event. The Supervisor post response monitors the UAV before considering the UAV stable and returns to Nominally Monitoring the UAV.
Modeling Notes:

- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.
- If UAV is operational:
  - The Supervisor engages in the "Acknowledge Notification" task of __ secs and __ workload.
  - The Supervisor engages in the "Post-Response Monitoring" task of the affected UAV for __ secs with a workload of __.
    - The post-response monitoring task occurs in parallel with the "Nominal Monitoring" task of *N*-1 UAVs.

B.2.7.6 UAV Damaged Mid Flight and Maintains Limited Flight Capabilities

Description: UAV sustains damage while flying, not due to a collision (i.e., hit by a projectile) and remains operational, but with limited flight capabilities.
Event Severity: 9 (warning [Williams et al, 2021])
Supervisor Notification Need: 5
Supervisor Response Need: 5
Autonomy Aware: Yes
Responder: Autonomy
Supervisor Aware: Yes
Supervisor Notified: Yes
Additional Supervisor Monitoring Required: Yes
Supervisor Perception Possibilities: Notified by C^2 station

- Text Log without Audible Alert
- Text Log with Audible Alert
- Glyph Change with Audible Alert
- Glyph Change without Audible Alert

Notes: If operational, but with some limitations, and the Autonomy determines that UAV can continue with the mission, then the Supervisor reviews the situation and decides whether or not to permit the UAV to continue with the mission, RTL, or land either in place or an alternative landing site. The Supervisor post response monitors the UAV for a period of time before Nominally Monitoring it again.
Modeling Notes:

- The recording and safe guarding of the event, data, etc. logs will eb the responsibility of others (e.g., the recovery team, mechanical team, manufacturer), not the Supervisor.
- If UAV is operational, but with some limitations:
  - The Supervisor engages in the "Acknowledges Notification" task for ___ secs and workload of ____.
  - The Supervisor completes the "Reviews Situation" task for ___ secs and workload of ____.
  - The Supervisor "Decide to permit UAV to continue with the mission or RTL" task for ___ secs and workload of ____.
  - The Supervisor engages in the "Post-Response Monitoring" task of the affected UAV for ____ secs with a workload of ____.

- The "Post-Response Monitoring" task occurs in parallel with the "Nominal Monitoring" task of *N*-1 UAVs.

B.3 Distraction Events

Exemplar potential distraction events were developed collaboratively by A26 team members. A number of assumptions were derived, as listed in Table 44. Ten potential distractions were identified based on consideration of both internal and external distractions common in a shared workplace environment. The distraction events were organized into the following categories based on their predicted impact on workload and task performance: high and low severity. A simple taxonomy of distractions is available in Figure 3. Blue lines indicate low severity distractions, while gold lines reflect high severity distractions. Further, various components of a given distraction were also identified, including auditory, speech, visual, cognitive, and haptic. These components were considered given the broad nature of distractions and how distractions may affect human supervisors directly.

Table 44. Distraction event use case modeling assumptions.

Subject Matter Expert-Based Assumptions:
Supervisor's shift includes mandatory breaks.
Supervisors manage UAV systems in a shared work environment, simultaneously occupied by other personnel.
Distractions derive from the external work environment, or from within the Supervisor
Supervisors have some limited access to personal devices and may receive communications.
Distractions are comprised of various components, and can be auditory, speech-based, visual, cognitive, or haptic in nature.
There exists a *Watch Supervisor*, responsible for broad oversight of Supervisor performance.

Distractions represent demands that impact the Supervisor's workload and exist outside the UAV control system, and as such, they must be handled solely by a human Supervisor, and not the autonomy. Based on the typical administrative structure in flight operations settings (e.g., air-traffic control), the presence of a *Watch Supervisor* was included as a necessary component for Supervisor distraction management. The Watch Supervisor's primary responsibility is that of oversight of individual Supervisors and their performance. The Watch Supervisor is not in direct control of any UAV systems or operations and is solely responsible for the management of a team of Supervisors. Generally, the Watch Supervisor oversees flight operations at a broad level and maintains awareness of overall levels of individual Supervisor performance, and thus will be able to identify whether a given Supervisor is distracted.

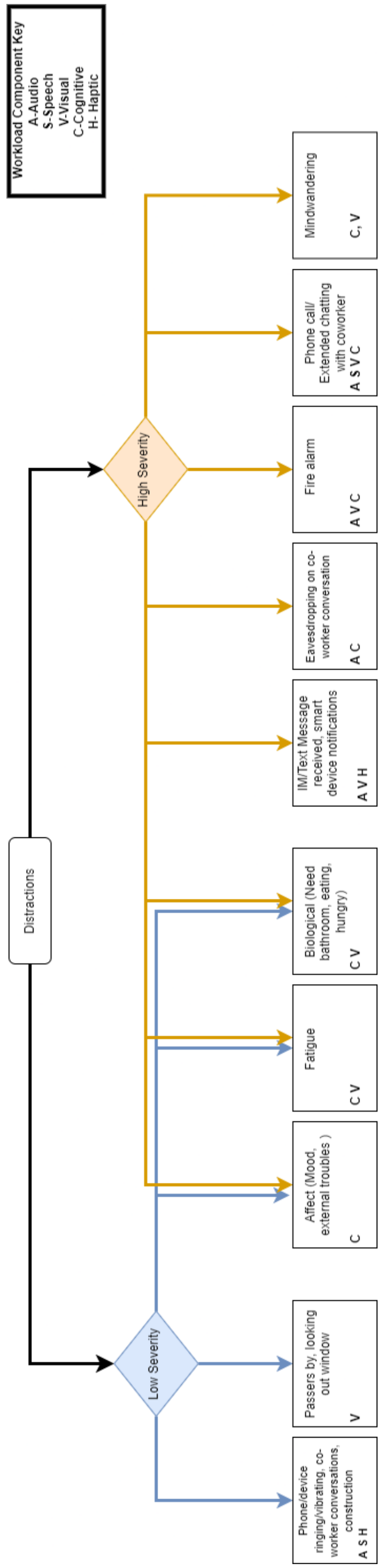

Figure 3. The distractions taxonomy hierarchy.

Each distraction description contains the following fields:

- *Description:* A brief statement describing what the particular distraction represents.
- *Event Severity:* The distraction's potential danger or damage to UAV operations [1 (low), 10 (high)].
- *Supervisor Response Need:* Describes how crucial it is to have the Supervisor respond to the distraction [1 (low), 10 (high)].
- *Responder:* Describes the party responsible for initially and directly addressing the distraction, although others may also respond.
- *Supervisor Aware:* Describes whether the Supervisor is cognizant of the distraction's occurrence.
- *Type of Distraction:* Lists ways in which the Supervisor's performance is affected by the distraction.
- *Duration of Distraction:* Describes how long a given distraction may be expected to persist normally [1 (short – 30 secs), 2 (long – 120 secs)].
- *Watch Supervisor Intervention:* Describes whether the situation requires the intervention of the Watch Supervisor
- *Leave Workstation:* Identifies whether the distraction requires the Supervisor to leave the C^2 workstation
- *Notes:* Contains general comments about the distraction, details on the distraction or Supervisor response to the distraction.

B.3.1 Low Severity Distractions

B.3.1.1 Auditory Distraction (e.g., Phone Ringing, Construction, Conversations)

Description: Supervisor experiences some auditory interference (e.g., near-by construction or another co-workers' phone ringing).
Event severity: 3
Supervisor response need: 1
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Audio, Speech, Haptic
Duration of distraction: Short
Watch Supervisor intervention: No
Leave workstation: No
Notes:

- Assumes Supervisor is working in a shared environment and is not sound isolated.
- Sequence of events
  - Supervisor perceptual experiences a loud noise at their workstation, that is unrelated to their workstation. This event may be speech related or not (loud conversation vs. Construction).
  - Supervisor immediately returns to monitoring task.

B.3.1.2 Visual Distraction (e.g., People Walking by Desk, Something Outside Window)

Description: Supervisor notices something crossing their visual field (e.g., someone walking by their desk, or looking out a window).
Event severity: 3
Supervisor response need: 1
Responder: Supervisor
Supervisor aware: No
Type of distraction: Visual
Duration of distraction: Short
Watch Supervisor intervention: No
Leave workstation: No
Notes:

- Assumes Supervisor is working in shared environment with other personnel, or visual stimulus available.
- Sequence of events
    - Supervisor looks up from their workstation and notices an interesting visual stimulus.
    - Supervisor immediately returns to the monitoring task.

B.3.2 Low or High Severity Distractions

B.3.2.1 Affect

Description: Supervisor experiences some affective response that is occupying their attention. This type of distraction may be low in degree (i.e., bad mood) or more severe (i.e., grief from family member dying).
Event severity: 3-8
Supervisor response need: 3-8
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Cognitive
Duration of distraction: Long
Watch Supervisor intervention: No
Leave workstation: No
Notes:

- Dependent on severity related to the cause of affect, may be low-level or high-level distraction.
- Sequence of events:
    - Supervisor experiences some type of emotional response that may be interfering with their work.
    - Diverts Supervisor attention away from monitoring task or reduces engagement in monitoring.
    - If affective experience continues, it degrades the Supervisor’s performance for entire shift.

B.3.2.2 Biological Need

Description: Supervisor must address a biological need (i.e., hunger, bathroom, sickness) and based on type of need may need to immediately leave the C^2 station to address the personal biological need.
Event severity: 3-8
Supervisor response need: 3-8
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Cognitive, Visual
Duration of distraction: Short or Long
Watch Supervisor intervention: No
Leave workstation: Yes or No
Notes:

- May require Ramp down and Ramp up procedures
- Sequence of events:
    - Supervisor perceives a biological need and depending on its severity may have to leave their workstation
        - If need can be addressed at the workstation (i.e., eating a snack) or can wait until a scheduled break, normal monitoring continues.
    - If Supervisor needs to leave workstation to address need, the Supervisor progresses through a normal Ramp down (i.e., the need is severe, but not highly sever), or hands-off all UAVs to another Supervisor (i.e., a highly severe need) and attends to need.
    - Supervisor recovers and returns, based on need, the time away from the workstation may be short (i.e., bathroom break) or long (i.e., food poisoning) in duration, after which normal monitoring resumes.

B.3.2.3 Supervisor Fatigue (Supervisor unaware)

Description: Supervisor is experiencing a form a fatigue (perceptual or cognitive).
Event Severity: 8
Supervisor Response Need: 8
Responder: Watch Supervisor
Supervisor Aware: No
Type of distraction: Cognitive, Visual
Duration of distraction: Long
Watch Supervisor Intervention: Yes
Leave workstation: Yes
Notes:

- Requires Ramp down and Ramp up procedures.
- Sequence of events:
    - The Supervisor experiences cognitive or perceptual fatigue and does not realize fatigue is impacting job performance. The Watch Supervisor notices the degraded performance, sends Supervisor on a break to refocus.
    - The Supervisor Ramps down the UAVs being supervised and is sent on/ takes a break.
    - The Supervisor recovers and returns after break, proceeds with a normal Ramp up, after which normal monitoring resumes.

B.3.3 High Severity Distractions

B.3.3.1 IM/SMS/Notification Received

Description: Supervisor receives a personal communication or notification and attends to notification.
Event severity: 8
Supervisor response need: 8
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Audio, Visual, Haptic
Duration of distraction: Short
Watch Supervisor intervention: No
Leave workstation: No
Notes:

- Assumes Supervisor has access to their personal devices, includes wearable devices (e.g., smart watches).
- Sequence of events:
  - Supervisor receives a notification aurally or through vibration.
  - Supervisor views the notification message, ignoring their C^2 station for a moment, and then continues normal monitoring.

B.3.3.2 Eavesdropping on Coworker Conversation

Description: Supervisor is listening in to another conversation and is diverting a portion of their attention towards understanding the conversation.
Event severity: 8
Supervisor response need: 8
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Audio, Cognitive
Duration of distraction: Short
Watch Supervisor intervention: No
Leave workstation: No
Notes:

- Assumes Supervisor working in shared environment.
- Sequence of events
  - Supervisor is engaging in normal monitoring, but is distracted by a coworkers' conversation.
  - Supervisor neglects the C^2 station for the duration of eavesdropping, and then continues normal monitoring.

B.3.3.3 Fire Alarm

Description: During a normal shift, a fire alarm goes off and Supervisor is required to evacuate.
Event severity: 10
Supervisor response need: 10
Responder: Supervisor
Supervisor aware: Yes

Type of distraction: Audio, Visual, Cognitive
Duration of distraction: Long
Watch Supervisor intervention: No
Leave workstation: Yes
Notes:

- Assumes Supervisor is working in shared environment or structure where there exists a fire risk.
- Assumes C^2 station is not in proximity to event causing alarm.
- Requires Ramp down and perhaps Ramp up procedure
- Sequence of events
    - Supervisor is engaged in normal monitoring when fire alarm goes off.
    - Supervisor initiates emergency hand-off and leaves workstation.
    - Supervisor returns when given all clear and resumes normal monitoring performance.

B.3.3.4 Emergency Phone Call, Conversation

Description: Supervisor must immediately leave the C^2 station to address a personal emergency phone call
Event severity: High
Responder: Supervisor
Supervisor aware: Yes
Type of distraction: Audio, Visual, Speech, Cognitive
Duration of distraction: Short
Watch Supervisor intervention: No
Leave workstation: Yes
Notes:

- Assumes Supervisor has access to personal communication device
- May require Ramp down and Ramp up procedures
- Sequence of events:
    - Supervisor receives an emergency phone call and cannot wait until break, and has to leave the workstation.
    - Supervisor Ramps down UAVs and attends to call.
    - Supervisor recovers and returns, normal monitoring resumes

B.3.3.5 Mindwandering (Supervisor unaware)

Description: The Supervisor is experiencing Mindwandering and is not focusing on the monitoring task.
Event Severity: 8
Supervisor Response need: 8
Responder: Watch Supervisor
Supervisor Aware: No
Type of distraction: Cognitive, Visual
Duration of distraction: Long
Watch Supervisor Intervention: Yes
Leave workstation: Yes

Notes:

- Requires Ramp down and Ramp up procedures
- Sequence of events:
  - The Supervisor does not realize mindwandering is occurring, but the Watch Supervisor notices degraded performance and sends the Supervisor on break to refocus.
  - A normal Ramp down occurs and upon completion, the Supervisor is sent on/ takes a break.
  - The Supervisor recovers and returns after the break.
  - After the break, the Supervisor enters the normal Ramp up.

A. APPENDIX C. TIGHTLY COUPLED SCENARIO USE CASE: RIDGELINE AERIAL IGNITION

The team was asked by the FAA to consider a disaster response scenario for the tightly coupled use case. The team decided to focus on wildland fire response and spent many months interviewing subject matter experts in order to identify an appropriate multiple UAV tightly coupled scenario within this domain. The team decided to focus on ridgeline aerial ignition.

C.1 Nominal Use Case

Many countries use controlled burns as wildland fire prevention or suppression for active fires. The objective of such controlled burns during active wildland fires is to strategically control and manipulate a fire's movement or intensity, while also minimizing the spread of embers that can start new undesirable fires. Typically, based on predetermined fuel levels and weather conditions, a series of ignitions occur. Such controlled ignitions are often used when direct suppress methods are unsuccessful in controlling the fire.

Multiple UAV Aerial Ignition Concept: A multiple UAV scenario was developed to represent an example deployment for aerial ignition when used to control wildland fire spread. The *Ignition UAV*s carry and drop the ignition spheres that ignite fire, while the *Surveillance UAVs* provide persistent surveillance of the fire activities. The Surveillance UAVs replace the need to position human wildland firefighters throughout the mission area to monitor the fire activities.

The use case assumes that a small team of individuals will be deployed to the designated ridge to conduct the ridgeline aerial ignition task. The team will drive an appropriate vehicle to the site with all necessary equipment. The example use case includes three individuals: the Communications lead, the UAV Supervisor and the Logistics Coordinator. These individuals have distinct responsibilities.

Supervisor: The Supervisor is responsible for fully understanding the mission plan, reviewing it with all other team members, deploying the UAVs, monitoring the UAVs, making any necessary flight adjustments, and maintaining the safety of the UAV flights.

Radio Communications lead (Communications lead): The Communications lead is responsible for all local communications, which are conducted via radio frequency. This individual is responsible for communications with any spatially relevant response personnel, within radio range, not connected with the Aerial Ignition Deployment team, as well as inter-team communications. If long distance communications (e.g., cellular) are available, this person is responsible for communication with the Incident Command Center. This individual may also review incoming sensor information from the UAVs. This individual serves as the Supervisor's safety monitor, ensuring that the Supervisor is safe when mobile and supervising the mission (e.g., heads down).

Logistics Coordinator: The Logistics Coordinator is responsible for preparing the UAVs for launch and breakdown/packing of UAVs for transport. The coordinator places the UAVs out for launch and recovers any UAVs that land. This individual verifies the safety of each UAV prior to launch and visually inspects the UAVs upon landing. Further, this individual is responsible for ensuring batteries are charged and manually swapping UAVs' batteries during the mission. During down times, this individual may review incoming sensor information from the UAVs.

C.1.1 Assumptions

A number of domain relevant assumptions are incorporated into the nominal use case example, as specified in Table 45.

Table 45 Ridgeline Aerial Ignition Use Case Assumptions.

Proposal Assumptions:
UAV operations will be conducted from the surface to 500' AGL, with additional evaluation of the potential for operations up to 1,200'AGL.
UAV operations will be conducted over other than densely populated areas, unless all UAV comply with potential criteria or standard that demonstrates safe flights over populated areas.
UAV will not be operated close to airports or heliports. 'Close' is initially defined as greater than 3 miles from an airport unless permission is granted from air traffic control or airport authority. A distance of greater than 5 miles will be examined if needed to support an appropriate level of safety.
Small UAV are potentially designed to an Industry Consensus Standard and issued an FAA Airworthiness Certificate or other FAA approval.
The multiple UAV may be operating in scenarios that include *n* UAV that have *n* unique paths distributed over an area of operation.
Deployment Environment Assumptions:
The deployment areas are remote, and include rough terrain wilderness, typically along ridge lines.
There is no, or exceptionally limited, cellular or other long range (e.g., radio frequency) communications available at the deployment area. Humans can use radios for local communications. Satellite communications are rare. The crew may not have real time communications with the incident command center.
Ignition begins at the top of the hill and moves down. The result is generally a low intensity fire with a lot of smoke.
All necessary maps are generated prior to departing the mission preparation center.
Most deployments occur at night when the humidity is higher, winds are lower and the overall conditions are better for controlled burns. There are limited daytime operations.
Ignition missions can only be completed when the prevailing winds are 15 or less mph winds.
The deployment environment conditions (e.g., fire behavior, terrain) may differ from those anticipated prior to mission deployment.
Depending on the actual environmental conditions, the developed mission plan may require modification (e.g., launch area, ignition area).
Responder Specific Assumptions:
Three-person team: The UAV Supervisor, the Communication lead on the radio communicating with other responders, and the Logistics Coordinator who prepares and manages the physical UAVs during the mission.
The team coordinates with incident command to establish an ignition plan prior to departing to conduct the mission.
The human driven vehicles have limited cargo capacity and must accommodate safety gear, UAVs, UAV batteries, one or two small generators, etc.
The small (i.e., three person) team is transported via truck, sometimes (not often) with a trailer. Reaching the deployment area often requires driving poorly maintained rutty dirt roads.
UAV Specific Assumptions:
Multiple UAVs (i.e., 4-10) are required to complete these missions.

Mission UAVs will include Ignition UAVs, that carry and deploy the ignition spheres and Surveillance UAVs that provide sensor feedback of the fire status, deployment area, and the other mission UAVs.
Surveillance UAVs fly higher than the Ignition UAVs. The Surveillance UAVs permit monitoring where humans and other UAVs are located, gathering information to update (off-line) the fire map, etc.
A single Ignition UAV can carry 400-450 ignition spheres, dropping a maximum of 120 spheres per minute. Typically, UAVs drop spheres every 2 – 5 meters.
Each UAV has a maximum safe flight time between fifteen and twenty-minutes.
A low power supply UAV replacement (Swap) behavior, when a UAV's battery is depleted prior to mission completion the UAV returns to the launch area and is replaced by another UAV with a fresh battery, is used to provide continuous mission execution.
All UAVs fly at least 100 ft above ground.
All UAVs can operate up to 15 km from the Supervisor.
All UAVs have a typical flight speed of 5 meters per second, with a maximum speed of 15 meters per second (approximately 35 mph).
Typical UAV sensors include a long-wavelength infrared camera, a visual camera, array of thermal cameras, thermistors, and GPS. Wind speed, both vertical and horizontal, sensors are usually incorporated as well.
While real-time communication of sensor information is possible, it is bandwidth limited beyond 1 km. On-board UAV processing determines in real time what information (e.g., images, video, other sensor data) to send to the Supervisor and all data are stored for post-mission analysis.
Supervisor Specific Assumptions:
The Supervisor's control interface must support a single person, be portable and small (e.g., laptop, tablet or smart phone). Not a ground station with multiple suitcases.
The Supervisor typically uses a map-centric interface on which paths, areas or waypoints can be specified.
Dynamic checklists can be used to: validate sensor information and function, or provide deployment specifications and verifications.
The Supervisor is not directly responsible for monitoring sensor feeds (e.g., cameras), but does have the ability to view the sensor feeds directly on the control interface.
Communication Lead Specific Assumptions:
The Communications lead is responsible for communicating with other responders in the area, and if reachable, with incident command.
The Communications lead is responsible for monitoring the sensor feeds (e.g., camera) and notifying the Supervisor of any pertinent information or needed mission changes.
During the mission deployment, the Communication lead is positioned near the Supervisor to facilitate direct verbal communication (i.e., no radio communication required).
The Communication Lead's activities will not be modeled or detailed in the use case specifically; however, as part of the Supervisor's activities, interactions tasks on the Supervisor's side of the interaction will be modeled in Task 4.
Logistics Coordinator Specific Assumptions:
The Logistics Coordinator is responsible for all UAV hardware specific tasks, including verifying launch zone spacing, hardware readiness, battery swaps, etc.
The Logistic Coordinator's tasks are not modeled or detailed in the provided use cases.

Unexpected Event Assumptions:
If a UAV crashes, the practice is to leave it and let it burn.

C.1.2 Pre-Deployment Activities

Since the mission deployment occurs in a remote area, potentially without communications with incident command, a number of pre-deployment activities area necessary in order to enable mission readiness upon arrival at the mission deployment site. These activities are conducted at the mission preparation center with the knowledge that access to communications is likely to be limited at the mission deployment site.

The information required to conduct the ridgeline aerial ignition mission includes:

- Known fire line hazards
- Current and predicted fire behavior and weather (wind is the most important factor for the fire behavior)
- Current fire activities and progress of the wildland fire in question
- Ignition strategies, sequence and technique (e.g., potential burn patterns)
- Ground cover fuel type, density in the ignition area
- Topography and other necessary maps
- Ingress and Egress routes for the team (options).

This information is used to develop a safe mission plan that incorporates all the above plus the expected weather conditions and required number of ignition spheres per square area (area is designated on a mission specific basis), number of Ignition and Surveillance UAVs, designation of the flight region and geofence, deconfliction plan, flight plan - including navigation plans, and expected mission duration.

The mission plan will include predetermined burn patterns to be created via the user provided drop points or navigation paths. The UAVs' navigation path plans will either include specified drop points (e.g., waypoints), or a density factor that automatically determines how many spheres to drop every few meter(s). If the Supervisor provides a burn pattern (e.g., a pattern with points at which the ignition spheres are to be dropped from the Ignition UAVs), the system automatically generates navigation paths for all Ignition UAVs, and monitoring locations for all Surveillance UAVs. The developed mission plan is reviewed with the relevant incident command personnel and approved prior to completion of the pre-deployment activities.

C.1.3 Ridgeline Aerial Ignition Mission Deployment

Deployment Location Arrival and Preparation

1. The team of three individuals (i.e., UAV Supervisor, Communications Lead and Logistics Coordinator) deploys with two to ten UAVs via a first response truck. The team deploys to conduct aerial ignition along a mountain ridge accessible via dirt roads and off-road access.
2. While driving to the deployment zone, the aerial ignition system Supervisor reviews the mission plan, including:
    a. Deconfliction
    b. Weather

c. Fire behavior
d. Ground fuel level
e. Geofence and Flight plans
f. Topography
g. Known hazards
h. Logistics
i. Safety plan

3. Upon arrival at the deployment location,
   a. If communications are available with the incident command center, the Communication lead communicates the team's arrival at the deployment location.
   b. The Communication lead communicates to other responders, if any, within radio range the intent to launch the mission.
   c. The responder team assesses the local conditions for safely deploying the UAVs and conducting the mission. The location has to be inspected to ensure that it is safe for the responders to set up and deploy the UAVs from this location. The responder team must consider the listed factors. If dangers are identified in the pre-mission departure specified launch/landing area, the team must identify a new safe launch/landing location at which they will set up and from which they will launch the UAVs. The team may also update the mission plan.
      i. Fire behavior
      ii. Terrain
      iii. Weather
      iv. Known hazards
   d. The team identifies a launch/landing area and a location for the communications equipment (e.g., open terrain with no tree coverage, no dangerous obstacles). The communications equipment allows the UAVs to communicate locally with the team.
   e. The team sets up the UAVs and communications equipment, prepares extra UAVs to be used later in the mission as replacement UAVs when power sources are depleted on deployed UAVs.
   f. The team completes safety checks on the UAVs and communications equipment.

Pre-Launch Preparation

1. If communications are available with the incident command center, the Supervisor verifies:
   a. Mission plan, including navigation routes.
   b. Fire behavior
   c. Weather

   d. Deconfliction

2. The team
   a. Reviews the mission plan and each individuals' role.
   b. Places prepared UAVs in the launch area.
   c. Completes final safety checks on all systems: Supervisor controller, communications, and UAVs.
3. If communications are available with the incident command center, the Communication lead communicates intent to launch the mission.
4. The Communication lead communicates to others in radio range the intent to launch the mission.

Mission Deployment

1. The Supervisor validates that the mission plan is ready for launch, which requires
   a. Loading mission plan into the Supervisor's interface
   b. Opening the mission plan nodes (like nodes in a graph) and visually reviewing the node elements: requires tactile and fine grain, visual and cognitive workload
2. The Supervisor validates any dynamic checklist items.
3. The Supervisor validates team readiness for eminent deployment.
   a. The Supervisor asks the Communications lead if the team is ready (does not require a radio to do so).
   b. The Communications lead provides a verbal response. The Supervisor does not have permission to launch the mission until the Communications lead indicates mission readiness. Mission readiness requires verifying with the Logistics Coordinator that all UAVs are mission ready and it is safe to being.
4. If communications are available with the incident command center, the Communication lead communicates eminent mission launch.
5. The Communication lead communicates to others in radio range eminent mission launch.
6. The Supervisor launches the mission plan, the mission plan may launch the UAVs in different configurations, represented by "Variants".
   a. Variant 1. All UAVs launch simultaneously
      i. The *x* UAVs launch and begin executing the mission. The *y* Ignition UAVs launch and autonomously navigate to the respective locations to commence dropping ignition spheres. The *z (x – y)* Surveillance UAVs autonomously launch and navigate to the respective monitoring locations.
      ii. Upon arrival at the start locations, all Ignition UAVs hold until the Supervisor initiates the ignition sphere drop mission.
      iii. The Supervisor commences ignition drop mission once all Surveillance UAVs have reached their monitoring locations.
      iv. Note: This approach may waste power if the Ignition UAVs must hover in place while waiting for other UAVs to arrive at their starting locations.

b. Variant 2. Surveillance UAVs launch first.

   i. The *z (x – y)* Surveillance UAVs autonomously launch and navigate towards their respective monitoring locations.

   ii. Once the *z* Surveillance UAVs are in an appropriate location (e.g., at a location between the launch zone and their respective monitoring waypoints) that allows the Ignition UAVs to arrive at their assigned start locations at approximately the same time the Surveillance UAVs will arrive at their designated location, the *y* Ignition UAVs launch and autonomously navigate to the respective locations to commence dropping ignition spheres.

   iii. Upon arrival at their start locations, the Supervisor commences ignition drop mission once all Surveillance UAVs have reached their monitoring locations.

c. Variant 3: Both types of UAVs launch in sequence to ensure all UAVs arrive at their start locations at approximately the same time. Note: This variant is likely to be the most common.

   i. A subset of UAVs, of both types, launch and begin executing the mission. This pattern repeats until all UAVs are launched. The UAVs with the furthest mission start locations launch first. The launch sequence ends with the UAVs that have mission start locations located closest to the launch zone.

      1. There are multiple mission plan launch nodes representing sub-missions.

      2. First launch node command is sent.

      3. UAVs for that node take off and begin moving to their designate locations.

      4. Once the UAVs clear out of the airspace above the launch zone, repeat steps 2-4 until all mission plan launch nodes are completed.

   ii. The UAVs fly to their designated start ignition waypoints.

   iii. Once all UAVs arrive at their respective locations to commence the actual mission, the Supervisor commences ignition drop mission once all Surveillance UAVs have reached their monitoring locations.

7. The Supervisor verifies the locations within view of the Surveillance UAVs. Note: this step can occur simultaneously and interchangeably with steps 8 – 11.

   a. Supervisor looks at the UAV specific locations and orientation (e.g., UAV orientation indicates the UAV's camera viewing angle and if the camera is pointing in general intended direction) of the UAVs on the map.

   b. Supervisor verbally asks Communication lead if the surveillance UAVs are monitoring the assigned areas.

   c. Communication lead verifies on separate interface (not modeled) and verbally affirms.

d. Simultaneously,

   i. The Logistics Coordinator verifies that all remaining UAVs are prepped and ready for launch when the power swap behavior is activated.

   ii. The Communications lead monitors all radio traffic, weather changes, overall team safety and the information provided by the Surveillance UAVs.

8. As the mission plan executes, the Ignitor UAVs drop the ignition spheres along their planned paths. Note: this step can occur simultaneously and interchangeably with steps 7, 9 – 11.

   a. Note, the locations at which the spheres hit the ground do not have to be precise, and are usually not precise. The intent is to ignite a fire in the general area of the drop point.

   b. As the Ignition UAVs drop spheres, the Supervisor visually monitor's their mission progress and determines if there is a need to increase or decrease the density of spheres being dropped in an area in order to create the desired fire level.

      i. During the monitoring task the Supervisor discusses the resulting fire with the Communications lead to determine if the density is good, needs to increase or decrease.

      ii. If the density of drops needs to increase, the Supervisor provides the necessary increment.

         1. The Supervisor adjusts the density by X meters via the control interface.

         2. The Supervisor verbally verifies the new drop density with the Communication Lead.

         3. Upon Communication Lead verification, the Supervisor visually verifies the change before the change is committed and the update sent to the Ignitor UAVs and the mission planner.

      iii. Once the Supervisor provides the necessary density adjustment:

         1. The specific UAV's on-board planner automatically replans its path and drop positions.

         2. Simultaneously, the centralized mission planner autonomously adjusts the overall mission plan to ensure the entire pre-specified area is covered with ignition spheres. The result is:

            a. Adjusted navigation plans for the currently deployed Ignition UAVs.

            b. Adjusted navigation plans for the yet to be deployed Ignition UAVs.

      iv. Once the plan(s) are adjusted, the Supervisor reviews them and makes necessary adjustments. UAVs in the air will automatically begin executing a new navigation plan once it is generated on-board. If no adjustment is needed, the Supervisor resumes visual monitoring of the overall mission. If further adjustments is required, return to the top of #8.

9. The Communications lead or Logistics Coordinator, possibly the Supervisor, monitors the Surveillance UAVs' positions and sensor feeds. Note: this step can occur simultaneously and interchangeably with steps 7-8 and 10 – 11.
    a. Note: It is unlikely the Supervisor is viewing raw sensor feeds, especially cameras. This job typically falls to one of the other team members. This task will not be modeled for the Supervisor.
    b. The individual monitoring the surveillance information communicates important mission relevant information to the Supervisor. This communication may be verbal (e.g., "The camera on UAV 10 shows that the fire is spreading more slowly than intended; there is a need to increase the drop density of the spheres." Or "Please look at the video feed from UAV 10" – This case requires the Supervisor to open UAV 10's camera feed on the Supervisor's control system), verbal and visual (e.g., "Please look at the video feed from UAV 10" – This case requires the Supervisor to look at a different screen being used to monitor the surveillance information).
        i. The Communication Lead is monitoring the sensor feeds. Most of the communication between the Supervisor and the Communication Lead is verbal, but the Communication lead can ask the Supervisor to view particular information (e.g., Surveillance UAV Alpha's camera feed). A conversation may occur between that Supervisor and the Communication lead.
10. If a UAV has a safety issue, as reported by one or more of the UAV's sensors, the Supervisor is presented with a dynamically adjusted checklist, which can require evaluating a set of parameterized checks using the information received from the sensor system. Note: this step can occur simultaneously and interchangeably with steps 7 – 9, and 11.
11. As the deployed UAVs' power levels are depleted, they will automatically request a replacement UAV (a lower power swap behavior). Note: this step can occur simultaneously and interchangeably with steps 7 – 10.
    a. Note: The deployed UAV will, depending on the criteria below, automatically execute a Return to Launch (RTL) behavior when a replacement UAV is available.
        i. The RTL behavior requires the UAV to navigate a path to the launch zone and land.
    b. Note: The time at which the replacement UAV swap is requested depends on how far away the UAV is from the launch/landing zone. UAVs that are spatially further from the launch zone will request a replacement UAV earlier than those located spatially closer to the launch zone.
    c. Note: The type of UAV task will also impact the swap behavior.
    d. Note: The swap behavior is automatic and the Supervisor is not required to do anything on the control interface to verify that a UAV is conducting the swap behavior, other than visual monitoring.

e. An Ignition UAV will request a UAV replacement and immediately begin the RTL behavior. Once the returning UAV's request is received, a replacement UAV will launch and navigate to the location at which the returning UAV left off. Upon reaching the returning UAV's last drop position, the replacement UAV begins completion of the remaining plan.

f. A Surveillance UAV may be designated to provide persistent surveillance or not.

    i. A Surveillance UAV that is not providing persistent surveillance will execute the lower power swap in the same manner as the Ignition UAVs.

    ii. A Surveillance UAV providing persistent surveillance will request a replacement UAV earlier than the other cases, as the replacement UAV must arrive at the returning Surveillance UAV's location at approximately the same time the returning Surveillance UAV begins navigating to the launch/landing zone.

        1. Upon receiving a replacement request from a persistent Surveillance UAV, the replacement UAV launches and navigates to the location of the Surveillance UAV to be replaced.

        2. Once the replacement UAV is within range of the UAV with lower power, the lower power UAV begins the RTL behavior.

g. Note: All navigation path planning is done automatically on-board the UAVs and is automatically deconflicted with the in-air UAVs.

h. The Supervisor monitors any activities.

i. As UAVs land with low batteries and it is safe to do so, the Logistics Coordinator

    i. Powers down the UAVs.

    ii. Visually inspects the UAVs and makes any necessary adjustments.

    iii. Swaps out the depleted battery for a fresh battery.

    iv. Powers on the UAVs so that they are ready to be replacement UAVs.

12. As an Ignition UAV completes is mission plan

    a. The UAV can RTL.

    b. If the UAV has remaining spheres and sufficient power

        i. The Supervisor can extend the UAV's mission by

            1. Providing a new path ending point, that results in extending the UAV's path. This specification requires the Supervisor to select the UAV in question, select a new ending waypoint, and issuing the change to the UAV. The UAV's on-board navigation planner replans the path and the mission plan is updated accordingly.

            2. Specifying a new start point, drop point distance, path end point.

        ii. The UAV's on-board planner develops the navigation path, automatically deconflicting with the other UAVs.

iii. The UAV continues the mission.

13. As the mission progresses, the Supervisor can
    a. Modify the mission assignment for Surveillance UAVs. Generally, this means modifying
        i. What areas a UAV is surveilling
            1. The Supervisor selects the UAV.
            2. The Supervisor specifies "look points" – places for the UAV to look at while flying its path – by clicking on the map to select the points.
            3. The Supervisor sends the look points to the UAV.
            4. The UAV receives the points and automatically replans the path.
        ii. How a UAV is conducting the surveillance (e.g., stationary hover, back and forth along a single path, lawnmower pattern).
            1. The Supervisor selects the UAV.
            2. If the UAV is switching from flying to a stationary hover, then the Supervisor selects a waypoint for the hover along with the hover mode. If the UAV is switching from a current path to a different path, then the Supervisor verifies the currently assigned flight area (i.e., the UAV's coverage area assignment) and selects the alternative pattern.
            3. The Supervisor verifies any changes and sends the command to the UAV.
            4. The UAV's on-board navigation planner generates any necessary navigation changes and begins executing the change.
            5. Simultaneously, the mission plan is automatically updated.
    b. If a Surveillance UAV, or any number of Surveillance UAVs, is no longer needed, the Supervisor can initiate the RTL behavior to land the UAV(s).
14. It may be the case that all Ignition UAVs complete their mission and RTL, but the Surveillance UAVs remain for a period of time to monitor how the fire progresses.
    a. Upon completion of the surveillance monitoring, all Surveillance UAVs RTL and land.
15. Once all UAVs have landed and the mission is complete
    a. If communications are available with the incident command center, the Communication lead communicates the mission has completed.
    b. The Communication lead communicates to others in radio range the mission has completed.

Post-Mission

1. The Logistics Coordinator inspects all UAVs prior to breakdown and packing.

2. The team breaks down and packs all equipment.

C.2 Unexpected Events

The ridgeline aerial ignition tightly coupled use case creates new unexpected events that were not relevant to the loosely coupled delivery drone use case. Some of the loosely coupled use case unexpected events do apply to the tightly coupled use case. While this project will not model any unexpected use cases for the tightly coupled scenario, example unexpected events area listed with a high-level description. The full specification of the UEs is left as future work. No UEs will be modeled as part of Task 4, such modeling is left as future work.

C.2.1 Mission Related Issues

C.2.1.1 Configuration Threshold Too High

Description: The configuration threshold determines how close the Ignition UAV positions itself relative to the drop target locations or the Surveillance UAV positions itself for monitoring the situation. If this threshold is set to be too high, then the UAV may sense that it has reached a desired location, when in fact it has not reached a designated location. As a result, the Ignition UAV may drop the ignition sphere at the wrong location or the Surveillance UAV may be in the wrong position and obtain the wrong information during monitoring of the mission. This unexpected event requires the Supervisor to adjust the configuration threshold to ensure the UAV can properly sense its position relative to the desired locations specified for dropping the ignition spheres.

C.2.1.2 Configuration Threshold Too Small

Description: The configuration threshold determines how close the Ignition UAV positions itself relative to the drop target location or the Surveillance UAV positions itself for monitoring the situation. If this threshold is too small, then the Ignition UAV may be very close to the desired location, but is unable to actually get to the designated location due to environmental conditions (e.g., winds). As a result, the Ignition UAV never drops the ignition spheres. Similarly, the Surveillance UAV may be unable to get to the proper location for monitoring. This unexpected event requires the Supervisor to adjust the configuration threshold to ensure the UAV can properly sense its position relative to the desired locations specified for dropping the ignition spheres.

C.2.1.3 Ignition within the Dropper on the UAV

Description: An ignition sphere, after being injected with the dropper, becomes stuck in the dropper and will not fall from the UAV's dropper. The result is that the sphere will ignite within the dropper.
The Supervisor may be notified of the situation and in some circumstances has control over the actuators in the dropper.

C.2.1.4 Dangerous Temperature

Description: High temperatures from the fire can damage the UAV when the UAV flies too close to the fire.
The UAV has on-board thermistors to measure air temperature and thermal cameras to spot hot areas from a distance. The UAV, when it senses that the temperature will become too hot to allow

the UAV to safely fly through a hot area, can use this information to dynamically adjust (e.g., navigation planner) its flight path to avoid hot areas. If necessary to fly close to or over hot areas, because there are no other viable safe navigation paths to the UAV's goal location, the UAV's flight controller can dynamically adjust its flight altitude, based on knowledge of the other UAVs' locations, altitude restrictions, etc., to be high enough to maintain safety.

C.2.1.5 Dangerous Winds

Description: Horizontal and vertical winds (e.g., up and downdrafts) occur near fires and impact the UAV's flight control.
The temperature gradient can be combined with the internal sensors to estimate the winds/drafts. This information can be used on-board the UAV to adjust flight patterns and can be communicated to the Supervisor who can adjust flight patterns, burn patterns, and ignition sphere drop locations.

C.2.1.6 Detachable Ignition System, Trigger to Detach

Description: The ignition system can be detachably attached to the UAV. Upon detection of abnormal conditions that dramatically impact flight or that the ignition system is not properly attached, the ignition system can detach itself from the UAV. The ignition system can become suspended from the UAV using a combustible attachment (e.g., fishing wire), which allows the UAV to navigate to a safe location before the ignition system drops from the UAV.

C.2.2 Supervisor Failures

C.2.2.1 Supervisor C^2 System Failure

Description: The Supervisor's C^2 station crashes, freezes, is affected by communication outages, or experiences input or output device failure.

C.2.3 Hardware Failures and Difficulties

C.2.3.1 C^2 Link Loss

Description: A UAV's Autonomy has not communicated with the Supervisor's C^2 for an extended period of time; the Supervisor is unsure about the whereabouts of the UAV or its mission status.
Variations:

1. The C^2 station does not have a decision support system implemented to assist the Supervisor with information gathering and analysis.
2. The C^2 station's decision support system assists the Supervisor with information gathering and analysis.

C.2.3.2 UAV Experiences Temporary GPS Signal Loss

Description: UAV experiences a short-term GPS signal loss during the mission. The UAV is still capable of making mission progress despite occasional GPS loss.

C.2.3.3 UAV Detect and Avoid (DAA) Sensor Failure

Description: A UAV's DAA sensors stop functioning mid-flight.

C.2.3.4 UAV Partial Motor Failure

Description: A UAV experiences partial motor failure but is still capable of flying.

C.2.3.5 UAV Experiences Unexpected Flight Dynamics

Description: UAV suddenly experiences difficulty maintaining stability and control of pitch, yaw, or roll.

C.2.4 UAV Software Failure

C.2.4.1 UAV Flyaway

Description: UAV has significantly diverged from its flight path and is not attempting to correct back to the planned course.

C.2.4.2 UAV Unresponsive During Unexpected Event

Description: UAV is unresponsive to Supervisor's commands intended to address an ongoing unscheduled event affecting the UAV.

C.2.5 Collisions

C.2.5.1 Mid-Air Collision

A. *Description*: The UAV sustains damage from a collision with an object while airborne. Variations:

1. The UAV maintains flight capabilities, but loses airworthiness.
2. The UAV is airworthy and capable of completing the mission.

B. *Description*: UAV has crashed and is unable to fly., but the UAV's Autonomy is still capable of communicating with Supervisor.
Variations:

1. The UAV's autonomy is still capable of communicating with the Supervisor. The UAV is left in place and is recovered after the mission, only if its location is safely accessible to the responders
2. The UAV's autonomy is unable to communicate with the Supervisor. The UAV is abandoned in place.

C.2.5.2 UAV Loses Flight Capabilities and Crashes

(i.e., Full Motor Failure, Lightning Strike, Affected by Adverse Weather Conditions)
Description: UAV experiences a full loss of flight and crashes into the ground due to adverse weather conditions, or hardware failure; the Autonomy is incapable of communicating with the Supervisor.

C.3 Distraction Events

The distractions for the tightly coupled ridgeline aerial ignition differ substantially from the loosely coupled deliver drone use case. The provided example distraction events provide a representative description and are not intended to be an exhaustive list of such events. Only the Fatigue distraction will be modeled as part of Task 4.

C.3.1 Fatigue

Description: The Supervisor is experiencing a form of fatigue. *Impact on workload*: Fatigue is expected to decrease experienced workload due to the Supervisor being less able to focus on and complete tasks effectively. Fatigue distracts the Supervisor from task duties, while also making completing task duties less efficient.

C.3.2 Biological

Description: The Supervisor must address a biological need (i.e., hunger, bathroom, sickness) and based on type of need may need to immediately leave the C^2 station to address the personal biological need. *Impact on workload*: Biological issues are expected to reduce experienced workload, as they distract the Supervisor away from relevant monitoring duties. Extreme distractions of this nature may require the handing-off of all UAVs to another team member or the grounding of the UAVs if there is no other team member present that is qualified as a Supervisor.

C.3.3 Normal Environmental Discomfort

Description: Environmental conditions are a burden on the operator (i.e., cold, wet, heat, sun, bugs, uneven terrain), distracting them from tasks at C^2 station. *Impact on workload*: Normal discomfort is expected to decrease task relevant workload by distracting the Supervisor from the monitoring task. Discomfort likely has an additive effect on workload over extended periods, or when coupled with fatigue conditions.

C.3.4 Degraded Environmental Conditions

Description: Change or Non-normal or unexpected environmental conditions influence planning and task duties (e.g., smoke or unanticipated storm). *Impact on workload*: Degraded environmental conditions are expected to significantly decrease task relevant workload by distracting the Supervisor from the monitoring task, as they are forced to deal with the unexpected environmental conditions.

C.3.5 Teammates

Description: Failures or difficulties in team communication or job duties may lead to frustration in the Supervisor. *Impact on workload*: Failures to effectively communicate with teammates is expected to increase task workload, as it requires the Supervisor to manage/repeat/verify communications that usually are completed easily under nominal conditions.

C.3.6 Time pressure

Description: Given the dynamic nature of task and unpredictable nature of ignition, racing to beat constraints (e.g., weather, time on site, approaching daylight, advancing fire lines) can stress and preoccupy the Supervisor. *Impact on workload*: Time/task pressure is expected to significantly increase task workload, as increased pressure often leads to errors, tunnel vision, missed information, etc. The Supervisors is expected to need to double check or repeat work efforts, in addition to managing the stress of such time pressure.

C.3.7 Indirectly related but proximal operations

Description: Other operations that are occurring within the proximity of the ignition team may draw the Supervisor's attention (e.g., firefighting, evacuation or evacuation routes, other emergency operations). *Impact on workload:* Proximal activities are expected to decrease workload, as such activities likely will distract the Supervisor from task duties.

B. APPENDIX D. TASK ANALYSIS FOR SUPERVISOR, UAV, CENTRALIZED MISSION SYSTEM, FLIGHT ASSISTANT AND PACKAGE RECIPIENT.

Legend:	
Actors	Supervisor Monitoring
Requirements or Heuristics	Actor Not involved

Steps	Mission Phase	Supervisor (Human Operator)	UAV	Centralized Mission System	Flight Assistant	Recipient
1	Pre-Flight			Route Planner computes optimized flight profile	Conduct preflight inspection of UAV	Requests Delivery by UAV
2					Prepare Package for Delivery	
3			Adjust flight control parameters based expected change in flight dynamics due to package weight		Verify the package was securely placed in the UAV	
4				Upload Delivery Mission Data to UAV	Verify whether the mission flight path conforms to airspace restrictions	
5					Verify UAV is placed at launch site	

Steps	Mission Phase	Supervisor (Human Operator)	UAV	Centralized Mission System	Flight Assistant	Recipient
6			UAV in standby mode	PNF assigned to UAV		
7		Notified of Delivery Mission Assignment		Task Notification sent to Supervisor		
8		Acknowledges delivery mission assignment				
9		Verify completion of Flight Assistant Pre-Flight Checklist & Mission Validation				
10		Authorize launch				
11		(Monitor UAV mission flight info)				
12	Lift Off		Performs a "Climb Path Clear Assessment"			
13			Ascend			
14	Ascend to Cruising Altitude		Fly pre-planned route			
15	Enroute		Fly pre-planned route			
16	Delivery		Arrives to delivery location			
17			Performs a "Descent Path Clear Assessment"			
18			Descent from cruising altitude above delivery site			

Steps	Mission Phase	Supervisor (Human Operator)	UAV	Centralized Mission System	Flight Assistant	Recipient
19			Performs a "Delivery Area Clear Assessment"			
20			Descend			
21			Hover and Release Package			
22			Performs a "Climb Path Clear Assessment"			
23			Ascend to cruising altitude			
24	**Return (Enroute)**		Fly pre-planned route to Delivery UAV Warehouse			Notified: Package Delivered
25						Receives Package
26	**Descent from Cruising Altitude**		Fly pre-planned route			
27	**Landing**		Arrives to the landing site at Delivery UAV Warehouse			
28			Perform a "Landing Area Clear Assessment"			
29			Descend			
30			Land			

C. APPENDIX E. SUPERVISOR TASKS AND SUB-TASK NON-NOMINAL OUTCOMES AND HAZARDS FOR LOOSELY COUPLED SCENARIO

Task	Processing Stage	Sub-task	Outcome	Hazard
Acknowledge notification of unscheduled event	Information Acquisition	Attend to notification	Notification is not attended	Perception error
	Assessment	Interpret notification	Notification incorrectly interpreted	Decision error
			Notification not understood	Knowledge error
	Decision	Decide to initiate abnormal/ emergency procedure	Incorrectly decide to initiate procedure	Decision error; Violation
			Incorrectly decide not to initiate procedure	Decision error; Violation
Contact other party	Information Acquisition	Perceive contacts	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
		Recall contacts	Recall incorrect information	Skill-based error; Knowledge error
			Fail to recall relevant information	Knowledge error
	Assessment	Determine parties to contact	Non-applicable party identified	Decision error; Knowledge error
			No applicable party identified	Decision error; Knowledge error
	Decision	Decide who to contact	Choose less appropriate contact	Decision error; Violation
	Execution	Initiate communication	Ineffective communication	Skill-based error
			Communication not established	Skill-based error
Delay new task	Information Acquisition	Recall other tasks to complete	Recall incorrect information	Skill-based error; Knowledge error
			Fail to recall relevant information	Skill-based error; Knowledge error
	Assessment	Determine priority	Incorrectly assess priority of outstanding tasks	Decision error; Knowledge error
	Decision	Decide when to schedule delayed task	Schedule delayed task contrary to priority	Decision error
			Delayed task not scheduled	Decision error; Violation

Task	Processing Stage	Sub-task	Outcome	Hazard
	Execution	Execute delayed task according to schedule	Delayed task initiated at unplanned time	Decision error; Knowledge error; Violation
			Delayed task not initiated	Knowledge error; Violation
Handoff UAV (receiver)	Information Acquisition	Perceive handoff request from sender	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine if ready to accept control	Incorrectly determine ready	Decision error; Knowledge error
			Incorrectly determine not ready	Decision error
	Decision	Decide to accept handoff	Accept when not ready	Decision error; Violation
			Reject when ready	Decision error; Violation
	Execution	Accept handoff	Control not taken	Skill-based error; Violation
Handoff UAV (sender)	Information Acquisition	Perceive handoff request response from receiver	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine receiver is ready to accept control	Incorrectly interpret the receiving Supervisor is ready	Decision error; Skill-based error
			Incorrectly interpret the receiving Supervisor is not ready	Decision error; Skill-based error
	Decision	Decide to transfer control	Decide to transfer when receiving Supervisor is not ready	Decision error; Violation
			Decide not to transfer when receiving Supervisor is ready	Decision error
	Execution	Transfer control	Control not transferred	Skill-based error; Violation
Hold UAV	Information Acquisition	Perceive controls	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine appropriate control	Incorrect control identified	Decision error
			No control identified	Knowledge error
	Decision	Confirm need to hold	Incorrectly choose hold	Decision error; Violation

Task	Processing Stage	Sub-task	Outcome	Hazard
			Incorrectly reject hold	Decision error; Violation
	Execution	Execute the hold command	Command not executed	Skill-based error; Violation
Land UAV	Information Acquisition	Perceive controls	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine appropriate control	Incorrect control identified	Decision error
			No control identified	Knowledge error
	Decision	Confirm need to land	Incorrectly choose land	Decision error; Violation
			Incorrectly reject land	Decision error; Violation
	Execution	Execute the land command	Command not executed	Skill-based error; Violation
Manual Control (direct)	Information Acquisition	Perceive flight information	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine error in flight path	Error in flight path is estimated insufficiently	Skill-based error
			Error cannot be estimated	Perception error
	Decision	Decide how to control aircraft	Insufficient control technique determined	Skill-based error
	Execution	Exercise control	Inappropriate control exercised	Skill-based error; Violation
			No control exercised	Skill-based error; Violation
Manual Control (autopilot)	Information Acquisition	Perceive display	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine flight plan	Inappropriate flight planned	Decision error
	Decision	Decide on flight plan parameters	Some parameters conflict with new flight plan	Decision error
			Some parameters not chosen	Skill-based error; Knowledge error
	Execution		Some parameters programmed not as planned	Skill-based error; Violation

Task	Processing Stage	Sub-task	Outcome	Hazard
		Program flight plan parameters	Some parameters not programmed	Skill-based error; Violation
Monitor flight(s)	Information Acquisition	Perceive display	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
		Recall mission parameters	Recall incorrect information	Skill-based error; Knowledge error
			Fail to recall relevant information	Knowledge error
	Assessment	Compare system status to mission plan	Incorrectly determine system status conforms to mission plan	Decision error
			Incorrectly determine system status does not conform to mission plan	Decision error
	Decision	Decide to initiate abnormal/ emergency procedure	Incorrectly decide to initiate procedure	Decision error
			Incorrectly decide not to initiate procedure	Decision error; Violation
Return to launch	Information Acquisition	Perceive controls	Inaccurate information acquired	Perception error
			Some relevant information not acquired	Skill-based error; Perception Error
	Assessment	Determine appropriate control	Incorrect control identified	Decision error
			No control identified	Knowledge error
	Decision	Confirm need to return	Incorrectly choose return	Decision error; Violation
			Incorrectly reject return	Decision error; Violation
	Execution	Execute the return command	Command not executed	Skill-based error; Violation

D. APPENDIX F. SUPERVISOR TASKS AND SUB-TASK NON-NOMINAL OUTCOMES AND HAZARDS FOR TIGHTLY COUPLED SCENARIO

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
Communicate with teammate (receiver)	Communicate with teammate	Perception	Perceive speaker	Incomplete message heard	Perception error
				Message not heard	Perception error
		Encoding	Encode message	Incorrectly encode some of message	Skill-based error; Perception Error
				Fail to encode some of message	Skill-based error; Perception Error
		Interpretation	Interpret meaning	Incorrectly interpret the speaker's intention	Skill-based error; Decision error; Knowledge error
Communicate with teammate (sender)	Communicate with teammate	Generate	Form intention	Pertinent intentions generated incompletely	Decision error; Violation
				Irrelevant intentions generated	Decision error; Violation
		Transcribe	Transcribe message	Clearly transcribe incomplete intentions into words	Skill-based error
				Unclearly transcribe intentions into words	Skill-based error
		Transmit	Send message (speak)	Incomplete message spoken clearly	Skill-based error
				Message spoken unclearly	Skill-based error
				Message not spoken	Skill-based error; Violation
Discrete Control	Hold UAV	Info Acquisition	Perceive control	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
		Decision	Confirm need to hold	Incorrectly choose to launch	Decision error; Violation
				Incorrectly reject launch	Decision error; Violation
		Execution	Execute the hold command	Command not executed	Skill-based error; Violation
	Initiate ignition sphere drop mission	Info. Acquisition	Perceive control	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error
		Decision	Confirm readiness to drop	Incorrectly choose to drop	Decision error; Violation
				Incorrectly reject drop	Decision error; Violation
		Execution	Execute the drop command	Command not executed	Skill-based error; Violation
	Launch mission plan	Info. Acquisition	Perceive controls	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error
		Decision	Confirm readiness to launch	Incorrectly choose to launch	Decision error; Violation
				Incorrectly reject launch	Decision error; Violation
		Execution	Execute the launch command	Command not executed	Skill-based error; Violation
	Modify drop path	Info. Acquisition	Perceive display	Inaccurate information acquired	Perception error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine new drop path	Inappropriate flight planned	Decision error
		Decision	Decide how to position waypoints	Some parameters conflict with new flight plan	Decision error
				Some parameters not chosen	Skill-based error; Knowledge error
		Execution	Program new drop path	Some parameters programmed not as planned	Skill-based error; Violation
				Some parameters not programmed	Skill-based error; Violation
	Modify flight plan	Info. Acquisition	Perceive display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine new flight path	Inappropriate flight planned	Decision error
		Decision	Decide how to position waypoints	Some parameters conflict with new flight plan	Decision error
				Some parameters not chosen	Skill-based error; Knowledge error
		Execution	Program new flight plan	Some parameters programmed not as planned	Skill-based error; Violation
				Some parameters not programmed	Skill-based error; Violation
	Modify ignition/UAV parameters	Info. Acquisition	Perceive controls	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error
		Decision	Confirm need to change parameter	Incorrectly choose to change parameter	Decision error; Violation

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
				Incorrectly reject to change parameter	Decision error; Violation
		Execution	Change the parameter	Command not executed	Skill-based error; Violation
	Modify surveillance area	Info Acquisition	Perceive display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine where surveillance is needed	Incorrectly determine where surveillance is needed	Skill-based error; Decision error
				Cannot determine where surveillance is needed	Skill-based error; Decision error; Knowledge error
		Decision	Decide how to position new surveillance area	Inappropriate surveillance area selected	Decision error; Violation
		Execution	Program new surveillance area	Incorrectly program new surveillance area	Skill-based error
	Modify surveillance flight pattern	Info. Acquisition	Perceive controls	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error
		Decision	Confirm need to change flight pattern	Incorrectly choose change flight parameter	Decision error; Violation
				Incorrectly reject to change flight parameter	Decision error; Violation
		Execution	Change the flight pattern	Command not executed	Skill-based error; Violation
	Return to launch	Info. Acquisition	Perceive controls	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
		Assessment	Determine appropriate control	Incorrect control identified	Decision error
				No control identified	Knowledge error
		Decision	Confirm need to return	Incorrectly choose to return	Decision error; Violation
				Incorrectly reject return	Decision error; Violation
		Execution	Execute the return command	Command not executed	Skill-based error; Violation
Monitoring and Situation Assessment	Evaluate dynamic checklist	Info. Acquisition	Read checklist item	Incorrectly read checklist item	Skill-based error; Perception Error
		Assessment	Determine status of checklist item	Incorrectly determine that the item has been completed	Skill-based error; Decision error; Knowledge error
				Incorrectly determine that the item has not been completed	Skill-based error; Decision error; Knowledge error
		Decision	Decide what further action is necessary	Incorrectly check off item	Decision error; Skill-based error
				Incorrectly decide to initiate procedure	Decision error
	Evaluate ignition mission progress	Info. Acquisition	Perceive Display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Knowledge error
			Discuss mission with team	Some relevant information miscommunicated	Skill-based error
				Some relevant information not communicated	Skill-based error
		Assessment	Determine current mission effectiveness	Effectiveness insufficiently estimated	Skill-based error; Decision error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
				Effectiveness cannot be determined	Skill-based error; Decision error; Knowledge error
			Compare current mission progress to mission plan	Incorrectly determine that the current progress conforms to the mission plan	Skill-based error; Decision error
				Incorrectly determine that the current progress does not conform to the mission plan	Skill-based error; Decision error
		Decision	Decide whether current mission progress is satisfactory	Incorrectly decide that the current progress is satisfactory	Decision error; Violation
				Incorrectly decide that the current progress is unsatisfactory	Decision error; Violation
	Monitor flights	Info. Acquisition	Perceive display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Knowledge error
		Assessment	Compare system status to mission plan	Incorrectly determine system status conforms to mission plan	Decision error
				Incorrectly determine system status does not conform to mission plan	Decision error
		Decision	Decide to initiate abnormal/emergency procedure	Incorrectly decide to initiate procedure	Decision error
				Incorrectly decide not to initiate procedure	Decision error; Violation
	Monitor video feed	Info. Acquisition	Perceive display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Knowledge error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
		Assessment	Compare sensor information to mission plan	Incorrectly determine sensor information conforms to mission plan	Skill-based error; Decision error
				Incorrectly determine sensor information does not conform to mission plan	Skill-based error; Decision error
		Decision	Decide whether further action is necessary	Incorrectly decide further action is necessary	Decision error; Violation
				Incorrectly decide further action is unnecessary	Decision error; Violation
	Review flight plan	Info. Acquisition	Perceive Display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
		Assessment	Determine if there are any issues with the flight plan	Incorrectly detect no issues with the flight plan	Skill-based error; Decision error; Knowledge error
		Assessment	Determine if there are any issues with the flight plan	Incorrectly detect an issue with the flight plan	Skill-based error; Decision error; Knowledge error
		Decision	Decide whether flight plan is acceptable	Incorrectly decide the flight plan is acceptable	Decision error; Violation
				Incorrectly decide the flight plan is unacceptable	Decision error; Violation
	Validate mission plan	Info. Acquisition	Perceive environment	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Skill-based error; Knowledge error
		Assessment	Determine feasibility of mission plan	Incorrectly determine mission plan is feasible	Skill-based error; Decision error
				Incorrectly determine mission plan is not feasible	Skill-based error; Decision error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
		Decision	Decide whether mission can proceed	Incorrectly approve mission plan	Decision error; Violation
				Incorrectly disapprove mission plan	Decision error; Violation
	Validate team readiness	Info. Acquisition	Verbally obtain other teammates' status	Teammate is misheard	Perception error
				Teammate is not heard	Perception error
		Assessment	Determine each teammate's readiness	Incorrectly interpret teammate as ready	Skill-based error; Decision error
				Incorrectly interpret teammate as not ready	Skill-based error; Decision error
		Decision	Decide team is ready	Incorrectly decide team is ready	Decision error; Violation
				Incorrectly decide team is not ready	Decision error; Violation
	Validate UAV position	Info. Acquisition	Perceive display	Inaccurate information acquired	Perception error
				Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Knowledge error
		Assessment	Compare UAV position to mission plan	Incorrectly determine UAV position conforms to mission plan	Skill-based error; Decision error
				Incorrectly determine UAV position does not conform to mission plan	Skill-based error; Decision error
		Decision	Decide whether the UAV is in the correct position	Incorrectly decide UAV is in the correct position	Decision error; Violation
				Incorrectly decide UAV is in the incorrect position	Decision error
		Info. Acquisition	Perceive Display	Inaccurate information acquired	Perception error

Task Category	Task	Processing Stage	Sub-task	Outcome	Hazard
	Verify locations within view of Surveillance UAV			Some relevant information not acquired	Skill-based error; Perception Error
			Recall mission plan	Recall incorrect information	Skill-based error; Knowledge error
				Fail to recall relevant information	Knowledge error
		Assessment	Compare current surveillance area to mission plan	Incorrectly determine surveillance area conforms to mission plan	Skill-based error; Decision error
				Incorrectly determine surveillance area does not conform to mission plan	Skill-based error; Decision error
		Decision	Decide whether current surveillance area is appropriate	Incorrectly decide the surveillance area is appropriate	Decision error; Violation
				Incorrectly decide the surveillance area is not appropriate	Decision error

E. APPENDIX G. HAZARD TO CAUSE MAPPING.

Note: Exemplars not provided for violations or out of scope causes (i.e., "X" indicates Boolean membership). "HFACS" indicates the cause is explicitly given as an example of the respective hazard by Shappell and Weigmann (2000).

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Accountability	Decision ownership						
Air traffic	Misinterpretation/misuse of relevant information						
Alert system failure	Flawed system assessment						
Attentional control		Visual scan patterns					
Attentional lapse / change blindness		Visual scan patterns					
Authorized unnecessary hazard						X	
Authorized unqualified crew for flight						X	
Automation adaptability	Decision-based interactions with autonomy	Skill-based interactions with autonomy					
Awareness	Understanding alternatives		Readiness to perceive				
Boredom					X		
Breakdown in visual scan		HFACS					
C^2 station malfunction		Loss of or insufficient control	No display to perceive				
Cannot cancel orders		Doing		Untrained procedures			

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Channelized attention	Ignore other relevant information		Ignore other relevant information				
Cluttered display			Attention, perception				
Color vision			Color perception				
Comfort		Manner/technique of performing task					
Communication mode	Decision what to communicate	Sender failure	Receiver failure				
Communication of uncertainty	Decision-based interactions with autonomy						
Complacency	Decision-based interactions with autonomy						
Compliance	Decision-based interactions with autonomy						
Confidence	Decision confidence						
Control mode		Doing					
Coordination	Poorly executed procedures	Manner/technique of performing task		Missing information from teammate			
Counterproductive work behavior	Distraction				X		
Culture							X
Demographics							X

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Detection failure			Detection				
Display flexibility	Planning	Technique	Perceptibility of information				
Display layout	Planning	Technique	Perceptibility of information				
Display navigability	Planning	Technique	Perceptibility of information				
Display type	Situation assessment		Perceptual information processing				
Disrupted flight performance	Planning						
Distractions	Loss of focus		Competition for attention				
Distress	Situation assessment	Inadvertent omission of actions					
Engagement						X	
Equipment/facility resources							X
Exceeded ability	HFACS						
Excessive physical training						X	
Executive functioning	Thinking						
Experience	Planning	Highly practiced behavior		Inexperience with unexpected situations			
Failed to adhere to brief					HFACS		

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Failed to back-up (crewmember)	Improper choice		Failed to perceive request for help	Not trained how to help			
Failed to communicate/coordinate		Sender failure	Receiver failure				
Failed to conduct adequate brief						X	
Failed to correct document in error						X	
Failed to enforce rules and regulations						X	
Failed to identify an at-risk aviator						X	
Failed to initiate corrective action						X	
Failed to prioritize attention		HFACS					
Failed to properly prepare for the flight					HFACS		
Failed to provide adequate brief time						X	
Failed to provide correct data						X	
Failed to provide guidance						X	
Failed to provide operational doctrine						X	
Failed to provide oversight						X	
Failed to provide training						X	
Failed to report unsafe tendencies						X	

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Failed to track performance						X	
Failed to track qualifications						X	
Failed to use all available resources	Inadequate plan			Existence of available resources unknown			
Failure of leadership				Leadership experience, training			
Faith	Decision-based interactions with autonomy						
Feedback	Decision			Uncertainty of outcomes			
Flew an overaggressive maneuver					HFACS		
"Get-home-itis"	Bias						
GPS failure	Flawed system assessment						
Handoff failure				Aware of new responsibility			
Haste	Rushed judgment	Insufficient control	Channelized attention		X		
Heterogeneity of UAVs	Adapting procedures						
Human resources							X
Iconography	Misinterpretation of information		Perceptibility of information				
Improper manning						X	

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Improper procedure	HFACS						
Inadvertent use of flight controls		HFACS					
Inappropriate maneuver	HFACS						
Incompatible intelligence/aptitude	Thinking						
Incompatible physical capability		Doing					
Incomplete/inaccurate understanding of autonomy's capabilities	Misuse of relevant information			Incomplete knowledge			
Inefficiency	Planning	Doing					
Insufficient reaction time	Rushed judgment						
Intentionally exceeded the limits of the aircraft					HFACS		
Level of autonomy	Decision-based interactions with autonomy	Skill-based interactions with autonomy					
Link loss/degradation	Flawed system assessment						
Medical illness							X
Mental fatigue	Reduced executive function		Vigilance				
Misdiagnosed emergency	HFACS						
Misinterpretation of traffic calls	Misinterpretation						
Misjudged distance/altitude/airspeed			HFACS				

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Mission not in accordance with rules/regulations						X	
Monetary/budget resources							X
Motivation	Bias						
Multitasking ability		Manner/technique of performing task					
Nefarious Supervisor					X	X	
Neglect	Misuse of relevant information				X		
Not current/qualified for the mission					HFACS		
Number of UAVs	Workload	Workload	Workload				
Obstacles in environment	Misinterpretation/misuse of relevant information						
Omitted checklist item		HFACS					
Omitted step in procedure		HFACS					
Organizational culture							X
Organizational operations							X
Organizational oversight							X
Organizational policies							X
Organizational procedures							X
Organizational structure							X
Over-controlled the aircraft		HFACS					

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Perceptual sensitivity			Perceptibility of information				
Personal attachment	Decision-based interactions with autonomy						
Personality							X
Physical fatigue		Doing					
Physiological impairment							X
Physiological incapacitation							X
Poor decision	HFACS						
Poor technique		HFACS					
Predictability	Decision-based interactions with autonomy						
Progress tracking	Planning						
Provided inadequate opportunity for crew rest						X	
Relevancy of communication/ information	Distraction		Receiver failure				
Reliability	Decision-based interactions with autonomy						
Reliance	Decision-based interactions with autonomy						
Resilience						X	

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Response bias	Biased decisions						
Responsibility					X		
Self-medicating						X	
Sensor failure	Flawed system assessment						
Serial/parallel tasks/processing	Information processing		Perceptual information processing				
Signal modality			Modal compatibility				
Situational awareness	Flawed situation assessment						
Spatial ability	Thinking		Spatial perception				
Spatial disorientation			HFACS				
Strategy	Planning						
Supervisor absence						X	
Supervisor excessively edits mission parameters					X		
Supervisor loss of control		Doing					
Supervisor overloaded	Poorly executed procedures, shallow thinking	Technique degradation	Insufficient attention				
Supervisor Personal Emergency						X	
Supervisor receives unreliable UAV state information (e.g., position, altitude)	Flawed system assessment						

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Task delegation	Planning						
Task prioritization	Planning						
Task queue availability	Planning	Forgotten intentions					
Task saturation	Deadlock, prioritization		Insufficient attention				
Task switching	Decision when to switch	Manner/technique of performing task					
Taskload	Workload	Workload	Workload				
Team organization	Poorly executed procedures	Manner/technique of performing task		Missing information from teammate			
Technical Competence	Decision-based interactions with autonomy						
Training	Poorly executed procedures	Highly practiced behavior		Untrained procedures			
Transparency	Decision-based interactions with autonomy			Limited understanding of autonomy			
Trust in automation	Decision-based interactions with autonomy						
Usability		Technique					
Utilization	Planning	Doing					
Vigilance			Misses				
Violated training rules					HFACS		

	Hazards						
Cause	**Decision Error**	**Skill-based Error**	**Perception Error**	**Knowledge Error**	**Routine Violation**	**Exceptional Violation**	**Out of Scope**
Violation of bottle-to-throttle requirement						X	
Violation of crew rest requirement						X	
Visual illusion			HFACS				
Visual limitation			Perceptual ability				
Working memory capacity				Memory failure			
Workload	Poorly executed procedures	Forgotten intentions, omitted items					
Worry	Decision-based interactions with autonomy						
Wrong response to emergency	HFACS						

F. APPENDIX H. CAUSE CATEGORIZATION.

Part 1: Condition of the Operator, Personnel Factors, Environmental Factors

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Accountability								
Air traffic								Obstacles in physical environment
Alert system failure							Equipment/controls	
Attentional control	Acute psychological condition							
Attentional lapse / change blindness	Acute psychological condition			Limited senses				
Authorized unnecessary hazard								
Authorized unqualified crew for flight								
Automation adaptability							Automation	
Awareness	Acute psychological condition							
Boredom	Acute psychological condition							
Breakdown in visual scan	Attentional control							
C^2 station malfunction							Equipment/controls	

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Cannot cancel orders			Knowledge gap				Controls/interface	
Channelized attention	HFACS						Display/interface design	
Cluttered display	Perception	Visual illusion		Limited senses			Display/interface design	
Color vision				Limited senses				
Comfort		Acute physical state		Ergonomics				
Communication mode					Communication		Design of controls	
Communication of uncertainty	Decision, understanding						Automation design	
Complacency	HFACS						Automation bias	
Compliance	Trust in automation							
Confidence	Attitude, decision							
Control mode							Controls	
Coordination	Strategy				Coordination			
Counterproductive work behavior	Motivation					Neglect of duty		
Culture					Cultural effects between teammates			
Demographics								

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Detection failure	Perception	Visual illusion		Limited senses				
Display flexibility				Limited senses			Display/interface design	
Display layout							Display design	
Display navigability			Knowledge gap				Display/interface design	
Display type							Display/interface design	
Disrupted flight performance							Sensor failure	Wind, weather
Distractions	Acute mental condition				Teammates may distract each other		Elements of equipment or display/interface may be distracting (e.g., sounds, lights)	Elements of environment may be distracting (e.g., sounds, lights)
Distress	Acute psychological condition							
Engagement	Acute psychological condition							
Equipment/facility resources								
Exceeded ability			Exceeded mental ability	Exceeded physical ability				
Excessive physical training						HFACS		

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Executive functioning	Acute psychological condition		Mental aptitude					
Experience			Mental aptitude					
Failed to adhere to brief	Decision		Knowledge gap					
Failed to back-up (crewmember)					HFACS			
Failed to communicate/coordinate					HFACS			
Failed to conduct adequate brief					HFACS			
Failed to correct document in error								
Failed to enforce rules and regulations								
Failed to identify an at-risk aviator								
Failed to initiate corrective action								
Failed to prioritize attention	Attentional control, task fixation							
Failed to properly prepare for the flight							Aircraft not prepared	
Failed to provide adequate brief time								

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Failed to provide correct data								
Failed to provide guidance								
Failed to provide operational doctrine								
Failed to provide oversight								
Failed to provide training								
Failed to report unsafe tendencies								
Failed to track performance								
Failed to track qualifications								
Failed to use all available resources					HFACS			
Failure of leadership					HFACS			
Faith	Trust							
Feedback	Decision, learning						Automation design	
Flew an overaggressive maneuver	Decision, manual control							
"Get-home-itis"	HFACS							
GPS failure							Equipment/controls	

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Handoff failure					Coordination, communication, teamwork			
Haste	HFACS							
Heterogeneity of UAVs							Taskload	
Human resources								
Iconography	Perception, understanding		Knowledge gap				Display/interface design	
Improper manning								
Improper procedure	Decision		Knowledge gap					
Inadvertent use of flight controls	Manual control						Design of controls	
Inappropriate maneuver	Decision		Knowledge gap					
Incompatible intelligence/aptitude			HFACS					
Incompatible physical capability				HFACS				
Incomplete/inaccurate understanding of autonomy's capabilities	Understanding		Knowledge gap					
Inefficiency					Efficient teamwork	Ready to be effective	Controls/display/interface design	
Insufficient reaction time			Mental reaction time	Physical reaction time				

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Intentionally exceeded the limits of the aircraft	Decision, manual control							
Level of autonomy							Automation design	
Link loss/degradation							Equipment/controls	
Medical illness		HFACS						
Mental fatigue	HFACS					Sleep		
Misdiagnosed emergency	Assessment, decision							
Misinterpretation of traffic calls					HFACS			
Misjudged distance/altitude/airspeed	Perception	Visual illusion		Limited senses			Sensor failure	Weather, altitude, terrain, heat, lighting
Mission not in accordance with rules/regulations								
Monetary/budget resources								
Motivation	HFACS							
Multitasking ability			Mental aptitude					
Nefarious Supervisor						Betrayal of duty		
Neglect	Acute psychological condition					Neglect of duty		

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Not current/qualified for the mission						Not ready for duty		
Number of UAVs							Taskload	
Obstacles in environment								Terrain, aircraft
Omitted checklist item	Forgetting		Knowledge gap				Checklist is missing item	
Omitted step in procedure	Forgetting		Knowledge gap					
Organizational culture								
Organizational operations								
Organizational oversight								
Organizational policies								
Organizational procedures								
Organizational structure								
Over-controlled the aircraft	Manual control							
Perceptual sensitivity	Perception			Limited senses				
Personal attachment	Trust							
Personality	Mental condition							
Physical fatigue		HFACS						
Physiological impairment		HFACS						

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Physiological incapacitation		HFACS						
Poor decision	Decision							
Poor technique	Manual control		Mental aptitude					
Predictability	Trust							
Progress tracking	Situational awareness							
Provided inadequate opportunity for crew rest								
Relevancy of communication/information	Distraction		Ability to filter input		Team chatter		Display/interface design	
Reliability	Decision, trust						Automation	
Reliance	Trust in automation							
Resilience	Acute psychological condition							
Response bias	Attitude, decision							
Responsibility						Integrity		
Self-medicating						HFACS		
Sensor failure							Equipment/controls	
Serial/parallel tasks/processing			Processing limitations				Display/interface design; task factors	

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Signal modality				Modality interference				
Situational awareness	Mental condition						Display/interface design	
Spatial ability			Mental aptitude					
Spatial disorientation	Perception	Acute psychological condition					Sensor failure	
Strategy	Planning				May require coordination			
Supervisor absence		Physically absent			Affects team composition	Abandonment of duty		
Supervisor excessively edits mission parameters	Beliefs, understanding, trust in automation							
Supervisor loss of control							Loss of signal, engine failure, workstation failure	
Supervisor overloaded	Acute psychological condition		Mental limits					
Supervisor Personal Emergency					May lead to absence	Not ready for duty		
Supervisor receives unreliable UAV state information (e.g., position, altitude)	Causes flawed assessment						Equipment, automation	

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Task delegation	Decision				Teamwork		Automation	
Task prioritization	Decision						Automation design	
Task queue availability							Display/interface design	
Task saturation	HFACS							
Task switching	Strategy							
Taskload							Task factors	
Team organization	Strategy				Crew-related			
Technical Competence	Trust							
Training								
Transparency	Understanding						Automation design	
Trust in automation	Attitude, personality				Coordination with automation		Automation	
Usability				Ergonomics			Design of equipment	
Utilization	Strategy, workload					Ready to be effective	Task constraints	
Vigilance	Sustained attention		Fatigue	Fatigue				
Violated training rules	Decision		Knowledge gap					
Violation of bottle-to-throttle requirement						HFACS		
Violation of crew rest requirement						HFACS		

	Condition of the Operator				Personnel Factors		Environmental Factors	
Causes	**Adverse mental state**	**Adverse physiological state**	**Failure to account for mental limitations**	**Failure to account for physical limitations**	**Crew resource management**	**Personal readiness**	**Technological environment**	**Physical environment**
Visual illusion	Perception	Acute psychological condition		Limited senses			Display/interface design	Weather, altitude, terrain, heat, lighting
Visual limitation				HFACS				
Working memory capacity			Mental aptitude					
Workload	Acute psychological condition							
Worry	Acute psychological condition							
Wrong response to emergency	Decision		Knowledge gap					

Part 2: Condition of the Operator, Personnel Factors, Environmental Factors

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Accountability						Formal accountability for actions	
Air traffic							

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Alert system failure			Known deficient equipment		Equipment maintenance		
Attentional control							
Attentional lapse / change blindness							
Authorized unnecessary hazard				HFACS			
Authorized unqualified crew for flight				HFACS			
Automation adaptability							
Awareness							
Boredom						Working atmosphere	
Breakdown in visual scan							
C^2 station malfunction			Known deficient equipment		Equipment maintenance		
Cannot cancel orders							
Channelized attention							
Cluttered display							
Color vision							
Comfort							
Communication mode							
Communication of uncertainty							

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Complacency							
Compliance							
Confidence							
Control mode							
Coordination		Crew pairings					
Counterproductive work behavior	Oversight		Accepted amounts of loafing			Accepted amounts of loafing	
Culture						Organizational culture	
Demographics					Human resources		
Detection failure							
Display flexibility							
Display layout							
Display navigability							
Display type							
Disrupted flight performance			Known deficient equipment		Equipment maintenance		
Distractions							
Distress							
Engagement							
Equipment/facility resources					HFACS		

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Exceeded ability							
Excessive physical training							
Executive functioning							
Experience							
Failed to adhere to brief			Known deficient individual	Rules willfully disregarded		Loosely enforced rules	
Failed to back-up (crewmember)		Crew pairings					
Failed to communicate/coordinate		Crew pairings				Communication channels	
Failed to conduct adequate brief	Guidance						
Failed to correct document in error			HFACS				
Failed to enforce rules and regulations				HFACS			
Failed to identify an at-risk aviator			HFACS				
Failed to initiate corrective action			HFACS				
Failed to prioritize attention							
Failed to properly prepare for the flight					Equipment/resource management		
Failed to provide adequate brief time		HFACS					
Failed to provide correct data		HFACS					

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Failed to provide guidance	HFACS						
Failed to provide operational doctrine	HFACS						
Failed to provide oversight	HFACS						
Failed to provide training	HFACS						
Failed to report unsafe tendencies			HFACS				
Failed to track performance	HFACS						
Failed to track qualifications	HFACS						
Failed to use all available resources					Resource management		
Failure of leadership	Leadership					Chain-of-command	
Faith							
Feedback	Guidance						
Flew an overaggressive maneuver							
"Get-home-itis"							
GPS failure			Known deficient equipment		Equipment maintenance		
Handoff failure							
Haste		Operational tempo					Operational tempo, time pressures
Heterogeneity of UAVs					Equipment acquisition		

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Human resources					HFACS		
Iconography							
Improper manning		HFACS					
Improper procedure	Training						
Inadvertent use of flight controls							
Inappropriate maneuver	Training						
Incompatible intelligence/aptitude					Human resources		
Incompatible physical capability					Human resources		
Incomplete/inaccurate understanding of autonomy's capabilities	Training						
Inefficiency						Unspoken attitudes	
Insufficient reaction time							
Intentionally exceeded the limits of the aircraft			Known deficient individual			Loosely enforced rules	
Level of autonomy							
Link loss/degradation			Known deficient equipment		Equipment maintenance		
Medical illness							
Mental fatigue							Work schedules

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Misdiagnosed emergency	Training						
Misinterpretation of traffic calls							
Misjudged distance/altitude/airspeed			Known deficient equipment		Equipment maintenance		
Mission not in accordance with rules/regulations		HFACS					
Monetary/budget resources					HFACS		
Motivation	Motivation					Working atmosphere	Incentive systems
Multitasking ability							
Nefarious Supervisor	Oversight		Known deficient individual		Human resources	Working atmosphere	
Neglect							
Not current/qualified for the mission				If still allowed to fly			
Number of UAVs					Equipment acquisition		
Obstacles in environment							
Omitted checklist item	Training						
Omitted step in procedure	Training						
Organizational culture						HFACS	
Organizational operations							HFACS
Organizational oversight							HFACS

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Organizational policies						HFACS	
Organizational procedures							HFACS
Organizational structure						HFACS	
Over-controlled the aircraft	Training						
Perceptual sensitivity							
Personal attachment							
Personality					Human resources		
Physical fatigue							Work schedules
Physiological impairment							
Physiological incapacitation							
Poor decision							
Poor technique	Training						
Predictability							
Progress tracking							
Provided inadequate opportunity for crew rest		HFACS					
Relevancy of communication/ information							
Reliability							
Reliance							
Resilience							

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Response bias							
Responsibility							
Self-medicating							
Sensor failure			Known deficient equipment		Equipment maintenance		
Serial/parallel tasks/processing							
Signal modality							
Situational awareness							
Spatial ability							
Spatial disorientation			Known deficient equipment		Equipment maintenance		
Strategy	Guidance						
Supervisor absence		Assigned work to short team	Known deficient individual		Understaffed	Attendance loosely enforced	
Supervisor excessively edits mission parameters	Guidance, oversight, training						
Supervisor loss of control			Known deficient equipment		Equipment maintenance		
Supervisor overloaded		Assigned excessive work	Known deficient procedures				

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Supervisor personal emergency							
Supervisor receives unreliable UAV state information (e.g., position, altitude)							
Task delegation	Guidance						
Task prioritization	Guidance						Standard operating procedures
Task queue availability							
Task saturation							
Task switching							
Taskload		Assigned excessive work					
Team organization		Crew pairings					
Technical Competence							
Training	Training						Standards
Transparency							
Trust in automation	Training						
Usability							
Utilization							
Vigilance							
Violated training rules			Known deficient individual	Rules willfully disregarded		Loosely enforced rules	

	Unsafe Supervision				Organizational Influences		
Causes	**Inadequate supervision**	**Planned inappropriate operations**	**Failed to correct known problem**	**Supervisory violations**	**Resource/acquisition management**	**Organizational climate**	**Organizational process**
Violation of bottle-to-throttle requirement			Known deficient individual	Rules willfully disregarded			
Violation of crew rest requirement			Known deficient individual	Rules willfully disregarded			
Visual illusion							
Visual limitation							
Working memory capacity							
Workload							
Worry							
Wrong response to emergency	Training						

G. APPENDIX I. CAUSE TO MITIGATION MAPPING.

Cause category	Workspace design	Control station design	Display design	Procedure design	Training	UAV autonomy	Decision support	Organiza-tional support	Personnel selection
Adverse mental state	Distractions	Manual control	Perception	Planning	Knowledge	Decision	Decision		
Adverse physiological state	Ergonomics	Ergonomics	Perceptual illusions		Physical fitness				
Failure to account for mental limitations			Knowledge accessibility	Cognitive offloading		Cognitive offloading	Cognitive offloading		Mental aptitude
Failure to account for physical limitations	Ergonomics	Ergonomics	Perceptual sensitivity			Sensors beyond human perception			Physical capability
Crew resource management		Communic ation tools		Crew procedures	Crew training	Autonomy as crew member		Crew leadership and promotion policy	Crew selection
Personal readiness					Knowledge of duties				Personnel
Technological environment		Controls	Display	Checklist design	Technology training	Automation	Automation	Equipment	
Physical environment	Operational setting				Operations in different environments	Sensors beyond human perception			

Cause category	**Workspace design**	**Control station design**	**Display design**	**Procedure design**	**Training**	**UAV autonomy**	**Decision support**	**Organiza-tional support**	**Personnel selection**
Inadequate supervision					Management training	Manageme nt automation		Support for management	Management selection
Planned inappropriate operations					Management training			Risk management policy	Management selection
Failed to correct known problem					Management training			Disciplinary policy	Management selection
Supervisory violations					Management training				Management selection
Resource/ acquisition management								Organization -level	
Organizational climate								Organization -level	
Organizational process								Organization -level	

SUPPLEMENT 3: TASK 4 – COMPUTATIONAL MODELING FINAL REPORT

A26 A11L.UAS.74 Establish Pilot Proficiency Requirements: Multi-UAS Components
Task 4 Final Report

August 15, 2022

NOTICE

LEGAL DISCLAIMER

TECHNICAL REPORT DOCUMENTATION PAGE

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16. Abstract The reported research and results focus on modeling a single human Supervisor monitoring and interacting with multiple UAS for a Loosely Coupled drone delivery scenario (nominal use case, unexpected events and human distractions) and a Tightly Coupled ridgeline aerial ignition scenario (nominal use case and fatigue human distraction). The IMPRINT Pro tool is used to develop each model and generate the results demonstrating how human performance changes. The model development, experimental design, and results are provided.		
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ADD	Adjust Ignition UAV(s)' Drop Density
AGL	Above Ground Level
ANOVA	Analysis of Variance
ASSURE	Alliance for System Safety of UAS through Research Excellence
ATC	Air Traffic Control
C^2	Command and Control
C^2LL	C^2 link loss
CLR	Communications Lead Request Supervisor review Surveillance UAV(s) sensor feed
CSA	Change a Surveillance UAV(s) monitoring Area
EIM	Extend Ignition UAV(s)' Mission
EITA	Emergency In the Airspace
ESM	Extend Surveillance UAV(s)' Mission
FAA	Federal Aviation Administration
GPS	Global Positioning System
HRI	Human-Robot Interaction
IMPRINT	Improved Performance Research Integration Tool
LMP	Launch Mission Plan
MAC	Mid-Air Collision
Max	Maximum
Min	Minimum
mins	Minutes
RMSD	Root Mean Square Difference
SAFTE	Sleep, Activity, Fatigue, and Task Effectiveness
secs	Seconds
SHN	Switch a Hovering Surveillance UAV to a Navigating surveillance task
SNH	Switch a Navigating Surveillance UAV to a Hover surveillance task
UAS	Unmanned Aircraft Systems
UAV	Unmanned Aerial Vehicle
UE	Unexpected Event
VSA	Verify Surveillance UAV(s) coverage Area

EXECUTIVE SUMMARY

Commercial and public safety Unmanned Aircraft Vehicles (UAVs) are currently limited by the 14 Code of Federal Regulations §107.205 prohibition on operating multiple aircraft by one person. The public as well as UAV commercial operations in applications such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, wildland fire response, and infrastructure inspections, will benefit from modification to this prohibition. The Federal Aviation Administration (FAA) Center for Excellence for Unmanned Aircraft Systems Research, Alliance for System Safety of UAS through Research Excellence (ASSURE) study that this model development and analysis supports will help to inform FAA regulations and industry standards addressing single pilot and multi-UAV operations. The provided results are designed to inform ASSURE researchers and FAA sponsors on findings from the results provided by the developed models and identified research gaps.

The A26 literature review and analysis of human factors limitations and required aptitudes, which included the development of the loosely and Tightly Coupled use cases, served as the foundation for the developed corresponding models. A Loosely Coupled use case, in which a single human supervises up to 100 homogenous UAVs conducting independent tasks (e.g., drone package delivery) for a climate-controlled workspace was modeled and analyzed. The modeled and analyzed Tightly Coupled task focused on smaller teams of heterogenous UAVs (up to 11) conducting a ridgeline aerial ignition task conducted in difficult environmental and terrain conditions. As indicated in the literature review report, no viable models for human workload for multiple UAV scenarios exist; thus, one was developed and modeled. A nominal use case was modeled for both the loosely and Tightly Coupled tasks. Three unexpected use cases, with their best-case and worst-case paths were modeled for the Loosely Coupled task, no unexpected events were modeled for the Tightly Coupled task. Distractions can also impact the Supervisor's performance. The impact of fatigue, modeled as the number of hours slept each of the last four nights, was modeled for both the loosely and Tightly Coupled tasks. An additional distraction was modeled for the Loosely Coupled task.

The models developed for both task types represent a single human Supervisor responsible for monitoring multiple UAVs. These models were used to run experiments that vary the independent variables (e.g., Max # of UAVs to be monitored simultaneously by the human Supervisor). The modeling results demonstrate a human Supervisor's ability and limitations to safely monitor multiple UAVs conducting either a loosely or Tightly Coupled task in the national airspace. Importantly, the model results inform the types of human-in-the-loop evaluations that are needed to investigate 1:N UAV systems.

Knowledge gaps related to the modeling and assessment of human performance when a single human Supervises multiple UAVs were identified. As well, expectations about UAV capabilities necessary to support such systems were identified. The analysis of the results has generated additional questions to be resolved before the FAA is able to institute substantial regulations and guidelines for 1:N UAV systems. However, the project's results provide a clearer understanding of what further insight is necessary to safely permit multiple UAVs to operate in the nation's airspace.

14. INTRODUCTION & BACKGROUND

The *assess required aptitude and human factors differences for Supervisors of multiple Unmanned Aerial Vehicles* (UAV) task (Task 4) focuses on developing example models that provide example predictions of human factors performance. Two types of tasks are modeled, the Loosely Coupled Task (i.e., the en-route portion for multiple delivery drones) and the Tightly Coupled Task (i.e., multiple robot ridge line aerial ignition). Both sets of models incorporate a nominal use case focused on Supervisor workload. The Loosely Coupled Task also developed models and analyzed the associated results from three exemplar unexpected events and two distraction event use cases. Only one distraction event use case was modeled and analyzed for the Tightly Coupled Task. The literature review (Task 1), assessment of the human factors limitations (Task 3), and information collected from interviews with industry and government subject matter experts informed the developed models. The approach towards achieving this task was the development of the nominal use case model, including investigating potential workload models, conducting associated experiments, and data analysis. The same steps were repeated for both task types as well as for the unexpected event and distraction use case models.

The specifics of the selected modeling tool are provided in Section 15. A general summary of the Loosely Coupled Task (Section 15.1.1) and Tightly Coupled Task (Section 15.1.2) are provided prior to a detailed discussion regarding the options for workload function (Section 15.2). The document presents the Loosely (Section 16) and the Tightly (Section 17) Coupled Tasks' individually. Both task specific sections begin with the details of the workload model's log rate analysis. The Loosely Coupled Task section is decomposed to present the following by the nominal use case, unexpected event use cases, and the distraction use cases: model development details, experimental design, results, and discussion. This same general organization is applied to the Tightly Coupled Task. A conclusion addresses gaps in knowledge to support identifying the human factors limitations to supervising multiple UAVs.

15. MODELING TOOL – IMPRINT PRO

While a number of cognitive modeling tools are available, the Improved Performance Research Integration Tool (IMPRINT) Pro (Archer et al., 2005, Plott 2019) was used for developing the models for the A26 effort. IMPRINT Pro was developed by the U.S. Army Research Laboratory, Human Research and Engineering Directorate to support manpower and personnel integration and human systems integration. IMPRINT Pro incorporates network modeling and can accommodate dynamic, stochastic, discrete events. The resulting models can help develop system designs by modeling the interactions between humans and systems. IMPRINT Pro can inform system requirements; identify human performance driven system design constraints; and evaluate the potential personnel training capabilities and manpower requirements to effectively operate and maintain a system under environmental stressors. A number of plugins can provide additional capabilities, including unmanned systems, fatigue, and training effects. IMPRINT Pro has been used to model human interaction with manned aircraft and robotic systems (e.g., Harriott et al. 2013, Heard and Adams 2019, Heard et al. 2019, Schneider and McGrogan 2011).

IMPRINT Pro does not actually develop a model representing a user interface, but rather makes assumptions about the types of potential interactions a user may have with the respective system. As such, the developed models do not assume particular user interface designs, but rather consider a set of the potential interactions the Supervisor may have with a Command and Control (C^2)

station. The developed models focus on the predominant human factors results developed for A26 via Tasks 1 and 3.

More specifically, IMPRINT Pro permits the simulation of human behavior for a variety of conditions through the representation of task and event networks. IMPRINT Pro includes a number of pre-defined human performance moderators (e.g., workload) and permits the incorporation of those performance moderators not already pre-defined via the User Stressors module (Plott 2019). IMPRINT Pro provides the capabilities to set up complex task networks, model workload, and incorporate other human performance moderators (e.g., heat, cold, protective gear, sleepless hours, noise, whole body vibration, military rank, and training). Any human performance moderator can be added to the model via the User Stressors module, but the workload models are already integrated into the system (Plott 2019).

Models built in IMPRINT Pro use atomic task time, task ordering, number of crew members, training, equipment, stressors, and operator mental workload for each task as the model's inputs. Model outputs include values that measure mission success, mission time, and an individual's workload per unit of time. The stressors contained in IMPRINT Pro include a variety of human performance moderator functions (e.g., ambient temperature and humidity, whole body vibration, and noise level). Stressors can affect the timing and accuracy of tasks, which affects the number of tasks that can be accomplished in a certain amount of time by an individual and that individual's overall mental workload level during a mission.

Each modeled task requires a specified running time, title, and workload values. Each workload channel has a range of associated values. The Auditory, Cognitive, and Fine Motor channel values range from one to eight, the Visual and Gross Motor channels' range from one to seven, and the Tactile and Speech channels' ranges are from one to five. IMPRINT Pro provides task timing guidelines based on micromodels of human behavior developed from published psychology, human factors, and military user evaluation data (e.g., walking ten feet takes approximately 1.9 seconds) and task demand guidelines based on task type (e.g., walking on level ground is assigned a Gross Motor demand value of 1.0) (Plott 2019). Upon running the model, the assigned workload values for each task are in effect during the entire running time for each atomic task. Calculating the workload for an entire task or function requires weighting each task's workload values for the portion of time the specific task takes in the function.

Predicting workload requires modeling the task's subtask individually, where each subtask has an associated timing. IMPRINT Pro provides micromodels of human behavior to help determine task timings using established human factors data sets. For example, if a model contains a task for a human to walk 10 feet, the micromodels calculate the average time a human takes to walk that distance. The task timings were determined by estimating task times and using IMPRINT Pro's built-in micromodels of human behavior for tasks (e.g., speech). The secondary tasks were added via IMPRINT Pro's scheduled task feature.

The models also require the assignment of demand values. IMPRINT Pro provides guidelines for assigning tasks' demand values, which combines values on seven workload channels: Auditory, Visual, Cognitive, Fine Motor, Gross Motor, Tactile and Speech workload. The values on each channel were assigned based upon channel guidelines. Using the previous example of walking 10 feet, the Gross Motor workload value is based on walking on even terrain and there may be a visual component for looking where one is going, or an auditory component for listening for directions, depending on the modeled situation. The composition of each task is determined by the modeler.

The probability of success is the input. When the model executes, the
task executes successfully based on the expected task accuracy. If the task fails, the modeler specifies what happens (i.e., a different task executes, the model ends, or nothing happens). Workload for a given set of tasks can be computed via a time-weighted average of task demand values.

15.1. Use Case Overviews

15.1.1. Loosely Coupled Use Case

A detailed exemplar nominal Loosely Coupled use case focused on the delivery drone application was developed as part of Task 3 (Task 3 Final Report, Appendix B). The nominal use case incorporates a single Supervisor being responsible for a number of highly autonomous delivery UAVs in an assigned region where each UAV has a designated delivery goal. The Supervisor's primary responsibility is to monitor the UAVs in a controlled office environment using a C^2 station. This task is a Loosely Coupled task because the UAVs have independent goals and are not required to coordinate or cooperate in order to achieve their individual delivery goal. Further, the Supervisors are expected to have some training, but do not have training at the level of a crewed aircraft pilot or air traffic controller. The focus on the use case models is the enroute portion of the deliveries, as such no other flight phases are modeled.

Exemplar unexpected and distraction events were detailed in the Task 3 report. Most unexpected events were detailed as being handled by the autonomy, being handled by the Supervisor, or being handed off to an Unexpected Event Supervisor. Three unexpected events and two distraction events are modeled.

15.1.2. Tightly Coupled Use Case

The detailed exemplar nominal Tightly Coupled use case focused on the ridgeline aerial ignition for wildland fire response was developed as part of Task 3 (Task 3 Final Report, Appendix C). The ridgeline aerial ignition use case assumes a small team of humans are responsible for deploying 4-10 UAVs in a very rugged, remote wilderness location. The general purpose of ridgeline aerial ignition is to burn ground fuel ahead of a wildland fire in order to keep the fire from jumping the ridgeline and continuing to grow. It is noted that many areas in which this type of task are conducted will not have reliable communications (e.g., cellular, radio frequency), including communications to the incident commander.

The use case assumes there is a UAV Supervisor with a handheld C^2 station, a communication leader, and a logistics coordinator. This use case requires two types of UAVs: (1) Ignition UAVs that drop spheres that ignite ground fuel, and (2) Surveillance UAVs that provide sensor streams of the Ignition UAVs, the area, the fire's progress, etc. The Surveillance UAVs replace the need to position human wildland firefighters throughout the mission area to monitor the fire activities. This use case is considered Tightly Coupled because the Ignition UAVs have a low level of coordination to ensure that the desired area coverage is achieved for the controlled burn. Similarly, the Surveillance UAVs coordinate to ensure that there is sufficient coverage of the area.

While the Task 3 Report's narrative is divided into pre-deployment and mission deployment phases, only the mission deployment is modeled. Even though the deployment depends on the three individuals, only the Supervisor is modeled. The Task 3 Report outlined a number of unexpected and distraction events; however, only the fatigue distraction event will be modeled. Fatigue is expected to be a much larger factor for wildland responders given the very physical, harsh working conditions, long shift hours, high stress, and varying off-shift rest facility conditions.

15.2. Workload Model Option Analysis

The IMPRINT Pro tool was developed for different purposes than supervising multiple UAVs, and uses a linear model of overall workload. This linear model results in the same workload being added for each new UAV the Supervisor is assigned, irrespective of the mission domain. However, based on practical field work (Atherton, 2022), this linear overall workload model is not representative of the expected actual Supervisor workload for the use cases associated with A26. As such, the team investigated how to derive a relevant workload model. IMPRINT Pro is not unique in this limitation when attempting to model and assess human factors performance as the number of UAVs are scaled.

The A26 literature review (Task 1) determined that the majority of the related human subject evaluations were conducted in simulation, most of which do not provide the necessary kinematics and dynamics for the UAVs, and as such often lack ecological validity. Further, the majority of the evaluations focus on the collection of subjective metrics, rather than objective metrics that can be used to adequately develop a workload model for the A26 effort. Specifically, tasks with larger numbers of UAVs (>10-15) are not represented in the literature with the data necessary to develop an appropriate workload model for either the loosely or Tightly Coupled use cases. Further, in addition to the insufficient number of vehicles deployed and the subjective data collection issue, reported experiments also often conducted trials that are too short in duration to adequately model workload. Given these A26 Task 1 findings, the team began investigating alternative literature in order to determine if a relevant model was available for this modeling effort.

The Human-Robot Interaction (HRI) field has investigated humans interacting with multiple robot systems for over thirty years; however, the majority of the human subjects evaluations also suffer from the earlier cited limitations and likewise do not provide a clear workload model to be used for A26. There are, however, important lessons that can inform the A26 modeling effort based on the HRI field.

An important relevant paper in the HRI field investigated the premise that if there are n robots, the human's workload is either $O(n)$[1], where workload increases linearly with each additional robot or the human's workload is $O(1)$, or constant, in other circumstances where additional robots do not increase workload (Lewis, 2013). Unfortunately, at the time Lewis' manuscript was prepared, ground robots were the predominate robot morphology investigated and researchers were not conducting human subjects evaluations with actual UAVs, or even a single UAV. While there are some references to simulated UAVs, Lewis' primary context was ground robots that suffer from more reliability issues and subsequently require significantly more oversight by and interaction from the human.

Assuming n UAVs and $O(n)$ workload, based on Lewis' manuscript, then the UAVs perform independently, but identical activities, and the human devotes the same level of attention to each UAV in turn. This definition assumes the human has to take an action with each UAV and the human's work will be linearly proportional to the number of UAVs. This definition is applicable when the UAV must perform one or more independent tasks; however, in the context of Lewis'

[1] The $O(x)$, or Big O notation is common in mathematics and computer science to describe limiting behaviors of a function when the argument tends towards a particular value or infinity.

manuscript, independent tasks appear to be *n* different types of tasks.
The Loosely Coupled use case requires up to 100 UAVs, but all UAVs are performing the same task type, the enroute package delivery. The Tightly Coupled use case incorporates two types of tasks with a much smaller number of UAVs (e.g., up to eleven UAVs total), the ignition task for which up to four Ignition UAVs drop ignition spheres to start the controlled burn, the Surveillance UAVs (up to three) that monitor the ignition area and a pool of extra Ignition (up to two) and Surveillance (up to two) UAVs that replace deployed UAVs due to power depletion.

It is assumed by Lewis that monitoring robots for problems or failures or making necessary adjustments to the vehicles will be $O(n)$, which was a valid assumption at the time the manuscript was written. The Loosely Coupled scenario has *n* UAVs being monitored, but the monitoring task focus differs from Lewis' assumptions. For example, the primary Loosely Coupled scenario task is not to make adjustments when a UAV encounters an unexpected event, since many of those events will generally be handled autonomously or by a specialized unexpected event Supervisor (not modeled as part of A26). Similarly, the modeled Tightly Coupled scenario has multiple vehicles, although many fewer than the Loosely Coupled task, and also relies heavily on autonomy. The Supervisor does make a few mission modifications (e.g., an Ignition UAV's drop density, a Surveillance UAV's focus), but interventions are few[2]. This aspect completely changes Lewis' assumptions when applied to the A26 modeling efforts, and; thus, makes a linear model for workload seem less appropriate.

Lewis considers human judgement or decisions (e.g., target identification) to be $O(n)$. However, the Loosely Coupled scenario's human judgement and decisions, especially in the nominal case, are simpler and not nearly as cognitively taxing, as the human Supervisor typically cannot optimize most aspects of the UAV or task performance. Human judgement and decision making do play a more substantial part in the nominal Tightly Coupled scenarios that does permit a few basic mission modifications. These mission modifications can be for a group of vehicles (e.g., changing the drop density for all or some Ignition UAVs, extending the mission for some or all UAVs), while some modifications may be UAV specific (e.g., requesting a Surveillance UAV hover in place or change its surveillance path). These types of modifications will require the Supervisor to conduct a conversation with the broader team, adjust the mission plan followed by validating and verifying the mission plan adjustments before issuing those modifications to the respective UAV(s). While these types of modifications may imply on $O(n)$ complexity, the frequency of these tasks, in addition to the group mission plan nature of some modifications, will limit the necessity of individual modifications to individual UAVs by a given Supervisor. As a result, the $O(n)$ *likely* will provide an over estimation of the workload and complexity for the modeled Tightly Coupled use case.

The constant notation, $O(1)$, in the context of Lewis' manuscript, assumes that a single command issued or action taken by the human results in tasking an arbitrary number of fully autonomous robots. Importantly, this notion decouples the number of actions taken by the human from the number of robots. While this assumption is applicable to the Loosely Coupled scenario with a very large number of UAVs, a single action to task all scenario UAVs is unlikely given the nature of the task and mission parameters. However, this notion does have applicability to the Tightly Coupled scenario, in which execution of mission plan nodes allows for multiple UAVs,

[2] It is important to note that no unexpected events are modeled and only the Fatigue distraction event is modeled as part of A26 for the Tightly Coupled scenario, and additional analysis of those events and the impacts on workload model need to be considered as future work.

irrespective of type, to be tasked simultaneously. A nuance of the Tightly Coupled use case is the two UAV types and their associated specific behaviors; however, both of these subgroups can be tasked as a group by UAV type. Even though this group-level tasking is possible, it must also be noted that not all Supervisor tasking or actions will be applied to multiple UAVs.

Cascading robot demands requires more human effort and is classified as $O(>n)$ by Lewis. Cascading demands within Lewis' context represent robots' tasks that are dependent on one another. The robots in Lewis' contexts are executing complex tasks that are difficult for a human to directly control, or teleoperate. The exemplar nominal Loosely Coupled scenario will not encounter such cascading demands; however, if multiple UAVs have simultaneous Unexpected Events (UEs), then there is a possibility of cascading demands occurring, although unlikely. However, the A26 team has assumed that the Loosely Coupled scenario incorporates at least one UE Supervisor to whom UAVs experiencing UEs can be handed-off to. The UE Supervisors (not modeled as part of A26) exist specifically to handle the overload placed on the Supervisor due to UEs in general, which will include workload demands from cascading multiple concurrent UEs. The modeled example Tightly Coupled scenario also does not incorporate cascading demands; however, it is possible that such demands can arise with more complex instances of this use case. Given the simplistic nature of the current Tightly Coupled use case and the unlikelihood of cascading demands occurring within this context, the modeling of cascading demands is left as future research and is; thus, out of scope of A26.

The Loosely Coupled and Tightly Coupled scenarios are neither $O(n)$ or $O(1)$. Workload for either scenario is not linear, $O(n)$ since for every UAV added to the Supervisor's responsibility, workload does not increase equally for each additional UAV. Nor does either scenario have constant workload, $O(1)$. The addition of each new UAV for the Loosely Coupled scenario does change workload; thus, the workload does not remain constant. The Tightly Coupled scenario does permit the Supervisor to issue a single command to task an arbitrary number of UAVs, but the scenario also does contain human judgement and decision making, as well as situations in which a single UAV may require attention.

The notion of *fan-out* represents the number of robots a single human can command (Goodrich 2010). Fan-out relies on the ratio representing how many other robots the human can manage, or interact with, while one robot is being neglected. The time that a single robot can be neglected is called *neglect time*. Based on the concept of *neglect tolerance,* Lewis concluded that one can improve multiple robot team performance by minimizing or eliminating competing tasks for the human and reducing demands, like task switching. This conclusion implies that neglect time assumes that during every X time interval, the human has to do something for a particular robot and consequentially cycles through each robot being supervised. This cycling through robots is infeasible with very large numbers of robots and Adams' field work has demonstrated it is not necessary. The exemplar nominal Loosely Coupled scenario may require the Supervisor to do simple high-level tasks (Cummings and Guerlain 2007), such as visually scan the status of each UAV being supervised, and if a UE occurs, to possibly take action. The example Tightly Coupled task has similar demands, but it also incorporates the need to modify the mission plan. The plan modifications (e.g., adjusting Ignition UAV drop density) does create some task switching, but that task switching will be reduced. As such, fan out is not directly applicable to either the Loosely Coupled or the Tightly Coupled use cases.

Finally, the field of visual multiple object tracking (i.e., the perception of multiple objects and tracking them) was considered another potentially relevant domain from which to draw when modeling workload in to the A26 use cases. Visual multiple object tracking is relevant if one assumes that the Supervisor is actively visually scanning the C^2 station and all UAVs currently under the Supervisor's responsibility. While an investigation into the general visual perception of multiple objects found no workload models; however, this investigation led to the notion of visual scan paths that proved to be more fruitful.

No human subjects evaluations related to multiple UAV Supervisor's visual scan paths were identified; however, some research was identified exploring these paths in the Air Traffic Control (ATC) domain, which can be considered a close proxy of the modeled UAV tasks. The most common scan patterns used by ATC are circular and linear (McClung & Kang, 2016). A circular pattern tends to move clockwise or counterclockwise, following the edges of the display, and typically ends adjacent to where it began. A linear pattern tends to zig-zag from one side or corner of the display to the opposite side or corner. The circular pattern is more common, although there is some evidence that scan paths may become more linear as the number of vehicles increases. Unfortunately, despite the identification of these potentially relevant visual scanning patterns, the related ATC evaluation manuscripts did not report any explicit numeric information regarding workload. However, these ATC manuscripts did at least identify a related metric: *visual scan time*, that can be leveraged for modeling the visual scan paths.

McClung and Kang (2016) did observe individual differences in ATCs' strategies for completing a global scan of the display. Some participants quickly scanned every item in the display, followed by local scans of visual groups to evaluate possible conflicts (see Kang & Landry (2015) for a more thorough treatment of visual groups). Other participants incorporated local scans into their global scan, essentially bouncing around comparisons of visual groups until the full display was scanned completely.

McClung and Kang (2016) evaluated scan times for displays for 12, 16, and 20 vehicles, the most closely related research results. The results found that the scan times for those vehicle counts were a linear 1.4 seconds per vehicle. Through extrapolation of the scan times provided in McClung and Kang, a constant, with respect to the number of vehicles, results in a scan rate of 1.4 seconds per vehicle. The A26 models used this 1.4 second scan rate per UAV as both use cases' modeled scan rates. The models' implemented visual scan duration is dependent on the number of vehicles the Supervisor is scanning: *total visual scan time = number of UAVs * 1.4* seconds. If there are 20 UAVs, the total visual scan time is 28 seconds (i.e., 20 UAVs * 1.4 seconds = 28 seconds). If the number of UAVs increases to 50 UAVs, then the total visual scan time is 70 seconds (i.e., 100 UAVs * 1.4 seconds = 70 seconds).

The visual scan path research is relevant to deriving the timing associated with tasks, as the Supervisor's primary responsibility in either scenario is to monitor the deployed UAVs, while searching for visual anomalies across the multiple UAVs (A26 makes no assumptions about user interface design, but it is reasonable to assume that the UAVs will have some visual representation on the C^2 station). Fundamentally, the example nominal scenarios require the Supervisor to visually search for anomalies. The visual search literature generally focuses on understanding how the human brain processes visual information (Wolfe 2020, Wu and Wolfe 2018), and provides models regarding how the human brain conducts visual searches (Wolfe 2021). The literature also investigates humans' abilities to detect multiple events simultaneously; however, much of the research focuses on unique visual items (Wu and Wolfe 2016, Wu et al. 2017). However, the

Guided Search 6.0 visual model (Wolfe 2021) incorporates hybrid
guided visual search scenarios that are more representative of the A26 use cases. While the visual search literature is useful for structuring the timing of the tasks to be modeled for A26, fundamentally, none of the visual search and event detection literature focuses on workload models that can be used directly for the A26 modeling efforts.

The take away is that monitoring, as represented for the loosely or Tightly Coupled tasks, likely has an efficiency between $O(1)$ and $O(n)$. There is evidence in the literature supporting a logarithmic (i.e., $O(log\ n)$) visual search time functions of set-size (Wang, Lleras & Buetti, 2018). Assuming that workload varies linearly in relation to visual search time, a logarithmic function is appropriate for modeling workload given:

$$w = a + b \ln n, \tag{1}$$

where w is the workload from monitoring n UAVs, a is associated with the workload from monitoring a single UAV, and b is the rate at which workload grows as additional UAVs are added.

The workload for a single UAV, a, can be estimated using IMPRINT Pro's existing workload rubrics. The rate parameter, b; however, needs to be estimated based on other sources. One means of deriving this estimate is to rescale a logarithmic visual search time function of set-size, which can be achieved by factoring Equation 1:

$$w = a\left(1 + \frac{b}{a} \ln n\right),$$

and substituting a new parameter c for the quantity $\frac{b}{a}$:

$$w = a(1 + c \ln n). \tag{2}$$

The fundamental difference between Equations 1 and 2 is that b in Equation 1 has dimensions [workload items^{-1}], whereas c in Equation 2 has dimensions [items^{-1}]. This difference allows the logarithmic rate to be estimated directly from set-size gradients measured in units other than workload (e.g., search time). However, it is necessary to fit c for each of the Loosely Coupled and Tightly Coupled nominal use cases. The details of the selected c value for each use case model are detailed in Sections 16.1 and 17.1.

16. LOOSELY COUPLED (DELIVERY DRONES) USE CASE MODEL

The Loosely Coupled use case was modeled for an exemplar nominal situation (i.e., nothing goes wrong), three unexpected events, and two distraction events across a number of independent variables, including the number of vehicles supervised. The models focus on the enroute portion of the use case only.

16.1. Workload Model: Log Rate Analysis

As noted in Section 15.2, it was necessary to define an appropriate workload model. The workload equation (Eq. 2) was used for model development, but requires the specification of the log rate. The team conducted an analysis of various log rates using the nominal use case, as shown in Figure 4. Based on Adams' prior objective workload estimation work (Harriott et al. 2015, Heard et al. 2019) and her efforts with the DARPA OFFSET program (Atherton 2022), the logarithmic rate for the Loosely Coupled Task model trials was set to 0.5.

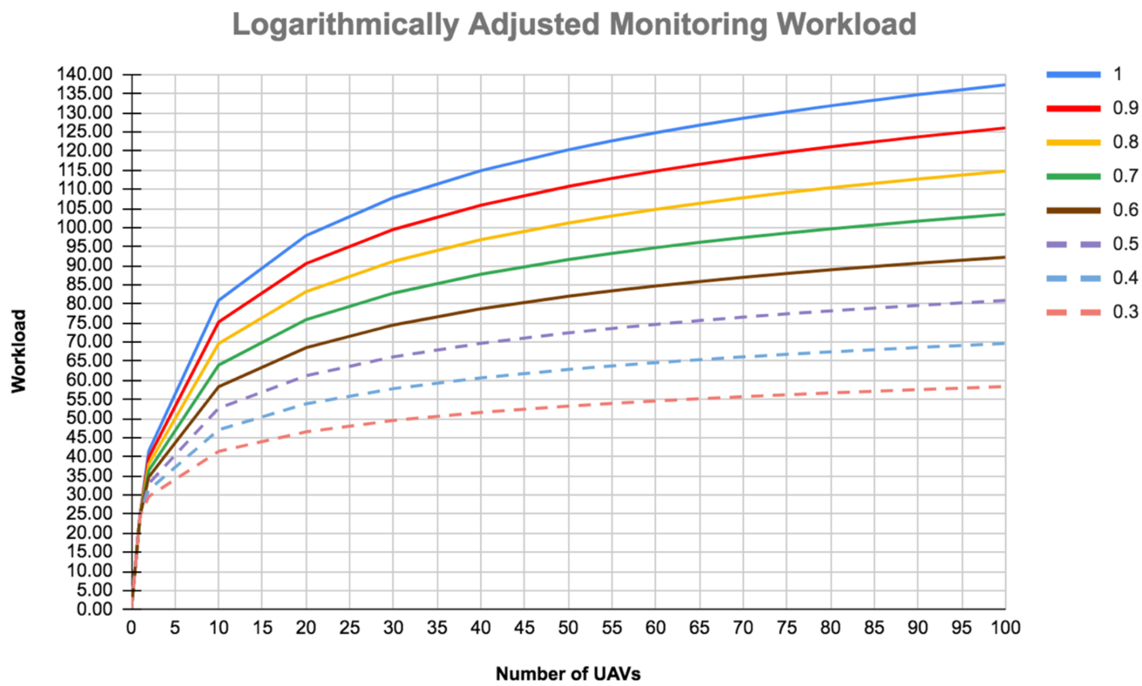


Figure 4. An analysis of resulting workload by the number of UAVs for the nominal Loosely Coupled use case using the logarithmic workload model with potential rates from 0.3 to 1.0.

16.2. Nominal Use Case

The nominal use case was developed using feedback from industrial partners and covers all flight phases, but based on guidance from the FAA sponsor, the reported modeling effort focused on en-route operations in which a single human, the Supervisor, is responsible for multiple UAV delivering packages. The nominal use case's decision tree is provided in Appendix B.

16.2.1. Model Development

The nominal use case model assumes that there is a single Supervisor responsible for managing multiple UAVs during a shift that also includes scheduled breaks. The nominal use case model does not incorporate any unexpected events with the UAVs, in the control room, or in the airspace, nor does the model include any human fallacies, such as distractions. The model does represent the tasks required for the Supervisor to monitor multiple UAVs entering and leaving the en-route and return after package drop-off flight phases of a drone delivery.

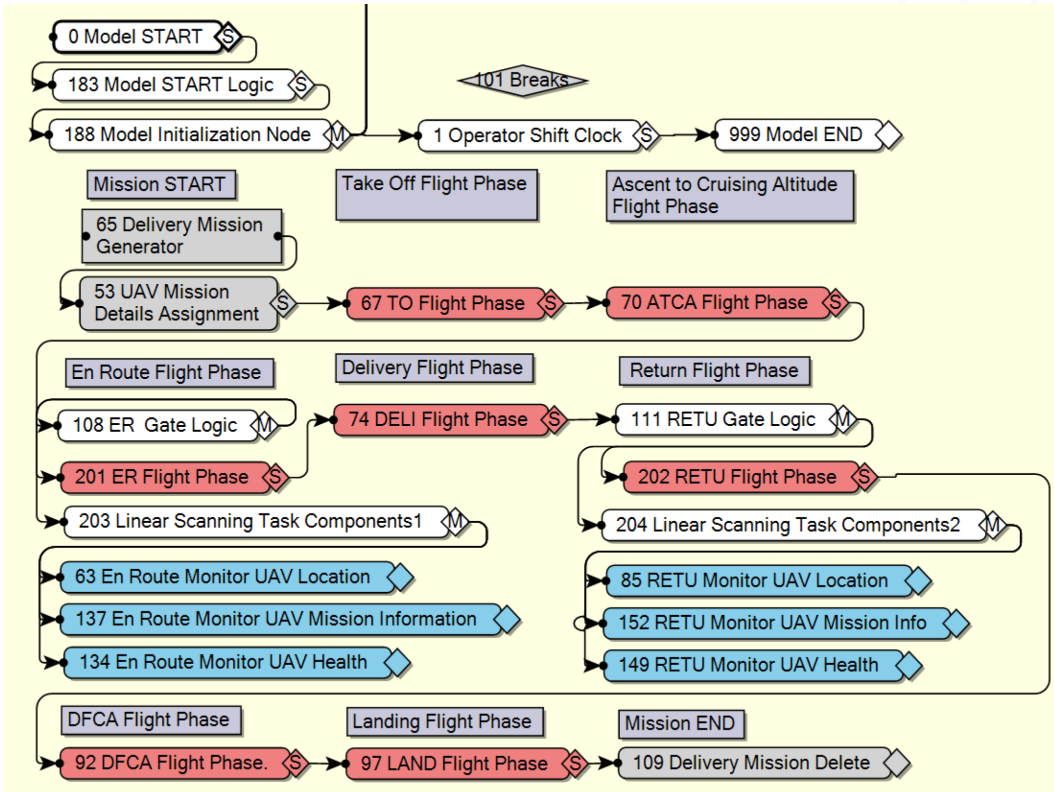


Figure 5. Screenshot of the Nominal Use Case Model within IMPRINT Pro.

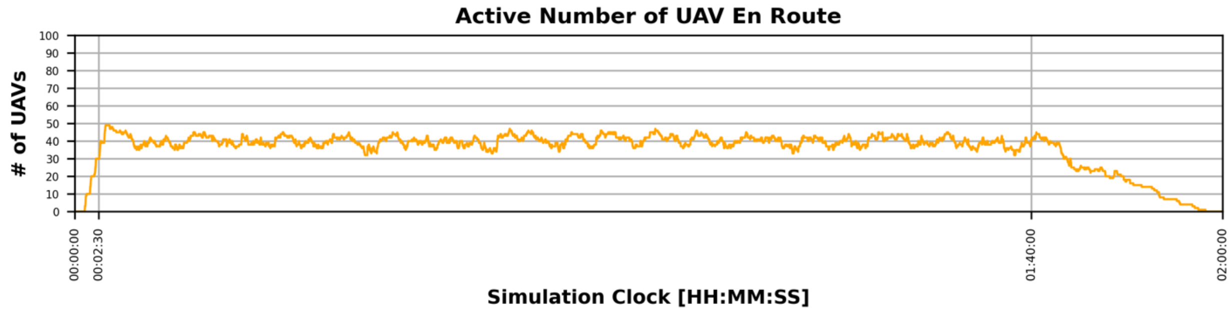
IMPRINT Pro permits the simulation of human behavior for a variety of conditions through the representation of task and event networks. The nominal use case was decomposed into atomic tasks, which are represented in the IMPRINT Pro model. Each atomic task requires specification of the time the task requires to complete and the associated workload values for the required workload components (i.e., cognitive, visual, speech, auditory, gross motor, fine motor and tactile). The individual workload channel value assignments, combined with the logarithmic model (described in Section 16.1) result in the overall workload value for a particular atomic task. Each workload channel has an independent value scale and IMPRINT Pro predefined guidelines for choosing an associated value. When the model executes, assigned workload values for each atomic task are in effect during its entire execution.

The IMPRINT Pro high-level nominal use case model is provided in Figure 5. The UAVs are simulated progressing through the different flight phases of their own delivery mission, and the Supervisor's workload is updated as the number of UAVs in the en-route outward bound (i.e., travel to the package drop-off location) and return flight phases (these two flight phases are generally referred to as en-route throughout this document) occur. UAVs are generated starting in the takeoff flight phase and travel from flight phase node to flight phase node. The duration for which the UAV stays in each flight phase is determined during mission generation. Each UAV's mission duration is a time between 5 minutes (mins) and 20 mins, determined by the UAV Mission Duration distribution in Table 47. Once the UAV reaches the en-route outward bound or return flight phases, the components of the monitoring task are activated and the Supervisor incurs the workload of being responsible for the UAV. Multiple UAVs can be in the same flight phase node simultaneously; therefore, the Supervisor's workload increases as a function of the number of UAVs currently in the en-route outward bound and return flight phase nodes.

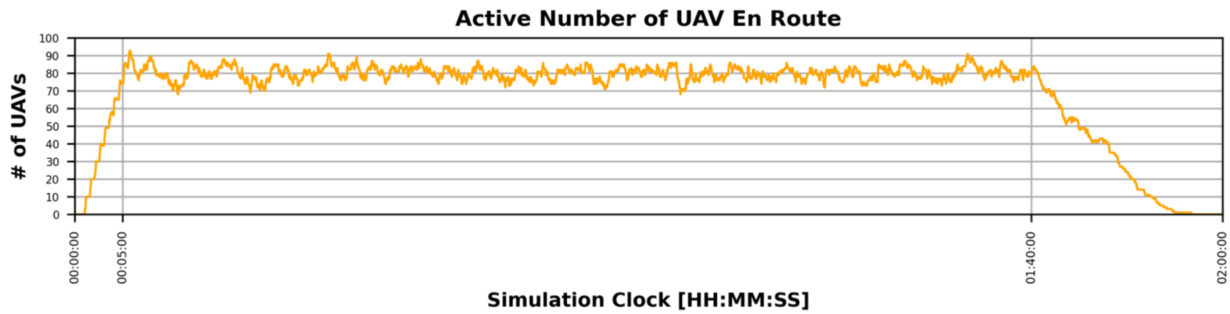
The model includes multiple states representing different stages of the Supervisor’s shift. The *Ramp up* state occurs when the Supervisor first comes on shift, and occurs each time the Supervisor returns from a break. The Ramp up state gradually increases the number of UAVs the Supervisor is responsible for based on the values used for Ramp up specific independent variables for each experiment.

The duration of the *Ramp up* stage is based on the three independent variables: the Maximum (Max) number (#) of UAVs, the Time to Launch a Wave of UAV(s), and the Max # of UAV(s) that can be Launched Simultaneously. Typically, a low Max # UAVs paired with a high Max # of UAVs that Launch Simultaneously results in short Ramp up durations. Meanwhile, a high Max # UAVs paired with a low Max # of UAV(s) that Launch Simultaneously results in a longer Ramp up duration. For example, if the Supervisor is to monitor at most 50 UAVs, and the Ramp up launches ten UAVs simultaneously and the time to launch a wave is 30 seconds, then 2.5 mins is required to launch the vehicles, as shown in Figure 6(a). Using the same parameters to launch 100 UAVs will result in a total Ramp up duration of 5 mins, as shown in Figure 6(b). The short Ramp up period ensures that both trials launch the majority of their UAVs begin returning. However, if the Ramp up for 100 UAVs only launches one UAV at a time using the same 30 second time to launch a wave, then the Ramp up duration will be 50 mins. Since the Ramp up duration is longer than the maximum delivery mission (i.e., 20 mins), UAVs begin returning from their delivery mission before the Ramp up period is completed, as seen in Figure 6(c). While this figure represents the extreme case, Ramp up periods greater than five mins can experience previously launched UAVs returning prior to the completion of the Ramp up. The Ramp up state is considered complete once the Max # of UAVs has been launched.

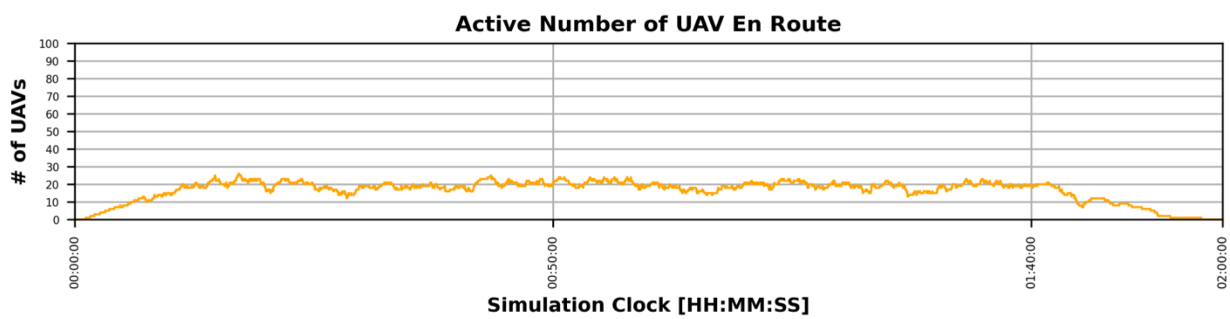
The *Steady state* occurs once the Ramp up period is completed and the Supervisor is monitoring up to the maximum defined number of UAVs, as defined for each experiment. During this time, the Supervisor is responsible for the UAVs that are cycling in and out of the en-route of the delivery mission. The en-route outward bound phase assumes that the UAV flies out to the delivery location and then returns to the launch area. It is assumed that the delivery occurs, but this aspect was considered out of scope by the FAA and is not included in the model of Supervisor performance. When a UAV takes off and is assigned to the Supervisor, it is generally assumed that this Supervisor will monitor the UAV throughout the entire en-route mission phases.



(a) The first work period for a trial with a maximum of 50 UAVs, a time to launch a wave of 30 secs and a launch wave size of 10 UAVs. The first gray line represents the end of the Ramp up period (2.5 mins), the second time stamp line represents the start of the Ramp down period.



(b) The first work period for a trial with a maximum of 100 UAVs, a time to launch a wave of 30 secs and a launch wave size of 10 UAVs. The first gray line represents the end of the Ramp up period (5 mins), the second time stamp line represents the start of the Ramp down period.



(c) The first work period of a trial with a maximum of 100 UAVs, a time to launch a wave of 1 sec and a launch wave size of 1 UAV. The first gray line represents the end of the Ramp up period (50 mins), the second time stamp line represents the start of the Ramp down period.

Figure 6. The number of UAVs being monitored by the Supervisor during the first work period from trials with three sets of independent variables. The plots demonstrate the differences in the number of vehicles supervised during the Ramp up (between zero and the first gray line), Steady state (between the two gray lines) and Ramp down (final gray line and right of chart).

During the Steady state, the Supervisor can only be assigned up to the experiment's Max # of UAVs and no more at any given time point. Typically, due to the different individual UAV delivery mission durations, the Supervisor frequently has a stable number of UAVs below the maximum during this state, as seen in Figure 6. A UAV completes its en-route phase when it returns to the launch/landing area, at which time it is unassigned from the Supervisor automatically. As the

UAVs complete their missions, the Supervisor is assigned new UAVs
at a rate dictated by the Max # of UAV(s) that Launch Simultaneously and the Time to Launch a Wave of UAV(s). This approach ensures that a Supervisor cannot be overwhelmed by receiving an unexpected spike in new UAVs to supervise; however, this approach rarely results in a Supervisor monitoring the Max # of UAVs. The Steady state Max # of UAVs will be close to the maximum in cases where the Time to Launch UAVs and the Max # of UAV(s) in a Launch Wave result in a shorter Ramp up period, such as in Figure 6(a) and (b). However, when there is a larger number of maximum UAVs to be supervised (e.g., 100 UAVs) combined with lower numbers of Max # UAV(s) to Launch Simultaneously (e.g., 1 UAV) over longer launch times (e.g., 30 seconds), the system assigns a substantially lower number of UAVs. Well below the total number of UAVs are assigned to the Supervisor during the shift, as shown in Figure 6 (c).

The *Ramp down* state occurs when the Supervisor is approaching a designated break period or the end of a shift. Ramp down begins 20 mins before either the start of a scheduled break period or the end of a shift. The maximum delivery mission duration allowed in the model is 20 mins. Further, it is assumed that the Supervisor will supervise all UAVs until their mission is completed. Therefore, tying the Ramp down to the maximum possible UAV en-route period ensures that the Supervisor has completed supervising all assigned UAVs by the end of the work period. Additionally, during the Ramp down period the only new UAV deliveries generated and assigned to the Supervisor are those that can complete their delivery mission within the Ramp down period, which is visible in Figure 6(a) and (b), where there is a slight increase in the number of assigned UAVs. All of the Supervisor's ongoing UAV deliveries continue as usual; however, over time, the number of UAVs in the air gradually decreases as the remaining UAVs finish their deliveries. The gradual decrease in UAVs continues until there are no active deliveries, which always concludes before the end of the Supervisor's work period. Since the Supervisor is only assigned new UAVs that can complete their delivery mission prior to the end of the work period, it is possible that all assigned UAVs will complete their missions and the Supervisor will no longer have UAVs to supervise prior to the completion of the work period. This result can occur regardless of the number of UAVs the Supervisor monitors during the work period, as shown at just before the end of the work period in Figure 6(b) and (c). The start of the break period or end of the shift mark the end the of the Ramp down state.

The A26 modeling effort focuses specifically on the en-route flight phases; however, the IMPRINT Pro model incorporates the take-off, ascent to cruising altitude, delivery, return to home, descent from cruising altitude, and home landing flight phases. Each of these phases have been modeled with a pre-defined duration, as provided in Table 46.

Table 46. Statically modeled flight phases and the associated durations.

Flight Phase	Duration
Take-off	10 secs
Ascend to Cruising Altitude	30 secs
Package Delivery	60 secs
Descent from Cruising Altitude	30 secs
Landing	10 secs

IMPRINT Pro facilitates modeling stochasticity via the usage of probability distributions as functions. The Loosely Coupled nominal use case model uses the functions to add variability in the selection of a UAV's mission's duration. During a UAV's delivery mission generation, the mission's duration is set based on a discrete uniform distribution that randomly selects a value between 5 and 20 mins. The static flight phase durations in Table 46 are combined with the variable mission duration, which results in varying both the en-route outward bound and return flight phase durations. The minimum (Min) and maximum (Max) values used for the mission durations and en-route phases are provided in Table 47.

The duration of the en-route outward bound and return flight phases are selected in a different manner. Assuming nominal flight conditions, the en-route outward bound and return flight phases are equivalent; however, realistically, UAVs will fly slightly faster or slower in either flight phase. Therefore, in order to account for this difference in flight phase durations, the combined duration of the en-route outward bound and return flight phases is determined by subtracting the durations of the other flight phases from the overall UAV mission duration. A discrete uniform distribution is used to select a value between 48% and 52%, which represents a percentage that is applied to the combined duration of the en-route flight phase. The resulting value is considered the duration of the en-route outward bound flight phase. The duration of the en-route return flight phase is determined by subtracting the en-route outward bound flight phase duration from the combined duration of the outward bound and return flight phases.

Table 47. Usage of distributions within nominal use case model.

Distribution Purpose	Distribution Type & Parameter Values	Min Value	Max Value
UAV Mission Duration	DiscreteUniform (300, 1200)	300 secs (5 min)	1200 secs (20 min)
En route UAV: Outward Bound+ Return Flight Phase Duration	*N/A*	160 secs (~2.6 min)	1060 (~17.6 min)
Percentage of Total En-Route Duration Allocated to Outward Bound flight phase	DiscreteUniform (48, 52)	48%	52%

Once the model completes execution, the model outputs the values for each independent variable and a list of the completed tasks, long with each atomic task. The results include the time required to complete the task and the associated workload value for each workload channel, as well as an overall workload value. The model output also includes a flight phase history for each modeled UAV. The results are used to generate a graph of the overall workload over the entire en-route nominal use case. The Figure 6 trials' corresponding overall workload is provided in Figure 7. This figure also demonstrates the corresponding increase in overall workload due to Ramp up, and modulating overall workload during the Steady state, and the decrease in overall workload during the Ramp down period. The nominal en-route use case assumptions are provided in Table 42.

Table 48. En-route nominal use case modeling assumptions.

Proposal Assumptions
Day, Visual Meteorological Conditions (VMC) operations only, with potential for night visual meteorological condition operations enabled by new standards and rules.
UAV operations will be conducted from the surface to 500' AGL, with additional evaluation of the potential for operations up to 1,200'AGL.
UAV operations will be conducted over other than densely populated areas, unless all UAV comply with potential criteria or standard that demonstrates safe flights over populated areas.
UAV will not be operated close to airports or heliports. 'Close' is initially defined as greater than 3 miles from an airport unless permission is granted from air traffic control or airport authority. A distance of greater than 5 miles will be examined if needed to support an appropriate level of safety.
Small UAV are potentially designed to an Industry Consensus Standard and issued an FAA Airworthiness Certificate or other FAA approval.
The multiple UAV may be operating in scenarios that include *n* UAV that have *n* unique paths distributed over an area of operation.
Subject Matter Expert-Based Assumptions
A human Supervisor sits at a Command-and-Control (C^2) station that permits monitoring and modifying UAV operations as needed.
The Supervisor has been trained, but may only have a high school diploma or equivalent.
The Supervisor's shift includes mandatory breaks.
Upon shift start or return from break, there is a Ramp up period during which UAV launch and are assigned to the Supervisor until the maximum number permitted is reached.
When approaching shift end or break period, no new UAV are assigned to the Supervisor within the window that the UAV will not complete their delivery before the Supervisor's shift end or break commences.
Each Supervisor has a maximum limit of UAVs to supervise simultaneously.
Each Supervisor is responsible for a sector of the operational area that is deconflicted from other Supervisors.
The UAVs are highly autonomous, and the Supervisor is generally monitoring progress with very little interaction.

Loosely Coupled Scenario Specific Assumptions
Each UAV is assigned a separate and independent goal location and the locations do not overlap.
Situation awareness is generally related to what is transpiring with the overall system, meaning all monitored UAVs are healthy and completing their task without issue.
The C^2 interface details are not specifically designed or defined.
At a minimum, a portion of the C^2 interface display contains a map of the Supervisor's area of responsibility that includes individual glyphs for each deployed UAV for which the Supervisor is responsible.
At a minimum, a portion of the C^2 interface display will provide the Supervisor with critical deployed UAV specific mission information (i.e., mission status, vehicle health status, time to delivery completion, airspeed, navigation path, communication connectivity).
At a minimum, the C^2 interface provides ability access relevant mission information (i.e., delivery location, package weight).
Each Supervisor shift is composed of multiple work periods with breaks between work periods.
At the start of the Supervisor's shift, or work period (after a break), there is a Ramp up period during which the Supervisor is assigned en route UAVs to monitor. The number of assigned vehicles continues to increase until the specified maximum is attained.
As the end of a work period or a shift approaches, the Ramp down period begins, such that the UAVs the Supervisor is monitoring have completed their en route flight phases prior the end of the Supervisor's work period. No new UAVs are assigned to the Supervisor during this period, to ensure that the Supervisor has no remaining UAVs at the end of the work period or shift.
During the Steady state period, as a UAV completes the en route portion of the task, the UAV is unassigned from the Supervisor. A new UAV entering the en route portion of the task is assigned to the Supervisor.
The assignment of UAVs to the Supervisor cannot exceed the specified maximum number of UAVs to launch at the specified interval.
The Supervisor can never exceed the maximum number of assigned UAVs.
The duration of a specific UAV's en route mission is between five and twenty minutes.
The UAV has sufficiently power supplies to complete the assigned missions.
No unexpected or distraction events occur during the nominal use case trials.

The Loosely Coupled nominal use case model is composed of a total of 2740 unique lines of code. This value excludes code native to IMPRINT Pro. The unique lines of code define the numerous features of the nominal model (e.g., simulation initialization, UAV mission generation, Ramp up and Ramp down activation, break activation, the logarithmic linear scanning workload adjustment).

16.2.2. Experimental Design

The Nominal Use Case experiments focused on the en-route deployment (i.e., outbound and return flight phases) and supervision of the delivery drones without any disruptions from unexpected events or distractions. The basic research questions were:

- Do any specific independent variables dramatically impact the Overall Workload and # of UAVs a single Supervisor can manage?
- How do the work period elements (i.e., Ramp up, Steady state, and Ramp down) impact the dependent variables?
- As the # of UAVs supervised increases, does Overall Workload increase?

- Given that Overall Workload is expected to increase as the # of UAVs increases, is there a significant difference in the conditions impact on workload?
- How do the different Ramp up and Ramp down parameters impact Supervisor Overall Workload?

16.2.2.1. Independent Variables

A number of independent variables were investigated, as shown in

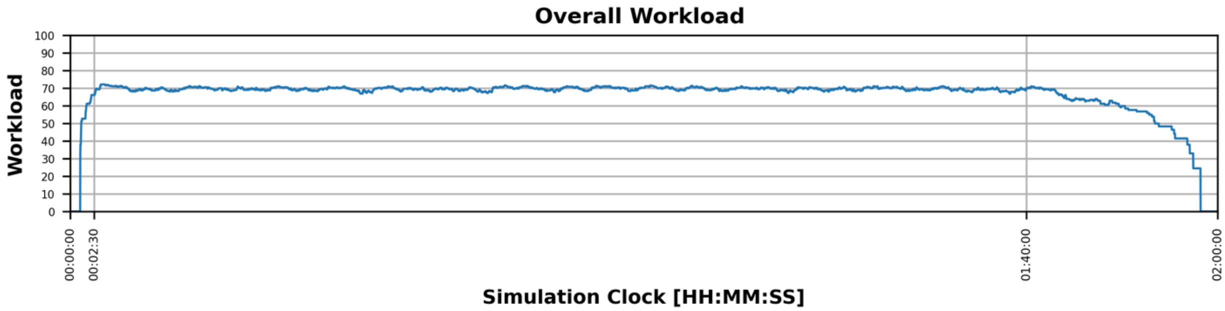
Table 49. The range of independent variables are based on interviews with industry subject matter experts.

Three variables focus on the structure of the Supervisor's shifts, including the duration in hours, and the duration of active work periods between scheduled Supervisor breaks. Expected Supervisor shifts are anticipated to range between 8 and 10 hours per day. It is well known in the human factors community that supporting humans working in similar situations requires providing frequent and consistent work breaks. Two durations are defined, in minutes. The first is the duration of the working period, and the second is the duration of the break. It was assumed that each work period and shift was the same duration during each trial. Another assumption is that the shift starts with a work period and after the specified working period duration, a break is required for the specified period, and this pattern is repeated for the duration of the shift.

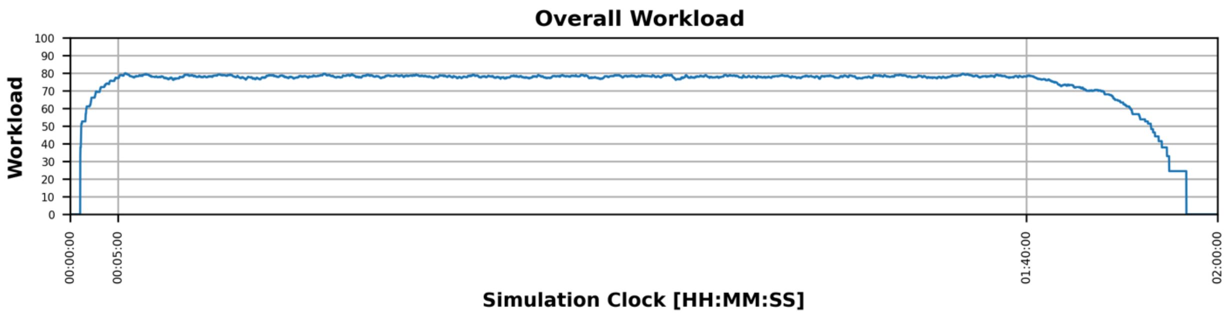
Table 49. Nominal use case independent variables.

Independent Variables	Min	Max	Tested Values
Max Shift Duration (hours)	8	10	8, 10
Working Period Duration (mins)	90	120	90, 120
Break Durations (mins)	30	60	30, 60
Max # of Active UAVs	10	100	10, 25, 50, 75, 100
Time to Launch a Wave of UAV(s) (secs)	30	60	30, 60
Max # of UAV to Launch Simultaneously	1	20	1, 2, 5, 10, 20

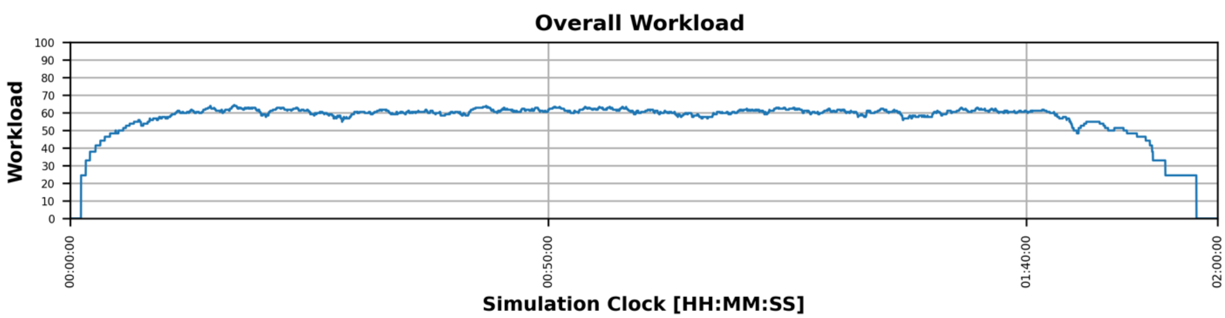
The next set of parameters are related to the UAVs themselves. The Max # of active UAVs represents the maximum number of vehicles the Supervisor can be assigned at any given time during the Supervisor's shift working periods. The number of vehicles and their frequency of launch will impact the Supervisor's performance. The time to launch a wave UAVs is the time between the UAV launches, while the Max # of UAVs launched simultaneously represents how many UAVs are in a particular launch wave. Note that a launch wave may contain only a single vehicle.



(a) The first work period for a trial with a maximum of 50 UAVs, a Time to Launch a Wave of 30 secs and a Launch Wave size of 10 UAVs. The first gray line represents the end of the Ramp up period (2.5 mins), the second time stamp line represents the start of the Ramp down period.



(b) The first work period for a trial with a maximum of 100 UAVs, a time to launch a wave of 30 secs and a launch wave size of 10 UAVs. The first gray line represents the end of the Ramp up period (5 mins), the second time stamp line represents the start of the Ramp down period.



(c) The first work period of a trial with a maximum of 100 UAVs, a time to launch a wave of 1 sec and a launch wave size of 1 UAV. The first gray line represents the end of the Ramp up period (50 mins), the second time stamp line represents the start of the Ramp down period.

Figure 7. The Supervisor's Overall Workload values corresponding to the trials in Figure 6. The plots demonstrate the differences in the generated Overall Workload for the respective Figure 6 subgraphs during the Ramp up (between zero and the first gray line), Steady state (between the two gray lines) and Ramp down (final gray line and right of chart).

16.2.2.2. Dependent Variables

Workload metrics represent the primary dependent variables. IMPRINT Pro represents Overall Workload as a combination of the workload channels. The workload channels include: Auditory, Cognitive, Fine motor, Gross motor, Speech, Tactile and Visual. The nominal use case does not require the Auditory, Gross motor, Speech, or Tactile channels, which are not reported for this experiment. The Cognitive, Fine motor, and Visual workload channels are analyzed in addition to Overall Workload. The maximum and minimum workload values are based on the IMPRINT Pro channel scales, as shown in Table 50. IMPRINT Pro considers a value above 60 to be overloaded.

Table 50. Nominal use case dependent variables.

Dependent Variables	Minimum	Maximum
Cognitive Workload	10.2	33.53
Fine Motor Workload	2.2	7.23
Visual Workload	12.1	39.78
Overall Workload	24.5	80.54
# of UAV En-route ($N_{En\text{-}route}$)	1	100

The number of UAVs that the Supervisor is responsible for varies at any given moment due to the different shift stages: Ramp up, Steady state or Ramp down. As well, the number of UAVs Supervised during the Steady state will vary, given the model design and distributions associated with the mission durations associated with each UAV.

The nature of the variability in the # of UAVs at any given moment and the direct impact on workload resulted in the recording of the results at three different timings: 1 sec, 5 secs and 10 secs. The purpose of these times was to determine what is a fine-grained enough scale at which to see the variations in the results, but not be so fine grained to hinder data analysis or experimentation trial duration.

The overall simulation runtime is dependent on the # of UAVs en-route at any given time, the larger the number of UAVs the slower the model runs, and the computer processing power. Therefore, this information was recorded, but is not reported.

16.2.2.3. Simulation Methodology

A total of 400 independent variable combinations were possible, but only 355 were simulated. This number of combinations excludes forty-five independent variable combinations that truncated the final working period before shift Ramp down. Some combinations with a truncated final work period resulted in work periods without a Steady state shift state, because the Ramp up shift state lasts until the start of the Ramp down shift state, 20 mins before the break. Therefore, the forty-five combinations without a Steady state shift state in the final work period were excluded.

Each combination of independent variables was run for 25 trials in order to account for variability in the model distributions provided in Table 47. A total of 8,875 trials were run (355 x 25 = 8,875).

16.2.2.4. Data Analysis Methodology

The data for a single trial consisted of a time series for each Overall Workload sampled at a given sampling rate. As each trial is composed of multiple working periods that occur during a shift, separated by breaks, as shown in the Section 16.4.2 Figures, data aggregation was necessary to compose a more manageable data set for each trial, and each combination of independent variables for analysis.

The time series for aggregation did vary based on shift state. Given that the combinations of independent variables can significantly impact the length of the shift states, time series were selected that permitted the retention of the maximum number of the 355 independent variable combinations. Some combinations of independent variables were dropped in some cases as they failed to produce reliable shift states (e.g., the model never reaches Steady state given a slow launch rate and 100 UAVs; the UAVs begin returning from completed missions before the Max # of UAVs – 100 – were launched). Therefore, 75 cases were excluded from the analysis, resulting in a final data set comprised of 353 combinations. A review of the raw data determined that certain minimum time intervals are appropriate for each shift state to further preserve the number of independent variable combinations. This interval for Ramp up was 30 secs, for Steady state the interval was 20 mins, and finally, the Ramp down interval was 6 mins. As there were approximately four work periods per each combination of independent variables (this number can vary based on independent variable condition), and a further 25 trials for each combination of independent variables, an initial round of data reduction consolidated the raw data into a single aggregate trial for each combination. It was necessary to ensure that this aggregation did not create any data artifacts; thus, a random 10% of the overall number of combinations were selected, and the four work periods were compared over a 5 minute period. Note that this comparison was completed solely within the 25 trials for a given independent variable combination, as the goal was to simply validate that work period performance did not vary under nominal conditions. There was no reason to believe such variance existed, given that fatigue and other factors (e.g., unexpected events) were not modeled in the nominal case, and the model was expected to run at 100% efficiency, regardless of whether the Supervisor was in their first or fourth shift work period. Results from this manipulation check indicated that there was no reliable effect of work period on observed Overall Workload in any of the selected combinations ($p > 0.05$), indicating that there was indeed no difference between the various work periods across trials and within an independent variable combination. Thus, it is valid to aggregate the data by averaging across the four work periods within each trial, followed by averaging each of the subsequent 25 trials to compose a final single trial for each independent variable combination.

Following the data aggregation, it is was necessary to examine the influence of the various independent variables on Overall Workload. A series of linear mixed models were conducted on discrete time intervals within the three shift state periods (i.e., Ramp up, Steady state and Ramp down). The variables that impacted shift characteristics (e.g., Shift Hours, Work period Duration, and Break Duration) in half the cases were examined to determine any effect on Overall Workload, and in a second set of analyses, task characteristics (e.g., Max # of UAVs, Time to Launch, Max # UAVs to Launch, Launch rate) were evaluated for their effect on Overall Workload. All analyses were evaluated for statistical reliability at ($\alpha = 0.05$), and effect sizes were reported in η^2.

16.2.3. Results

16.2.3.1. Shift Characteristics Nominal Use Case analysis across Work States

As a reminder, variables that are said to affect shift characteristics are the Shift hours (8 or 10 hours), Work period duration (90 or 120 mins), and Break duration (30 or 60 mins). During the Ramp up period, these variables were evaluated over the initial 30 secs, across 5 secs intervals. The Steady state period, a 20 minute period, was evaluated using 1 minute intervals. Finally, during the Ramp down period, a 6 minute period, with 1 minute intervals, was evaluated. All *F*-values are presented in Table 51.

Table 51. Analysis of Variance (ANOVA) table for shift characteristics for nominal scenario across shift states.

Factor	*df*⁺	*F*	η^2	α
Ramp up				
Shift hours	1, 314	3.78	0.01	0.053
Work period duration	1, 314	0.01	<.001	0.906
Break duration	1, 314	0.02	<.001	0.877
Shift hours x Work period duration	1, 314	0.06	<.001	0.814
Shift hours x Break duration	1, 314	0.26	<.001	0.612
Work period duration x Break duration	1, 314	3.48	0.01	0.063
Shift hours x Work period duration x Break duration	1, 314	6.39*	0.02	0.012
Time (sec)	5, 1570	0	<.001	0.99
Shift hours x Time (sec)	5, 1570	0	<.001	0.99
Work period duration x Time (sec)	5, 1570	0	<.001	0.99
Break duration x Time (sec)	5, 1570	0	<.001	0.99
Shift hours x Work period duration x Time (sec)	5, 1570	0	<.001	0.99
Shift hours x Break duration x Time (sec)	5, 1570	0	<.001	0.99
Work period duration x Break duration x Time (sec)	5, 1570	0	<.001	0.99
Shift hours x Work period duration x Break duration x Time (sec)	5, 1570	0	<.001	0.99
Steady state				
Shift hours	1, 344	0.01	<.001	0.935
Work period duration	1, 344	0	<.001	0.975
Break duration	1, 344	0.01	<.001	0.934
Shift hours x Work period duration	1, 344	0	<.001	0.958
Shift hours x Break duration	1, 344	0	<.001	0.959
Work period duration x Break duration	1, 344	0.08	<.001	0.783
Shift hours x Work period duration x Break duration	1, 344	0.15	<.001	0.694
Time (min)	1.84, 632.67	262.81**	0.001	<.001
Shift hours x Time (min)	1.84, 632.67	2.79	<.001	0.067
Work period duration x Time (min)	1.84, 632.67	0.2	<.001	0.797
Break duration x Time (min)	1.84, 632.67	0.23	<.001	0.776
Shift hours x Work period duration x Time (min)	1.84, 632.67	0.08	<.001	0.912
Shift hours x Break duration x Time (min)	1.84, 632.67	0.12	<.001	0.868
Work period duration x Break duration x Time (min)	1.84, 632.67	2.9	<.001	0.06
Shift hours x Work period duration x Break duration x Time (min)	1.84, 632.67	3.78*	<.001	0.027

Factor	df^{+}	F	η^2	α
Ramp down				
Shift hours	1, 347	0	<.001	0.979
Work period duration	1, 347	0.04	<.001	0.851
Break duration	1, 347	0.01	<.001	0.92
Shift hours x Work period duration	1, 347	0.01	<.001	0.939
Shift hours x Break duration	1, 347	0.09	<.001	0.768
Work period duration x Break duration	1, 347	0	<.001	0.983
Shift hours x Work period duration x Break duration	1, 347	0.15	<.001	0.694
Time (min)	2.02, 700.34	39522.73**	0.05	<.001
Shift hours x Time (min)	2.02, 700.34	0.24	<.001	0.79
Work period duration x Time (min)	2.02, 700.34	0.97	<.001	0.381
Break duration x Time (min)	2.02, 700.34	0.27	<.001	0.769
Shift hours x Work period duration x Time (min)	2.02, 700.34	0.09	<.001	0.92
Shift hours x Break duration x Time (min)	2.02, 700.34	0.24	<.001	0.786
Work period duration x Break duration x Time (min)	2.02, 700.34	1.48	<.001	0.228
Shift hours x Work period duration x Break duration x Time (min)	2.02, 700.34	0.62	<.001	0.539

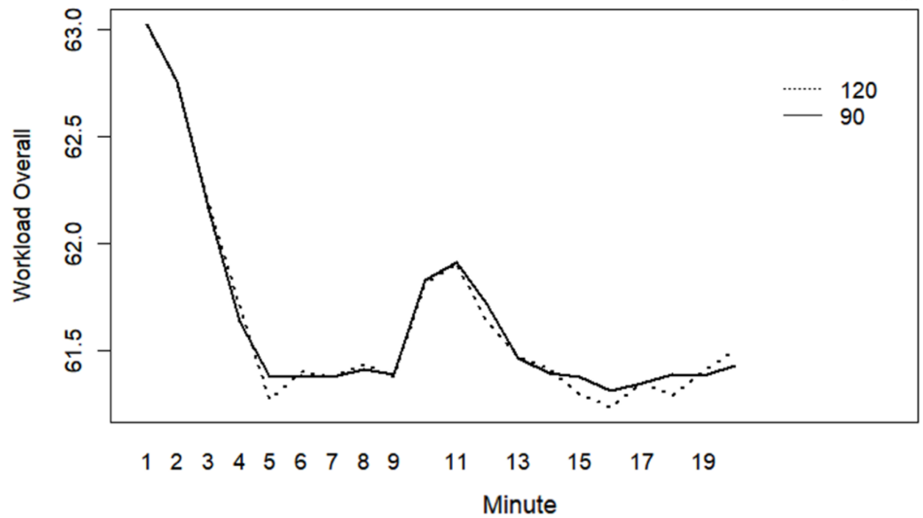
[+] Greenhouse-geisser corrections applied as needed

* p < .05, ** p < .001

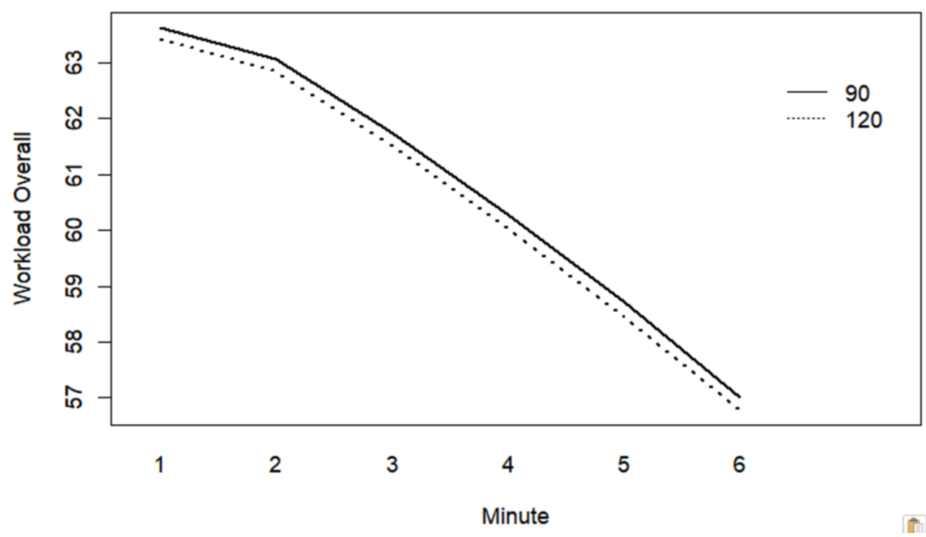
16.2.3.1.1. Main effects and interactions over work period

Overall, as is visible in Table 51, it appears that the shift characteristics have little impact on Overall Workload. Both Steady state and Ramp down phases' F-values for all shift variables approached 0, suggesting there is fundamentally no difference in Overall Workload observed across the various values for these independent variables. This result was mirrored in the Ramp up phase, especially for Work period duration and Break duration. However, there was a marginally significant effect of Shift Hours (p = 0.053, η^2 = 0.01) on Overall Workload during Ramp up, suggesting that longer shifts may impact Overall Workload. However, this effect was not statistically reliable, and reflects a very small effect size. This finding must be viewed with some skepticism.

A main effect of time interval existed for both the Steady state and Ramp down phases, which suggests that over time Overall Workload does significantly change and reduce over time. However, shift characteristics do not appear to interact with this change over time, as evidenced by the lack of any interactions between the shift variables and time interval. For example, work period duration during Steady state and Ramp down (shown in Figure 8a and b, respectively) did not interact with time. Further, during the Ramp up period no change in time was observed, likewise no interaction between time interval or any of the shift variables was demonstrated.



(a) Steady state shift state.



(b) Ramp down shift state.

Figure 8. The effects of work period duration on Overall Workload over time for the (a) Steady state and (b) Ramp down shift states.

In summary, for shift variables, it appears that these characteristics did not significantly affect Overall Workload within the nominal use case. These findings are perhaps unsurprising, as the Sleep, Activity, Fatigue and Task Effectiveness (SAFTE) model, which impacts Supervisor efficiency, was not implemented in the nominal use case. As such, the model efficiency maintained a steady 100%, regardless of factors (e.g., work period or break duration). The modeled Supervisor's performance remained at that optimal level for the duration of all trials and combinations.

16.2.3.2. Task Characteristics Nominal Use Case analysis across Work States

Independent variables that modify the task characteristics are Max # of UAVs (10, 25, 50, 75, 100), Time to launch (30 secs, 60 secs) and Max # of UAVs to Launch Simultaneously (1, 2, 5, 10, 20). As with the Shift characteristics in Section 16.2.3.1, these task characteristics were analyzed over a 30 secs period in Ramp up, a 20 minute period in Steady state, and a 6 minute period for the Ramp down phase. The time intervals within these periods were identical to the Shift characteristic analysis. All *F*-values are available in

Table 52.

Table 52. ANOVA table for task characteristics for nominal scenario across shift states.

	Factor	*df*	*F*	η^2	α
Ramp Up					
	Maximum # UAVs	4, 1886	1.35E+28**	0.11	< .001
	Time to Launch	1, 1886	1.41E+27**	0.003	< .001
	Maximum # UAVs Launch	4, 1886	1.13E+29**	0.89	< .001
	Time (secs)	5, 1886	0	<.001	0.99
	Maximum # UAVs x Time to Launch	4, 1886	0.89	<.001	0.47
	Maximum # UAVs x Maximum # UAVs Launch	14, 1886	0.93	<.001	0.53
	Time to Launch x Maximum # UAVs Launch	4, 1886	1.31	<.001	0.26
	Maximum # UAVs x Time (secs)	20, 1886	0	<.001	0.99
	Time to Launch x Time (secs)	5, 1886	0	<.001	0.99
	Maximum # UAVs Launch x Time (secs)	20, 1886	0	<.001	0.99
	Maximum # UAVs x Time to Launch x Maximum # UAVs Launch	14, 1886	0.88	<.001	0.99
	Maximum # UAVs x Time to Launch x Time (secs)	20, 1886	0	<.001	0.99
	Maximum # UAVs x Maximum # UAVs Launch x Time (secs)	70, 1886	0	<.001	0.99
	Time to Launch x Maximum # UAVs Launch x Time (secs)	20, 1886	0	<.001	0.99
	Maximum # UAVs x Time to Launch x Maximum # UAVs Launch x Time (sec)	70, 1886	0	<.001	0.99

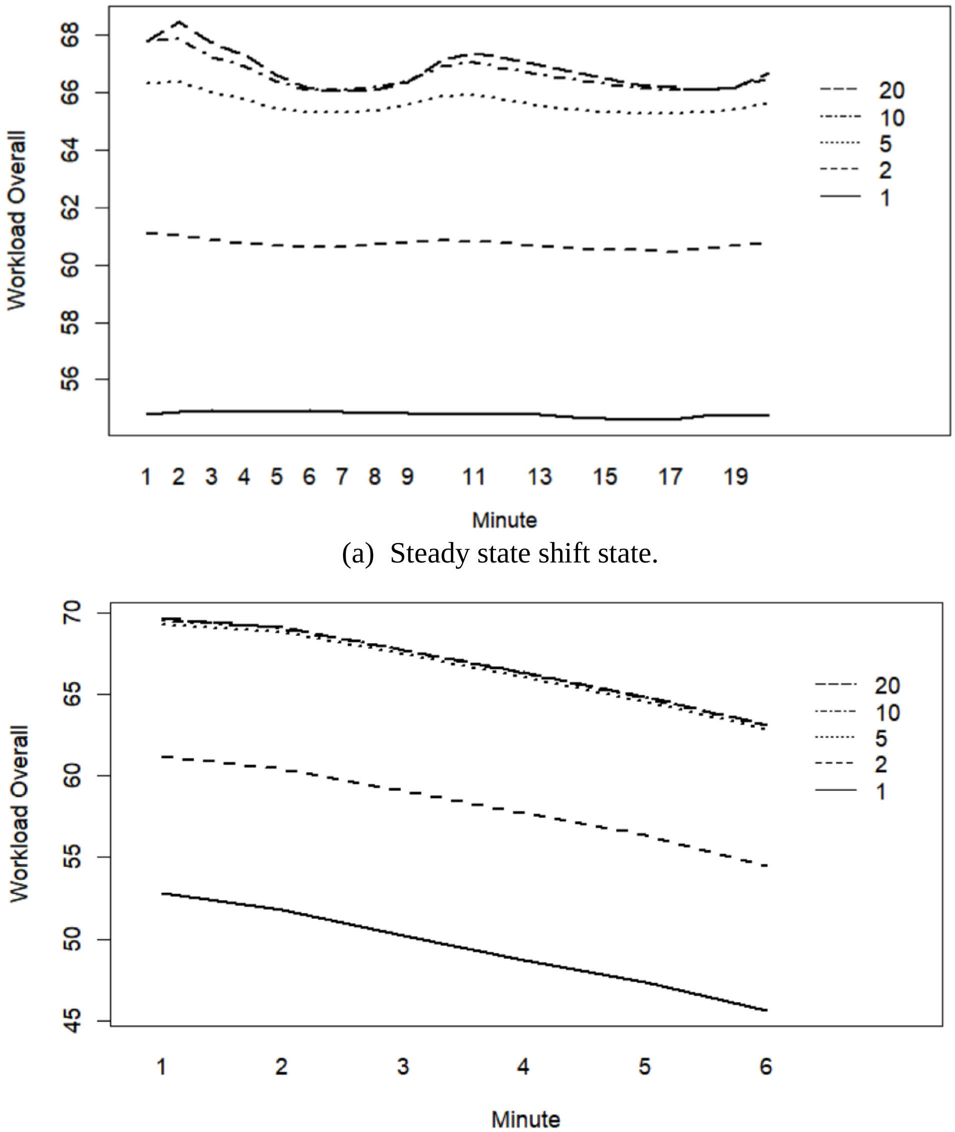
	Factor	*df*	*F*	η^2	*α*
Steady state					
	Maximum # UAVs	4, 303	2546.003**	0.07	< .001
	Time to Launch	1, 303	244.307**	0.00	< .001
	Maximum # UAVs Launch	4, 303	574.933**	0.02	< .001
	Time (mins)	19, 5757	2368.121**	0.31	< .001
	Time (mins) x Time to Launch	19, 5757	48.935**	0.01	< .001
	Maximum # UAVs x Time to Launch	4, 303	35.254**	0.00	< .001
	Time (mins) x Maximum # UAVs Launch	76, 5757	360.559**	0.19	< .001
	Maximum # UAVs x Maximum # UAVs Launch	16, 303	65.613**	0.01	< .001
	Time to Launch x Maximum # UAVs Launch	4, 303	49.282**	0.00	< .001
	Time (mins) x Maximum # UAVs x Time to Launch	76, 5757	15.568**	0.01	< .001
	Time (mins) x Maximum # UAVs x Maximum # UAVs Launch	304, 5757	46.769**	0.10	< .001
	Time (mins) x Time to Launch x Maximum # UAVs Launch	76, 5757	17.801**	0.01	< .001
	Maximum # UAVs x Time to Launch x Maximum # UAVs Launch	15, 303	14.78**	0.00	< .001
	Time (mins) x Maximum # UAVs x Time to Launch x Maximum # UAVs Launch	285, 5757	22.759**	0.05	< .001

	Factor	*df*	*F*	η^2	α
Ramp down					
	Maximum # UAVs	4, 305	2.43E+05**	0.49	< .001
	Time to Launch	1, 305	33652.74**	0.02	< .001
	Maximum # UAVs Launch	4, 305	60158.874**	0.12	< .001
	Time (mins)	5, 1525	1.13E+05**	0.28	< .001
	Time (mins) x Maximum # UAVs	20, 1525	82.989**	0.00	< .001
	Time (mins) x Time to Launch	5, 1525	40.911**	0.00	< .001
	Maximum # UAVs x Time to Launch	4, 305	2646.57**	0.01	< .001
	Time (mins) x Maximum # UAVs Launch	20, 1525	29.138**	0.00	< .001
	Maximum # UAVs x Maximum # UAVs Launch	16, 305	8461.917**	0.07	< .001
	Time to Launch x Maximum # UAVs Launch	4, 305	6756.719**	0.01	< .001
	Time (mins) x Maximum # UAVs x Time to Launch	20, 1525	6.57**	0.00	< .001
	Time (mins) x Maximum # UAVs x Maximum # UAVs Launch	80, 1525	4.881**	0.00	< .001
	Time (mins) x Time to Launch x Maximum # UAVs Launch	20, 1525	10.181**	0.00	< .001
	Maximum # UAVs x Time to Launch x Maximum # UAVs Launch	16, 305	868.075**	0.01	< .001
	Time (mins) x Maximum # UAVs x Time to Launch x Maximum # UAVs Launch	80, 1525	3.335**	0.00	< .001

* p < .05, ** p < .001

16.2.3.2.1. Main effects and interactions over work period.

Unlike the shift characteristic analysis, the task characteristics do appear to have a significant effect on Overall Workload. There was a significant impact of all task variables across all three shift phases (e.g., Ramp up, Steady state, and Ramp down), such that as the task characteristic independent variable values increased in magnitude, Overall Workload likewise increased. For example, as the maximum launch rate of UAVs increased, significant increases in Overall Workload were observed. Lower launch rates of 1 or 2 UAVs at a time produced low Overall Workload levels, whereas launch rates of 5 or more UAVs produced maximum levels of observed Overall Workload. This result is visible in Figure 9, by comparing the lines for different launch rate values in the Steady state and Ramp down phases, higher launch rates produce higher Overall Workload; note that Figure 6 also shows these values over time.



(a) Steady state shift state.

(b) Ramp down shift state.

Figure 9. The effects of Maximum UAV Launch Rate on Overall Workload over time for the (a) Steady state and (b) Ramp down shift states.

During both the Steady state and Ramp down periods, there was also a significant main effect of time interval, such that Overall Workload decreased over time (see Figure 9). For example, as can be seen in Figure 6(a), Overall Workload did decrease during Ramp down, which is a natural reduction in Overall Workload as UAVs returned. Further, all independent variables did interact with time interval during Steady state and Ramp down. This type of interaction is typified in the Figure 6(b), whereas the reduction of Overall Workload over time was more prominent for the high launch rate conditions (e.g., 5, 10, 20), but was negligible (i.e., the line is mostly flat) for low rate conditions (e.g., 1, 2). While these interactions are statistically reliable, it is important to point out that most effect sizes for these higher order interactions for both work phases were very low to nonexistent (~0.00). During Steady state only the interactions between time interval and Max #

of UAVs ($\eta^2 = 0.19$), as well as time interval and Max # of UAVs to Launch Simultaneously ($\eta^2 = 0.19$) produced effect sizes of any substance, whereas the same interactions during Ramp down produced very low effect sizes ($\eta^2 < 0.01$). As such, it is cautioned that these statistical effects not be over-interpreted, as while they indicate statistical significance, practically speaking these interactions produce very little to no effect on Overall Workload. There was no main effect of time interval, and no interactions with time interval observed in the Ramp up phase.

3.2.3.4 Nominal analysis Summary of Results

In summary, for the nominal scenario, manipulation of shift characteristics did not have a significant impact on estimated Overall Workload. Conversely, manipulation of task characteristics did have a significant effect on Overall Workload. However, despite these reliable effects for task characteristics, a majority of effect sizes were small to non-existent. The Max # of UAVs and Max # UAVs to Launch Simultaneously often produced the largest impact on the Overall Workload estimates, and it is recommended that focusing on these variables, and their interactions with time may identify those cases where these variables have the largest effect.

16.3. Unexpected Event Use Cases

Thirty-four potential example UEs were developed collaboratively by A26 team members and validated through interviews with various industrial partners as part of Task 3 (Task 3 Report, Appendix B). A complete and detailed analysis of all unexpected events for the Loosely Coupled scenario are not within the scope of this project. Three UE use cases were modeled. All decision trees for the modeled distractions and two additional UE use case decision trees that were not modeled (i.e., Biological Need and Phone Call) are provided in Appendix A.

16.3.1. Use Case Summaries

16.3.1.1. Emergency in the Airspace (Autonomy is unaware)

The Emergency in the Airspace UE is quite complex, with many varying situations that can arise and potential responses to this event, which presents too many alternatives to properly model. The exemplar modeled for A26 decision tree demonstrates the complexity of the potential responses to this particular event. The decision was to model two situations. The first situation causes the UE to be handed-off immediately to the UE Supervisor, who takes responsibility for all UAVs impacted by the Emergency in the airspace and relieves the primary Supervisor of responsibility for the UE. This hand-off to the UE Supervisor is expected to allow the primary Supervisor to maintain their Overall Workload or reduce it.

The second modeled case represents the worst case, from the perspective of the amount of work the primary Supervisor must do in order to respond to the event. This worst-case scenario requires the primary Supervisor to split the UAVs in the air at the time of the emergency into two groups, both addressed in a different manner. One group represents the UAVs that are physically in, nearby, or heading into the area of the emergency. The other represents UAVs that are outside of that area and are not heading into it. This case is expected to require high Overall Workload from the Supervisor until all UAVs are handled. Furthermore, when this UE occurs during the Ramp down shift state, the Supervisor automatically defaults to handing of the UAVs to the UE Supervisor, because there is there will likely not be enough time for the Supervisor to address the UE before the start of their break or end of shift.

16.3.1.2. Mid-air Collision (UAV can fly, but damaged and unable to complete mission)

The exemplar best case Mid-air collision UE requires the UAV autonomy to notify the Supervisor via the C^2 station and any necessary human-based response is handed-off to the UE Supervisor. The exemplar worst-case begins using a similar path as the best-case scenario that notifies the Supervisor, while simultaneously the UAV takes actions to attempt to land the UAV. If the UAV cannot return to the launch zone, there are no nearby safe landing sites, and the UAV cannot identify a nearby open area in which to land, then the Supervisor is notified and begins identifying potential nearby areas for the UAV to land before issuing the command to land the UAV, which notifies the UAV recovery team automatically. While the UAV is reasoning over the potential landing options, prior to the Supervisor beginning the process of identifying nearby open areas, the Supervisor has received notification of the event and begins working the tasks to determine the level of damage and the need to file an incident report to the Airspace Officials. This Supervisor is interrupted if the UAV Autonomy requires assistance selecting an open area in which to land. The Supervisor returns to the reporting task, if it was interrupted, once the landing command has been executed. Note that once the UAV lands, the responsibility for the UAV transfers to the UAV recovery team, who goes out to physically recover the landed vehicle.

16.3.1.3. C^2 Link Loss (decision support system is unavailable)

The exemplar C^2 link loss UE actually incorporates two UEs, the UAV Experiences C^2 Temporary Link Loss and the UAV Experiences C^2 Extended Link Loss. The Temporary Link Loss is expected to be more frequent, and only requires the Supervisor to monitor the activities. The primary focus for the current modeling effort is the Extended Link Loss UE for a single UAV. The case of multiple UAVs simultaneously experiencing C^2 link loss was not modeled, but the use case and decision tree remain the same and, in all likelihood, the UE Supervisor will assume responsibility for such a simultaneous link loss UE. The best-case scenario hands the UE off to the UE Supervisor, while the worst-case scenario requires the primary Supervisor to respond to the UE.

16.3.2. Model Development

The unexpected event use case models leverage the nominal use case model. Each UE use case model was developed based on its specific characteristics, as noted in Section 16.3.1. The model implementations generally require the same model elements, atomic tasks with associated timings, and Overall Workload component values as the nominal use case. However, a more realistic representation of Overall Workload required a looping module of linear scanning tasks that capture the Overall Workload associated with the Supervisor's monitoring the UAVs. This update, alongside the inclusion of new nodes specific to the UE model are shown in Figure 10. For example, new UE-specific modules nodes, denoted brown in the Figure contain the sequence of events of each UE. The detail for the Mid-Air collision UE is provided in Figure 11.

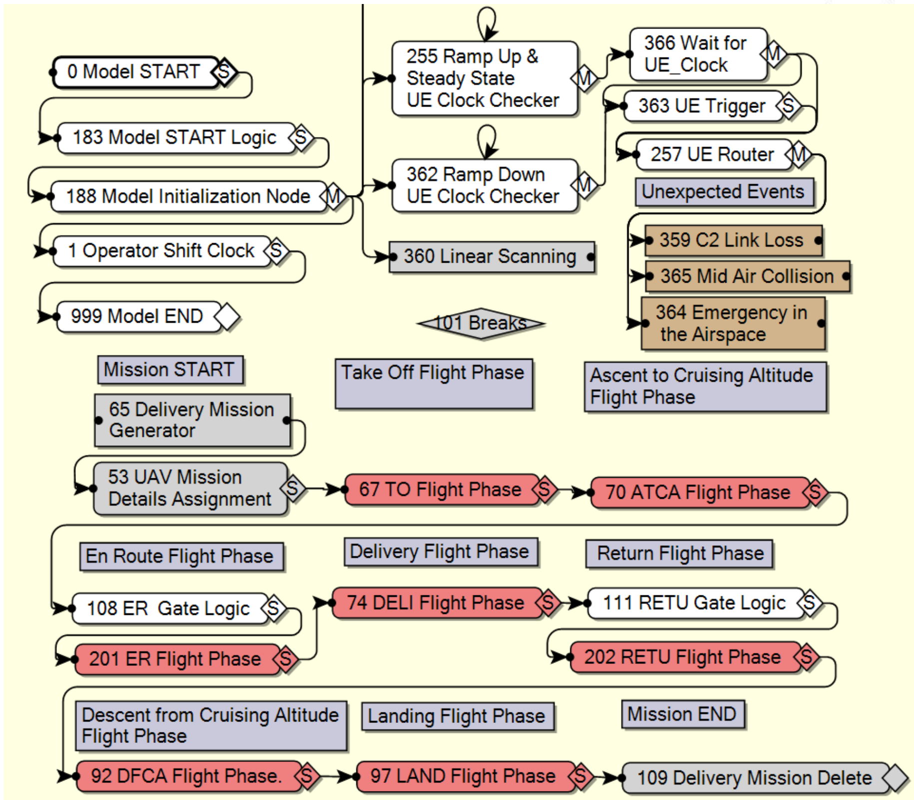


Figure 10. Overview of the UE use case model within IMPRINT Pro.

All three UE use cases discussed in Section 16.3.1 were implemented as togglable events within the same model. The UE model was designed to always have the UE occur in the Supervisor's second and fourth working period.

The setting of the UE's occurrence clock is accomplished in two distinct ways, depending on which shift state the UE is to occur. If the UE is to occur during either the Ramp up or Steady state, a UE occurrence clock is randomly selected using a discrete uniform distribution during a UE initialization period at the start of the simulation. Regardless of the desired shift state, the Min and Max value from the discrete uniform distribution respectively correspond to the start and end clock of the desired shift state, shown in Table 53. Meanwhile, if the UE is to occur during the Ramp down shift state, the UE occurrence clock is not selected until the start of the Ramp down shift state. The Ramp down shift state occurrence clock selection must be determined independently from the other shift states, because a UE occurrence clock selected at the start of the simulation is not guaranteed to have UAVs in the en-route flight phase when the clock time occurs. Therefore, at the start of Ramp down state, a UAV that has not completed the en-route flight phase is randomly selected by a discrete uniform distribution. Another discrete uniform distribution is used to select a random clock within the UAV's en-route phase. This method guarantees the UEs occurring in the Ramp down shift state will always occur with at least one UAV remaining in the en-route flight phase.

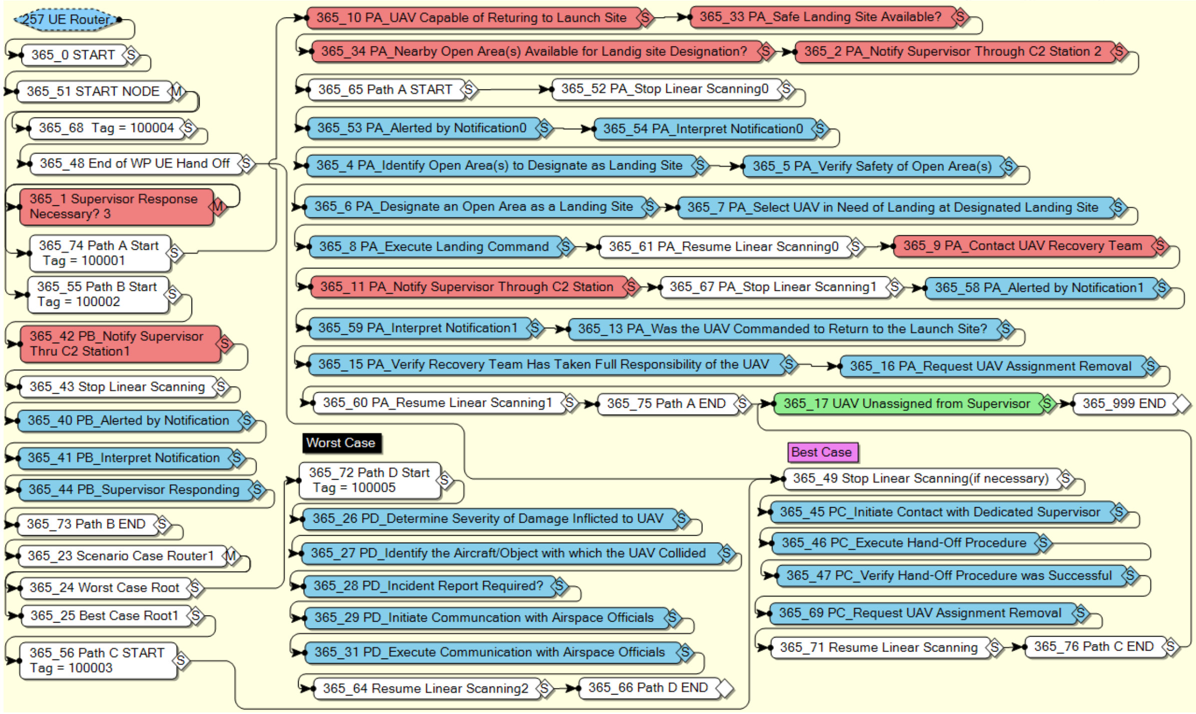


Figure 11. Screenshot of the Mid-air collision use case within the UE model.

The arrival of the UE occurrence clock, triggers the activation of the respective UE module containing the sequence of Supervisor and autonomy tasks, as presented in the respective Section 16.3.1 decision trees. Both the best-case and worst-case scenarios were implemented for the respective UE use cases. The activation of either case scenario was implemented as a togglable feature within the model. Figure 11 provides the node representation for the Mid-air collision UE use case model. Although the worst-case scenarios of the three UEs varies greatly, the best-case scenario across the three UEs is nearly identical. The only striking difference arises from the implementation of the Emergency in the Airspace UE, which requires UAVs to land as a result of the UE. The other modeled UEs require the Supervisor to hand-off the UAV encountering a UE, as described in the best-case scenario, after which the Supervisor returns to linear scanning of the remaining UAVs. However, the Emergency in the Airspace results in the Supervisor having no UAV to monitor, which implies that the linear scanning Overall Workload is a minimum value. The Mid-air collision and C^2 link loss UEs best-case scenarios do not result in zero active UAVs; therefore, the Supervisor simply resumes linearly scanning with at least one active UAV.

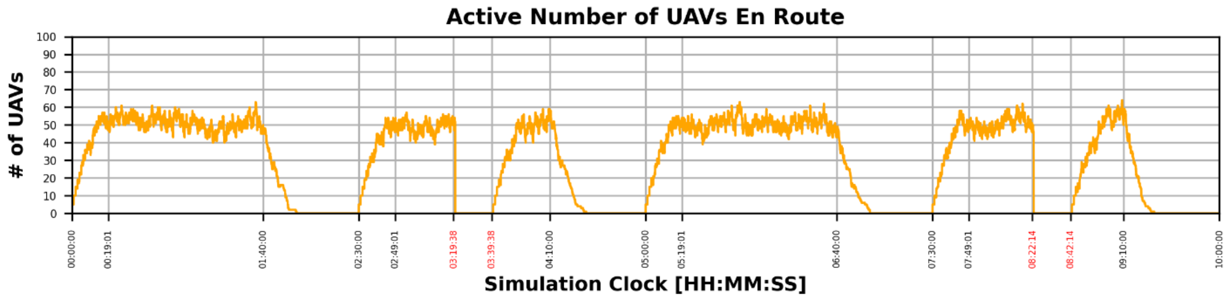
All of the variability in the nominal use case, as provided by the distributions in Table 47, is carried forward to the UE model. Additionally, the new variable items were integrated into the UE models, as shown in Table 53.

Table 53. Usage of distributions within the unexpected event use case model.

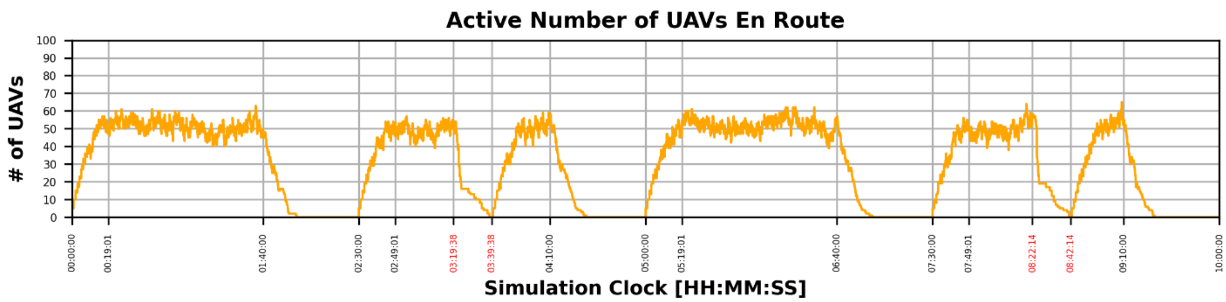
Distribution Purpose	**Distribution Type & Parameter Values**	**Min Value**	**Max Value**
Selection of Flight Phase for UE Occurrence. (Zero represents En-Route and one represents Return.) (UE in Ramp up or Steady state)	DiscreteUniform(0,1)	0	1
Selection of UAV to be Affected that is Currently in the Selected Flight Phase. (UE in Ramp up or Steady state)	DiscreteUniform(*UAV 1*, *UAV N*)	*UAV 1*	*UAV N*
Clock Selection for UE Occurrence. (UE in Ramp up or Steady state)	DiscreteUniform(1st sec, N^{th} sec)	1st sec	N^{th} sec
Selection of a UAV for the UE to Occur to. (UE in Ramp down)	DiscreteUniform(*UAV 1*, *UAV N*)	*UAV 1*	*UAV N*
Clock Selection for UE Occurrence in Selected UAV's En-Route Flight Phase (UE in Ramp down)	DiscreteUniform(UAV's 1st sec En-Route, UAV's N^{th} sec En-Route)	1st sec	N^{th} sec

The occurrence of a UE, such as C^2 link loss or Mid-air collision can result in the Supervisor multitasking between linear scanning the unaffected UAVs while also completing tasks to address the UAV affected by the UE. Properly modeling multitasking in IMPRINT Pro proved to be difficult to implement; therefore, the current model assumes that the Supervisor does not attempt to multitask and attempts to complete all the UE related tasks before returning to the linear scanning of the unaffected UAVs. While completing the UE related tasks, the Supervisor continues incurring Overall Workload associated with the linear scanning task.

Each UE was chosen to represent different types of Supervisor responses. Further, the best-case and worst-case paths will have differing impacts on the Supervisor. For example, the C^2 link loss does not dramatically change the number of UAVs the Supervisor is monitoring. The worst-case requires the Supervisor to continue working with the UAV, while the best case reassigns the UAV in question to the UE Supervisor, and the primary Supervisor is simply assigned a new UAV to monitor. However, an Emergency in the Airspace does directly impact the number of UAVs the Supervisor is monitoring. The best-case scenario again hands-off responsibility for the UE to the UE Supervisor, resulting in an immediate reduction in the number of UAVs the Supervisor is responsible for monitoring, as shown in Figure 12(a). However, that decrease in the Supervisor's UAVs differs for the worst-case scenario in which the Supervisor's immediate response is to ground all UAVs in the area of the Emergency. The Supervisor's secondary responsibility is to monitor and ensure that all of the Supervisor's UAVs outside of the Emergency area hold in place and do not enter the Emergency area. If the Emergency is quick, then the holding UAVs can continue their delivery missions. Otherwise, the UAVs consume their power sources and return the launch or land at a secondary launch area. Thus, the worst-case path results in a different pattern, as shown in Figure 12(b). Once the emergency is over, the Supervisor is assigned new UAVs to monitor, shown in both Figures. The associated Overall Workload Figures, as well as the Figures for the C2 link loss and Mid-air collision UEs are provided in Appendix A. The assumptions for the UE use case models are provided in Table 43.



(a) The best-case scenario for an Emergency in the airspace that occurs during Steady state of the Supervisor's 2nd and 4th work period, which hands-off the responsibility for the UE to the UE Supervisor. The red time periods represent the start and end of the UE.



(b) The worst-case scenario for an Emergency in the airspace that occurs during Steady state of the Supervisor's 2nd and 4th work period. The Supervisor initially grounds all UAVs within the emergency area, then continues monitoring any UAVs outside of the area. The red time periods represent the start and end of the UE.

Figure 12. The best-case (a) and worst-case (b) scenarios for responding to an Emergency in the Airspace. The differences in the number of UAVs the Supervisor is responsible for impact the number of UAVs that remain assigned to the Supervisor during the event (between the red time points during the 2nd and 4th work period). Once the emergency is over, new UAVs are assigned to the Supervisor.

Table 54. Unexpected event use case modeling assumptions.

Subject Matter Expert-Based Assumptions
The UAVs' autonomy will handle a majority of UEs and not require Supervisor intervention.
UEs requiring Supervisor attention will occur approximately once per week per UAV.
The human Supervisor generally does not need to be notified of UEs that are common (e.g., avoiding collisions with stationary or moving obstacles).
It is assumed that the system design is sufficiently mature so that safety critical UEs across the entire operation in which neither the system nor the human can reduce or prevent harm will be extremely rare.
The unmanned aircraft traffic management system will handle UAV deconfliction. If the UAV is not to collide with an obstacle, then obstacle detection and avoid automation will handle the situation. Detection and avoidance technology will be used for manned aircraft.

General UE Assumptions
The Unexpected Event Supervisor is dedicated to handling any type of UE across the system and assumes responsibility for a UAV experiencing such an event. The UE Supervisor is not modeled.
The best-case scenario assumes that UAV(s) experiencing a UE are handed off immediately to the UE Supervisor. The Supervisor has not responsibility for the UE and continues monitoring the remaining UAVs, with the UE affected UAV(s) being replaced with new en route UAVs.
The worst-case scenario assumes the Supervisor must handle all activities related to the UE.
The UEs are discrete and finite with regard to their impact on the Supervisor's performance.
The Supervisor's shift is composed of four work periods, for all modeled trials and UEs, no UEs occur during the 1st or 3rd work periods. UEs only occur during the 2nd and 4th work periods.
The worst-case scenario's Ramp up UEs assume that the Supervisor's tasks for handling the UE are completed prior to the start of the Steady state period.
The worst-case scenario's Steady state UEs assume that the Supervisor's task for handling the UEs are completed prior to the start of the Ramp down period.
The worst-case scenario's Ramp down UEs assume that the Supervisor handles all UE related tasks prior the end of the work period or shift.
A single UE occurs during the Steady state trials during the trials' 2nd and 4th work periods.
The Ramp up and Ramp down UE trials are combined into a single trial, with a single UE instance occurring during the 2nd and 4th work periods' Ramp up and Ramp down stages.
Each UE type was evaluated in an independent set of trials.
Emergency in the Airspace UE Assumptions
The Emergency in the airspace UE requires grounding safely a subset of the Supervisor's UAVs.
The Supervisor maintains responsibility for any unaffected UAVs.
No new UAVs assigned a goal or navigation path that enters the emergency area can enter the en route flight phase and be assigned to the Supervisor.
The Supervisor's responsibilities and assigned UAVs will drop based on the number of UAVs that are to be grounded.
Once the Emergency in the airspace UE is completed, the Supervisor is assigned new en route UAVs to monitor, that are assigned using the specific Ramp up parameters.
Mid-air Collision UE Assumptions
The affected UAV can continue flying, but is unable to complete the mission.
The UAV's autonomy can detect the event and commands the UAV to land.
The Supervisor is no longer responsible for the affected UAV once the UAV has handed. The worst-case scenario assumes that the landed UAV is handed off to the ground recovery team.
Once the Supervisor is no longer responsible for the affected UAV (i.e., best-case it is handed off to the UE Supervisor, worst-case it lands), then the UAV is replaced by a new en route UAV.
C^2 Link Loss UE Assumptions
There are two phases to this UE, the first represents the initial link loss period during which it is unclear if the loss is temporary. During this period, the Supervisor simply monitors the situation.
Once it is clear that the link loss has entered the prolonged period, then either the UE is handed off to the UE Supervisor (best-case) or the Supervisor handles the UE (worst-case).
This UE can occur for a single UAV or multiple UAVs, and it is assumed that the affected UAV(s) do not come back into communication.
The worst-case scenario assumes that the UAV(s) do not come back into communications, requiring the Supervisor to determine the UAV(s)' last known location, how long the link loss has been on going, and last known speed and heading. This information is communicated to the ground recovery team, who assumes responsibility for the UAV, relieving the Supervisor of any additional responsibilities.

Once the Supervisor is relieved of responsibility for the UAV(s), new en route UAV(s) are assigned to the Supervisor.

The UE model was developed specifically to reuse the nominal model, but the UEs introduce 1,298 new unique lines of code. The UE model's unique code is responsible for the initialization, activation, and execution of each UE use case as well as the logging of UE model data. The UE model in total is composed of about 4078 unique lines of code, not inclusive of IMPRINT Pro's inherent programming code.

16.3.3. Experimental Design

The Unexpected Event use case experiments focused on the impacts to the Supervisor's performance in response to three unexpected events, assuming the best case and worst-case paths through the decision trees for handling the events. The fundamental research questions were:

- How does Overall Workload differ from the nominal use case results?
- How do different Unexpected Events impact Overall Workload and the number of UAVs a Supervisor can manage, both for the best case and worst-case use case requirements?
- What is the impact of an Unexpected Event occurring during the Ramp up, Steady state, or Ramp down on the Supervisor's performance and the number of managed UAVs?

16.3.3.1. Independent Variables

The first independent variable is the type of Unexpected Event, as shown in Table 55. The UEs have multiple paths that the Supervisor can follow, depending on the event type and multiple other factors. The simplest path for the modeled UEs is to hand-off responsibility for the UE to the UE Supervisor, which is considered the best-case scenario, or Scenario Case. The most demanding path through each UE's decision tree, or the worst-case scenario, is also an independent variable. Further, each UE event and scenario case were evaluated for each Shift state.

The Max # of Active UAVs independent variable does not include ten (10) UAVs, which was the case for the nominal use case. All other number of UAVs are evaluated. The Ramp up period specific independent variables remain unchanged from the nominal use case experiments.

One difference from the nominal use case is that the UEs that occurred during the Ramp up and Ramp down shift states had occurrences in the same trial in order to reduce the total number of trials needed. The UEs are discrete events, therefore, multiple instances can be incorporated into a single trial. As such, the UEs trials for Ramp up and Ramp down shift states were combined into the same trial. An instance of the UE occurred during Ramp up, and another instance occurred during Ramp down of the same work period.

Table 55. Unexpected events experiment independent variables.

Independent Variable	**Tested Values**
Unexpected Event Type	C2 Link Loss, Emergency in the Airspace, Mid-air Collision
Scenario Case	Best-Case, Worst Case
Shift State	Ramp Up, Steady State, Ramp Down
Max # of Active UAVs	25, 50, 75, 100
Time to Launch a Wave of UAV(s) (secs)	30, 60

Max # of UAV to Launch Simultaneously	1, 2, 5, 10, 20

A few of the independent variables from the nominal use case were set, rather than varied for this experiment, primarily to reduce the required number of overall trials. A review of those variables resulted in the determination that setting those values was unlikely to change the overall results dramatically.

The Max Shift Duration was set to 10 hours, while the Duration of the Supervisor's Working Period was set to 120 mins. The Duration of the Supervisor's Breaks was set to 30 mins. The Logarithmic rate for the Overall Workload calculation was set to 0.5.

16.3.3.2. Dependent Variables

The dependent variables for the UE use case evaluation were almost identical to those for the nominal use case evaluation, provided in Table 50. The only new dependent variable is auditory Overall Workload with a maximum possible value of 2 and minimum value of 1.

Table 56. UE use case dependent variables.

Dependent Variables	Minimum	Maximum
Auditory Workload	1	2
Cognitive Workload	10.2	40.42
Fine Motor Workload	2.2	14.21
Visual Workload	12.1	45.71
Overall Workload	24.5	96.58
# of UAVs En-route ($N_{En\text{-}route}$)	1	100

16.3.3.3. Simulation Methodology

A total of 720 independent variable combinations are possible; however, to condense the data collection time, UE instances were consolidated into a single trial for the Ramp up or Ramp down shift state instances. Trials of said consolidated combinations have the UE occur twice in the 2nd and 4th working period, once in the Ramp up shift state and once during the Ramp down shift state. This consolidation is possible because the UEs are discrete instances that have a finite impact on the model's outputs. This consolidation lowered the total number of combinations to 480. Among the 480 combinations, 12 were considered invalid because they result in trials with very short Steady state shift states (1 min). If a UE was to occur within the 1 min Steady state, the majority of the Supervisor's response to the UE will occur during the subsequent Ramp down shift state, an undesirable characteristic for data analysis. It is noted that UEs will occur such that they cross between shift states during actual deployments, but the analysis of such cases is outside the scope of the current A26 effort. The current effort requires that the UE occurrences arise and are handled during the specific shift states, as this ensures that appropriate data and results are generated to reflect the impact of the UE on the Supervisor within a given shift state.

Each valid combination of independent variables was run for 25 trials in order to account for variability in the model distributions provided in Table 53. A total of 11,700 trials were run (468 x 25 = 11,700).

The current UE model does not incorporate a fatigue model; therefore, UEs that occur in later work periods during a shift will not be affected by fatigue. A model that incorporates the SAFTE fatigue model can adequately capture the impact of the interaction of fatigue and the UE's impact on Supervisor performance, but the combination of such variables is left as future work.

16.3.3.4. Data Analysis Methodology

The data for a single trial consisted of a time series for each dependent variable sampled at the given sampling rate. Only the data sampled at the 10 second rate was analyzed. The UE trials were designed to include UEs in the 2nd and 4th work periods. The timing of the UEs occurring in the Ramp up shift states in the 2nd and 4th working periods for a best-case (left) and a worst-case (right) scenario are illustrated in Figure 13(a) for a Mid-air collision UE trial. The dark red line during the 2nd and 4th working periods indicates the Overall Workload for the respective UE time periods. The light red shading above the graphed data covers the same periods and serves to make the time period more visible to the reader. The dark blue line indicates the Overall Workload for the paired timeframes in the 1st and 3rd working periods during which no UE occurred. The light blue shading above the graphed data covers the same periods and again is intended to make it easier to see the timeframe on the graph.

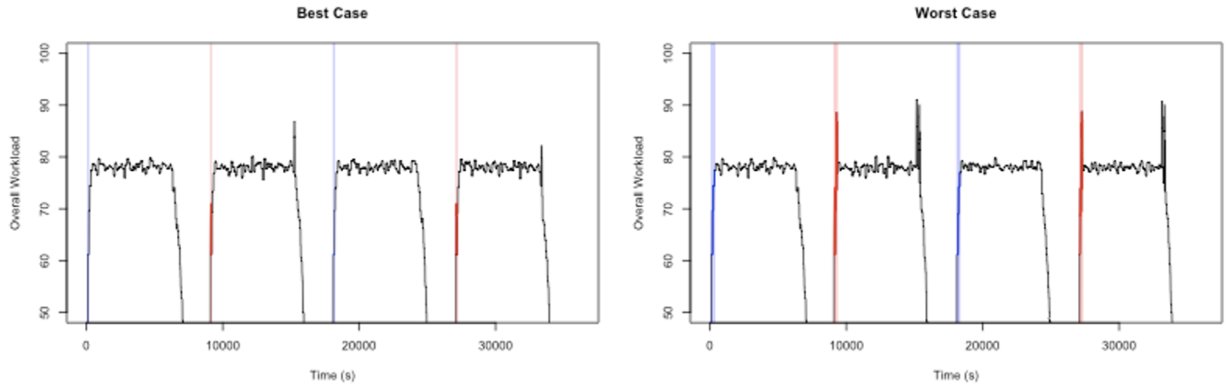
The corresponding time interval for each UE in the preceding (control) working period was identified (i.e., 2nd work period UE and the 1st work period with no UE) and subtracted the control interval's Overall Workload (1st work period) at each time step from the corresponding Overall Workload in the UE interval (i.e., 2nd work period). The net difference in UE's best-case Overall Workload between the 2nd and 1st working periods and the 4th and 3rd working periods, shown in Figure 13(b) left where the x-axis indicates the relative time since the start of the associated working period. The worst-case UE trial results are provided on the right side of Figure 13(b). As evident in Figure 13(b), the distributions of the net difference in Overall Workload vary considerably between the best- and worst-case UEs.

A single measure of change in Overall Workload for the UE was calculated. As illustrated in Figure 13(c), the derived dependent variable was created based on the Root Mean Squared Difference (RMSD) in Overall Workload between the UE's timeframe in the working period and the paired control working period's timeframe. See Equation 3 where W_{UE} is the Overall Workload for the UE timeframe and W_C is the Overall Workload for the associated control working period timeframe.

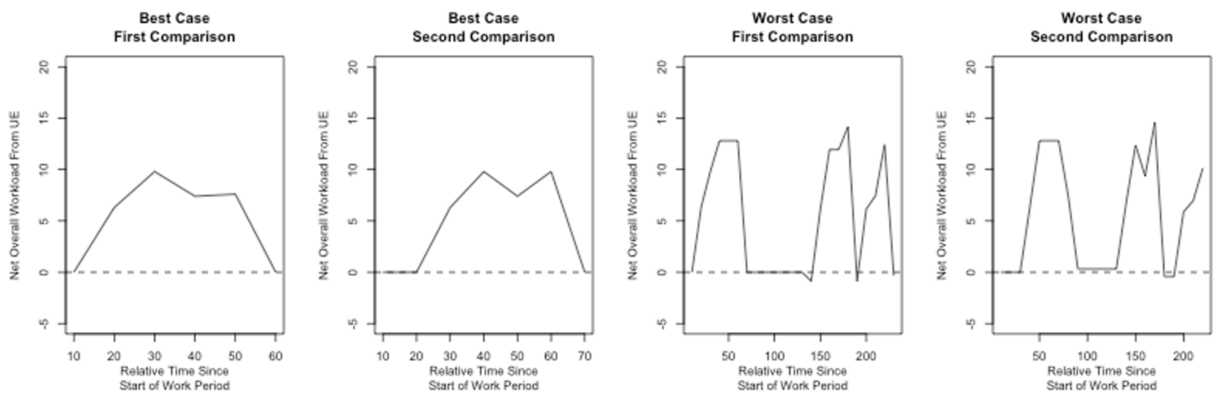
$$RMSD(W) = \sqrt{\text{mean}((\boldsymbol{W}_{UE} - \boldsymbol{W}_C)^2)} \tag{3}$$

Multi-factor Analysis of Variances (ANOVAs) were conducted using RMSD Overall Workload for the three shift states (i.e., Ramp up, Steady state, Ramp down) for each UE type (i.e., Emergency in the Airspace, Mid-air collision and C^2 link loss). A Type I Error rate (α) of 0.05 was used to determine significance.

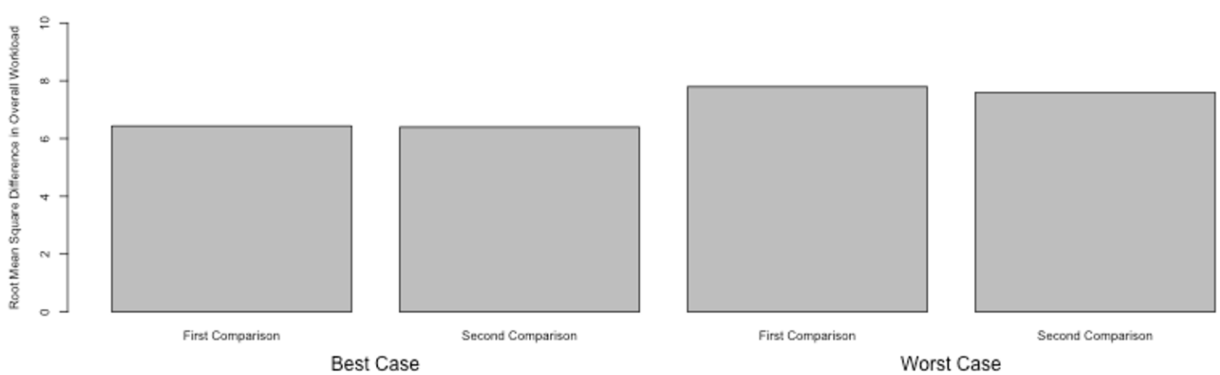
As described in Baker (2005), Olejnik and Algina (2003) propose *generalized eta squared g*, η_G^2, an effect size statistic that provides comparable estimates for the strength of an effect even when designs vary. There is no absolute meaning associated with this measure. Rather, its value has meaning in relation to the findings of other analyses. Baker (2005) reports that Cohen (1988) recommended that an η_G^2 of 0.02 is small, 0.13 is medium, and 0.26 is large.



(a) The UE occurrences (red) in the 2nd and 4th working periods and the associated comparison timeframes without UEs (blue) in the 1st and 4th working periods.



(b) The differences between the Overall Workloads of each UE and its associated comparison during the relevant timeframes by best- and worst-cases.



(c) The root mean squared difference Overall Workload measures by best- and worst-cases.

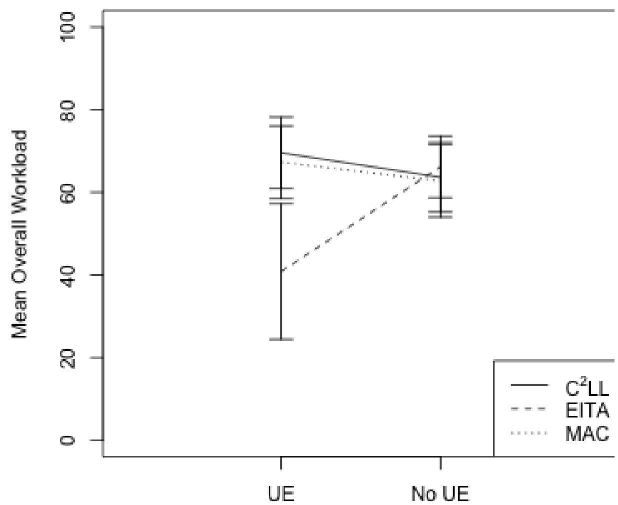
Figure 13. Mid-air collision Ramp up best-(left) and worst-case (right) scenario data analysis trial exemplars. The (a) UE occurrence timeframes, (b) differences between the Overall Workloads of each UE and its associated comparison, and (c) the root mean squared difference Overall Workload measures.

16.3.4. Results

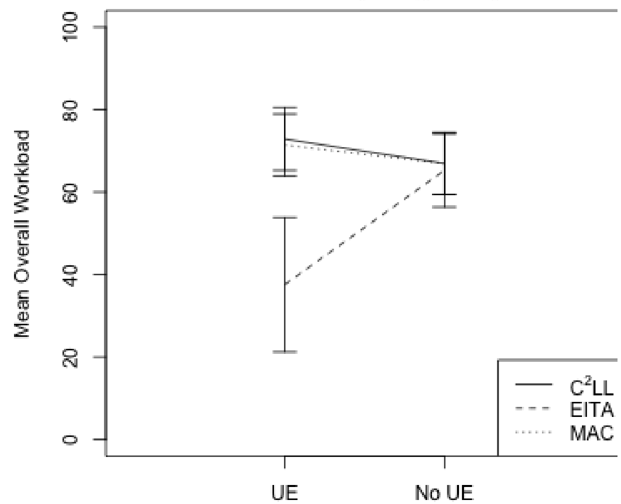
The descriptive statistics for Overall Workload for the three UE types by shift state are provided in Table 57. The means for Overall Workload for the C^2 link loss and Mid-air collision trials across the shift states fall between 65 and 73, while for Emergency in the airspace they are near 40 for Ramp up and Steady state and close to 3 in Ramp down. The Overall Workload values for the C^2 link loss and Mid-air collision trials are higher when the unexpected events are occurring (Figure 14). However, the mean Overall Workload for the Emergency in the airspace trials is lower during the UE as compared to when the events are not occurring.

Table 57. The Overall Workload descriptive statistics – mean (standard deviation) - for the UE types by shift state.

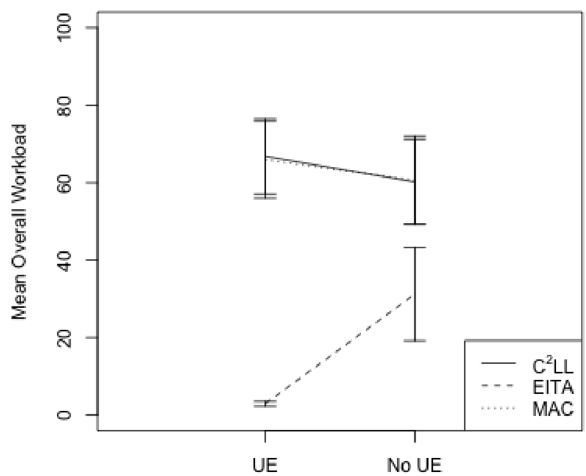
Types of unexpected events	**Ramp up**	**Steady state**	**Ramp down**
Emergency in the airspace	40.87 (16.41)	37.56 (16.28)	2.94 (0.62)
Mid-air collision	67.3 (8.79)	71.43 (7.53)	65.94 (9.95)
C^2 link loss	69.58 (8.63)	72.87 (7.61)	66.81(9.74)



(a) Ramp up



(b) Steady state



(c) Ramp down

Figure 14. Mean Overall Workload for the UE trials (Emergency in the airspace (EITA), Mid-air collision (MAC), and C^2 link loss (C^2LL)) during the UE and when they were not occurring: (a) Ramp up, (b) Steady state, and (c) Ramp down.

16.3.4.1. Emergency in the Airspace (Autonomy is unaware)

Although the planned Max # of UAVs to Launch Simultaneously independent variable included 5 values (i.e., 1, 2, 5, 10, and 20). The data for the launching of 1 UAV at a time when the Time to Launch a Wave of UAV(s) was set to 60 seconds, and the Max # of UAVs set to 100 was removed, because these trials were not valid. This data was removed in order to provide a complete factorial design. Additionally, as the Steady state trials and the Ramp up/Ramp down trials were executed separately, different trials were cleansed for the shift state analyses. There were 3198 Ramp up, 3200 Steady state, and 3198 Ramp down RMSD Overall Workload measures included in the data analysis.

The descriptive statistics for RMSD Overall Workload and each channel for Ramp up, Steady state and Ramp down shift states are presented in Table 58, Table 59, and Table 60, respectively. The cognitive and visual workload channels were the main contributors to the mean RMSD Overall

Workload (29.393 in Ramp up, 33.474 in Steady state, and 38.625 in Ramp down). The descriptive statistics for the standard deviations and Levene's test for homogeneity of variance indicate a lack of meeting the assumptions for applying ANOVA analyses to the RMSD data across the workload channels. Thus, ANOVA analyses are conducted on the RMSD Overall Workload measure, but the results need to be interpreted with care due to the lack of conformance with the underlying assumptions of ANOVA.

Table 58. Descriptive statistics for RMSD workloads in Emergency in the airspace UEs: Ramp up.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	29.393	0.028	12.349	2.661	14.474
Median	32.113	0.000	13.372	2.889	15.860
Standard deviation	14.975	0.066	6.119	1.329	7.443
Range	6.261-53.146	0.000- 0.455	3.093-22.126	0.554- 4.779	2.782-26.246

Table 59. Descriptive statistics for RMSD workloads in Emergency in the airspace UEs: Steady state.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	33.474	0.0277	14.023	3.020	16.499
Median	34.883	0.000	14.533	3.142	17.218
Standard deviation	13.727	0.067	5.631	1.224	6.812
Range	5.460-64.558	0.000-0.544	2.858-26.877	0.015-5.799	2.424-31.886

Table 60. Descriptive statistics for RMSD workloads in Emergency in the airspace UEs: Ramp down.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	38.625	0.027	16.092	3.477	19.070
Median	39.881	0.000	16.603	3.586	19.693
Standard deviation	10.886	0.066	4.522	0.973	5.382
Range	1.306-59.518	0.000-0.423	0.604-24.783	0.201-5.347	0.645-29.393

The significant multi-factor ANOVA results for the 4 Max # of UAVs (i.e., 25, 50, 75, 100) x 2 Time to Launch a Wave of UAV(s) (i.e., 30, 60 secs) x 4 Max # of UAVs to Launch Simultaneously (i.e., 2, 5, 10, 20) x 2 scenario case (i.e., best case, worst case) for the RMSD workload measures for Ramp up, Steady state, and Ramp down shift states are presented in Table 61, Table 62, and Table 63, respectively.

Table 61. RMSD Overall Workload ANOVA results for Emergency in the airspace UEs: Ramp up.

Factor	df	F	p	Effect Size
Max # of Active UAVs (Max UAVs)	3, 3134	1386.855	<.001	.5704*
Max # of UAV to Launch Simultaneously (wave size)	3, 3134	67.125	<.001	.0604*
Scenario case	1, 3134	65342.467	<.001	**.9542***
Max UAVs x Time to Launch a Wave of UAV(s) (launch)	9, 3134	6.753	<.001	.0064
Max UAVs x wave	3, 3134	45.846	<.001	.1163*
Launch x wave	3, 3134	86.221	<.001	.0762*
Max UAVs x Scenario case	1, 3134	178.243	<.001	**.1458***
Launch x Scenario case	3, 3134	477.116	<.001	**.1321***
Wave size x Scenario case	9, 3134	1094.039	<.001	**.5115***
Max UAVs x Launch x Wave	3, 3134	11.452	<.001	.0318*
Max UAVs x Launch x Scenario case	9, 3134	9.661	<.001	.0092
Max UAVs x Wave size x Scenario case	3, 3134	21.914	<.001	**.0592***
Launch x Wave size x Scenario case	9, 3134	21.048	<.001	.0197

The ANOVA results indicate that thirteen row factors (main effects, two-way interactions, three-way interactions) for the Ramp up shift start are statistically significant, with eleven (see the effect sizes marked with "*" in Table 61) having an effect size greater than the small criterion (0.02; Baker, 2005). As they were significant in the nominal cases (

Table 52), it was unsurprising that the six row factors that included the Max # of UAVs, Max # of UAV(s) to Launch Simultaneously, and Time to Launch a Wave of UAV(s), alone or in combination, were significant with effect sizes greater than 0.02. Five row factors involved the scenario case (defined in Table 55, see the bold effect sizes marked with "*" in Table 61; and Figure 15, Figure 16, and Figure 17). Given the difference in Overall Workload due to grounding aircraft during the Emergency in the airspace, it is not surprising that the large effect of scenario case (i.e., best- and worst-case) was found.

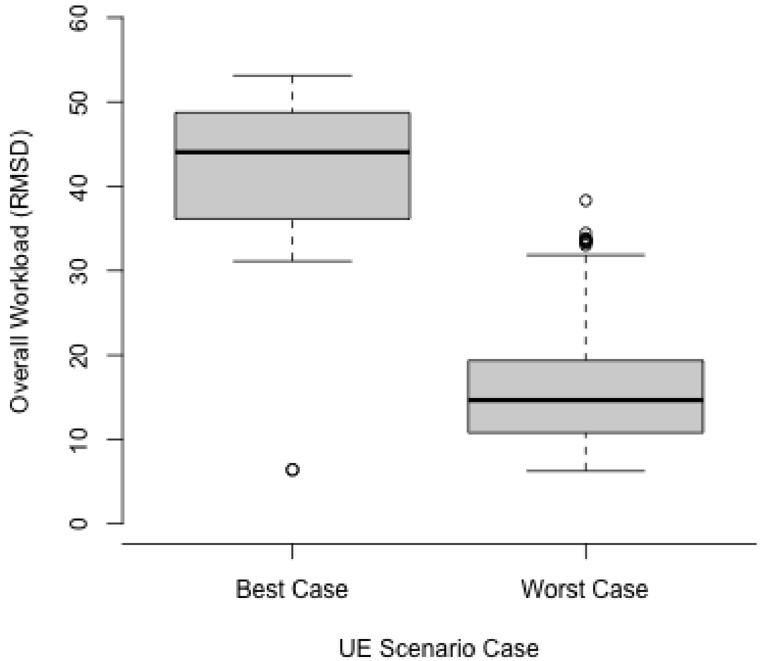
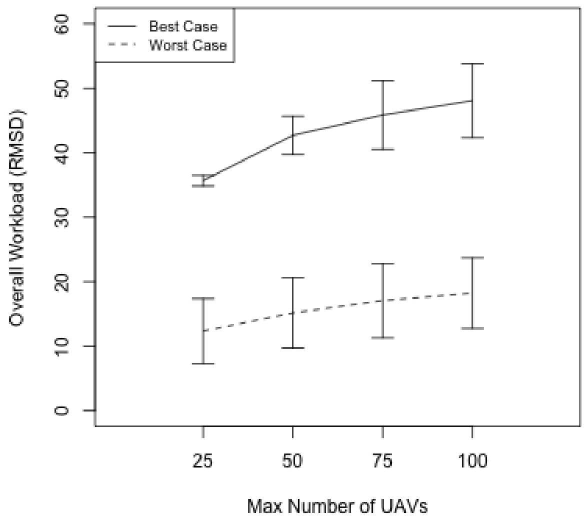
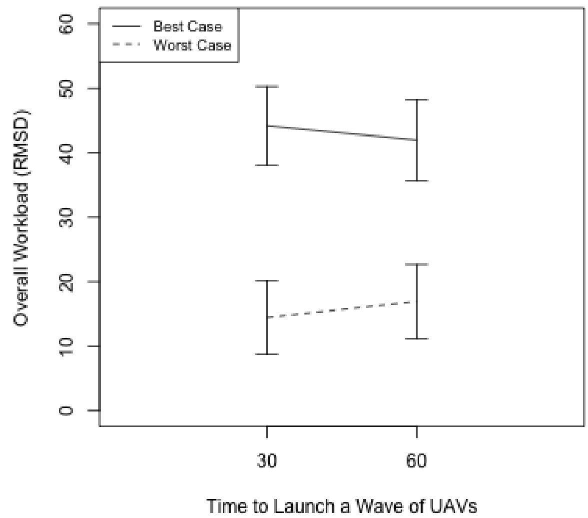


Figure 15. ANOVA results: RMSD Overall Workload box plots for Emergency in the airspace UEs: Ramp up trials by the best- and worst-case scenarios.

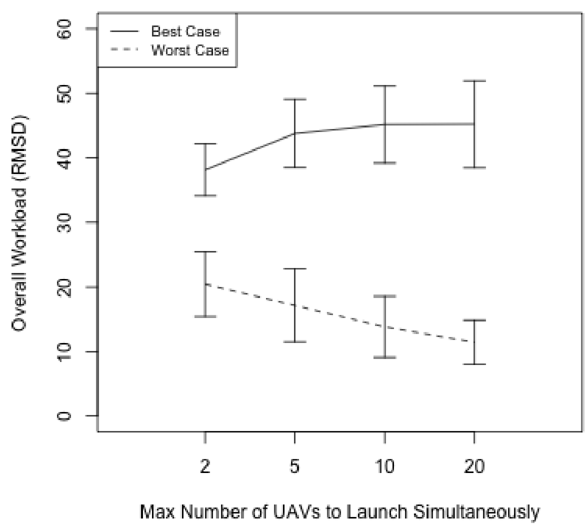
Regarding the two-way interactions that include the best- and worst-case scenarios, the RMSD Overall Workload increases at a higher rate as the Max # of active UAVs increases for the best-case scenario, shown in Figure 16(a). The RMSD in Overall Workload for the Time to Launch a Wave of UAV(s) increases with time for the worst-case, but decreases with time for the best-case, shown in Figure 16(b). RMSD in Overall Workload decreases with respect to the Max # of UAVs to Launch Simultaneously decreases in the worst-case scenario, but increases in the best-case, as indicated in in Figure 16(c).



(a) Max # of Active UAVs x Scenario case



(b) Time to Launch a Wave of UAV(s) x Scenario case



(c) Max # of UAV to Launch Simultaneously x Scenario case

Figure 16. ANOVA results: two-way interaction plots of RMSD Overall Workload for Emergency in the airspace UEs: Ramp up trials (a) Max # of Active UAVs x Scenario case; (b) Time to Launch a Wave of UAV(s) x Scenario case; (c) Max # of UAV to Launch Simultaneously x Scenario case.

The three-way interaction plot in Figure 17 helps to illustrate that the patterns seen in the two-way interaction plots in Figure 16 change at different rates between the best- (left) and worst-case (right) trials. Greater Max # of Active UAVs and greater Max # of UAV to Launch Simultaneously during the nominal use case (Section 16.2.3) yielded the highest peak workload. During the best-case scenario, these independent variable combinations have the most Overall Workload to lose (i.e., because the peak Overall Workload is greatest) when UAVs are handed off to the UE Supervisor; hence, they produce larger RMSD in Overall Workload (Figure 17 Best Case). The Supervisor is still responsible for UAVs unaffected by the Emergency in the airspace during the worst-case scenario, and the ratio of unaffected UAVs to total active UAVs at the same relative time in the control period drives RMSD in Overall Workload. The number of unaffected UAVs for an Emergency in the Airspace UE that occurs during Ramp up is dependent on the rate at which UAVs come under the Supervisor's command, or are launched. Greater Max # of UAVs to Launch Simultaneously (Figure 16(c) and Figure 17 worst-case) and shorter Time to Launch a Wave of UAV(s) (Figure 16(b)) lead to more UAVs launching faster, which causes the number of unaffected UAVs to be closer to the number of UAVs at the same relative time in the control work period (without UEs) and produces smaller RMSD in Overall Workload. Note that the Max # of Active UAVs does not affect this ratio, because it does not affect the launch rate, and; therefore, the change in RMSD for the worst-case in Figure 16(a) is in the same direction, albeit weaker, as the best-case.

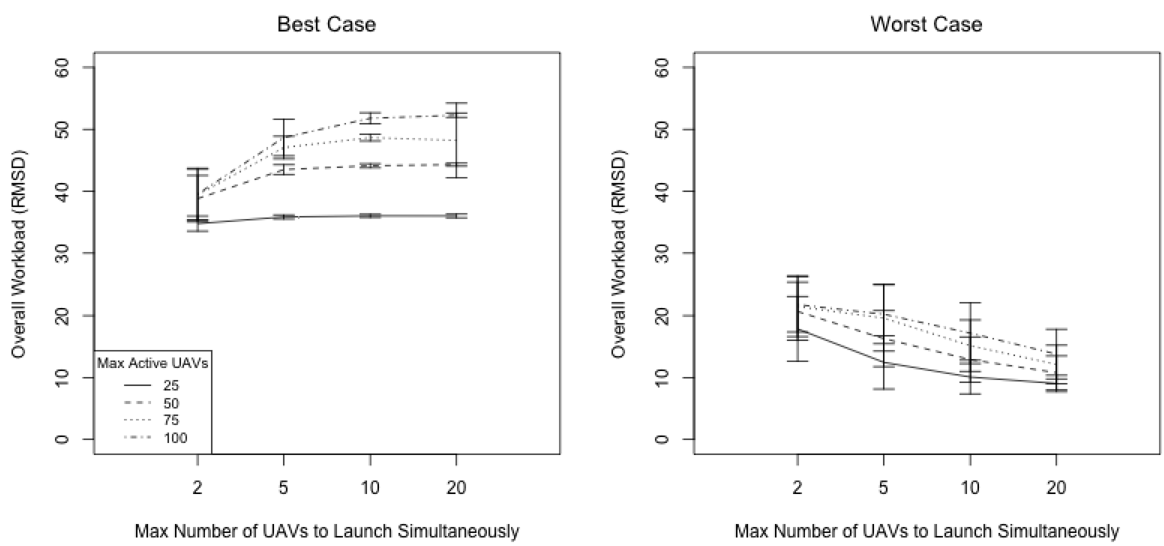


Figure 17. ANOVA results: three-way interaction plots of RMSD Overall Workload for Emergency in the airspace UEs: Max # of active UAVs x Max # of UAVs to launch simultaneously x Scenario case.

During Steady state, thirteen row factors (main effects, two-way interactions, three-way interactions) are significant; with seven having an effect size greater than 0.02 (see the effect sizes marked with "*" in Table 62). As they were significant in the nominal cases (

Table 52), it was unsurprising that the four row factors including Max # of UAVs, Max # of UAVs to Launch Simultaneously, and Time to Launch a Wave of UAV(s), alone or in combination, were significant, with effect sizes greater than 0.02. Three row factors involved the scenario case, best- or worst-case (see the significant effect sizes greater than 0.02 marked with a bold "*" in Table 62. The similarity between Figure 16(a) and Figure 18 and Figure 19 is because the ratio of unaffected UAVs is not affected during Steady state.

Table 62. RMSD Overall Workload ANOVA results for Emergency in the airspace UEs: Steady state.

Factor	**df**	**F**	**p**	**Effect Size**
Max # of Active UAVs (Max UAVs)	3, 3136	415.070	<.001	.2842*
Time to Launch a Wave of UAV(s) (launch)	1, 3136	40.481	<.001	.0127
Max # of UAV to Launch Simultaneously (wave)	3, 3136	108.652	<.001	.0942*
Scenario case	1, 3136	17176.477	<.001	**.8456***
Max UAVs x Launch	3, 3136	4.986	.002	.0047
Max UAVs x wave	9, 3136	19.830	<.001	.0538*
Launch x wave	3, 3136	25.770	<.001	.0241*
Max UAVs x Scenario case	3, 3136	124.361	<.001	**.1063***
Launch x Scenario case	1, 3136	19.782	<.001	.0063
Wave size x Scenario case	3, 3136	30.005	<.001	**.0279***
Max UAVs x Launch x Wave	3, 3136	4.821	<.001	.0136
Max UAVs x Wave size x Scenario case	9, 3136	4.241	<.001	.0120
Launch x Wave size x Scenario case	3, 3136	8.427	<.001	.0080

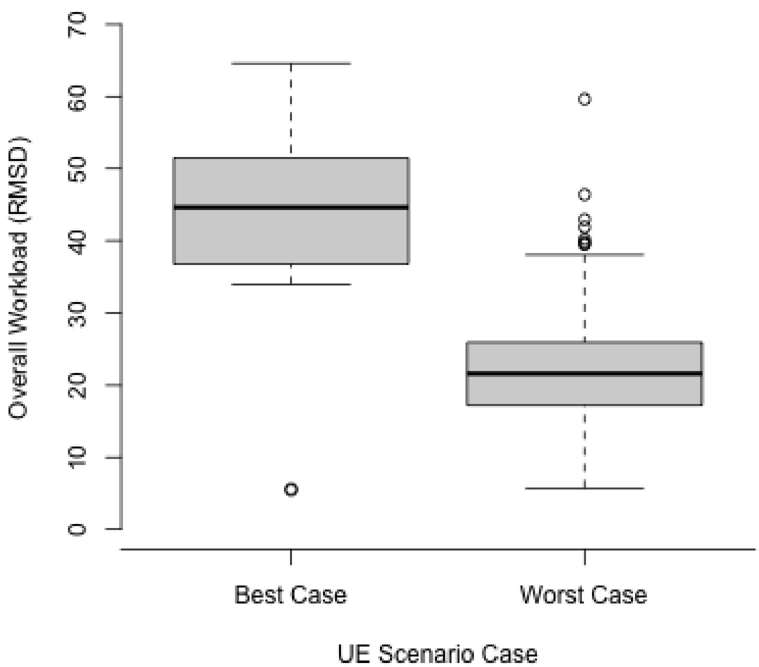
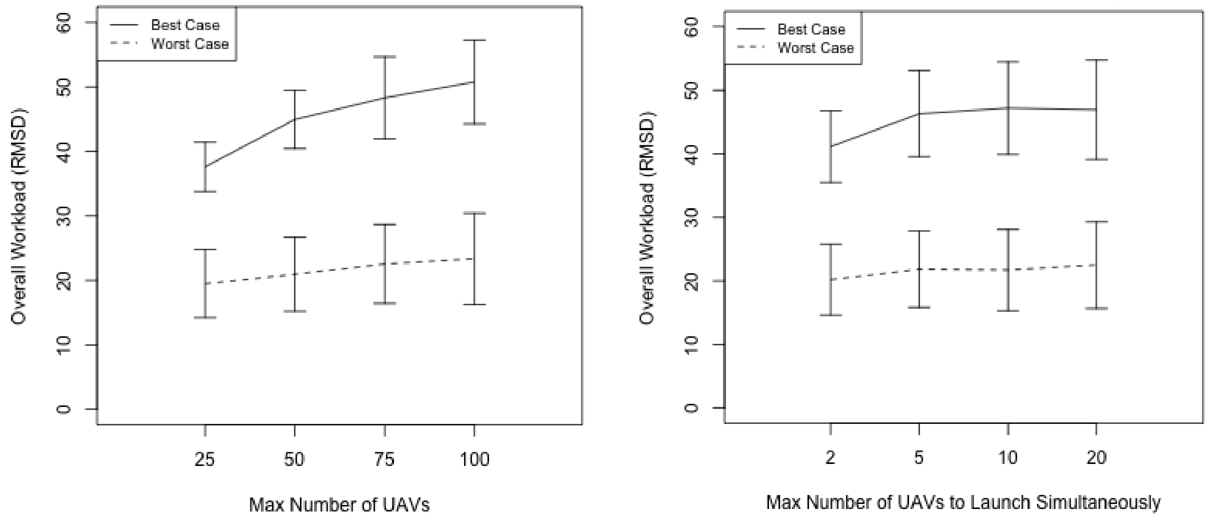


Figure 18. ANOVA results: RMSD Overall Workload box plots for Emergency in the UEs: Steady state trials by best- and worst-case.



(a) (b)

Figure 19. ANOVA results: two-way interaction plots of RMSD Overall Workload for Emergency in the airspace UEs: Steady trials a) Max # of active UAVs x Scenario case; b) Max # of UAVs to launch simultaneously x Scenario case.

Nine Ramp down row factors (main effects, two-way interactions, three-way interactions, four way-interactions) are significant; with two having an effect size is greater than 0.02 (see Table 63). Scenario case (i.e., best- vs. worst-case) was not a part of any significant row factor with an effect size greater than the small threshold.

Table 63. RMSD Overall Workload ANOVA results for Emergency in the airspace UEs: Ramp down

Factor	df	F	p	Effect Size
Max # of Active UAVs (Max UAVs)	3, 3134	175.397	<.001	.1438*
Time to Launch a Wave of UAV(s) (launch)	1, 3134	30.884	<.001	.0098
Max # of UAV to Launch Simultaneously (wave)	3, 3134	62.736	<.001	.0567*
Scenario case	1, 3134	5.492	.019	.0017
Max UAVs x Launch	3, 3134	5.133	.002	.0049
Max UAVs x wave	9, 3134	7.085	<.001	.0199
Launch x Wave	3, 3134	7.749	<.001	.0074
Max UAVs x Launch x Wave	9, 3134	2.756	.003	.0079
Max UAVs x Launch x Wave size x Scenario case	9, 3134	2.018	.034	.0058

16.3.4.2. Mid-air Collision (UAV can fly, but damaged and unable to complete mission)

Although the planned Max # of UAV(s) to Launch Simultaneously included 5 values (i.e., 1, 2, 5, 10, and 20), the launching a maximum of 1 UAV at a time data were removed from the analysis, as trials for the combination of Time to Launch a Wave of UAV(s) set to 60 seconds and the Max # of UAVs set to 100 were not valid. These trials were removed in order to obtain a complete factorial design. Additionally, as the Steady state trials and the Ramp up/Ramp down trials were executed separately, different trials were cleansed for the shift state analyses. The reduced data set RMSD Overall Workload measures were available for 3198 Steady state and 3188 Ramp up and Ramp down events. There were 3188 Ramp up, 3198 Steady state, and 3188 Ramp down RMSD Overall Workload measures included in the data analysis.

The descriptive statistics are provided for RMSD Overall Workload and each channel for the Ramp up (Table 64), Steady state (Table 65), and Ramp down (Table 66) shift states. The cognitive and visual workload channels were the main contributors to the mean RMSD for Overall Workload (6.632 in Ramp up, 6.680 in Steady state, and 7.527 in Ramp down). The descriptive statistics for the standard deviations and Levene's test for homogeneity of variance indicate a lack of meeting the assumptions of applying ANOVA analyses to the RMSD data across the workload channels. Thus, ANOVA analyses are conducted on the RMSD Overall Workload measure to provide insights into the results, but need to be interpreted with care due to the lack of conformance with the underlying assumptions of ANOVA.

Table 64. Descriptive statistics for RMSD Workloads in Mid-air collision UEs: Ramp up.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	6.632	0.346	3.515	0.946	2.800
Median	6.688	0.378	3.585	0.881	2.870
Standard deviation	1.042	0.196	0.565	0.258	0.556
Range	2.933-10.253	0.000-1.000	0.296- 5.297	0.000- 1.796	1.202-4.550

Table 65. Descriptive statistics for RMSD Workloads in Mid-air collision UEs: Steady state.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	6.680	0.339	3.536	0.945	2.838
Median	6.771	0.354	3.616	0.880	2.898
Standard deviation	1.204	0.195	0.596	0.243	0.617
Range	2.846-13.972	0.000- 0.913	0.717- 6.498	0.033-1.776	0.915-6.323

Table 66. Descriptive statistics for RMSD Workloads in Mid-air collision UEs: Ramp down.

	Overall	**Auditory**	**Cognitive**	**Fine Motor**	**Visual**
Mean	7.527	0.342	3.862	1.009	3.270
Median	7.057	0.354	3.691	0.923	3.041
Standard deviation	3.212	0.197	1.330	0.341	1.580
Range	2.192- 48.267	0.000-0.913	0.623-20.369	0.031- 4.686	1.012-23.332

The significant multi-factor ANOVA results for the 4 Max # of UAVs (i.e., 25, 50, 75, 100) x 2 Time to Launch a Wave of UAV(s) (i.e., 30, 60) x 4 Max # of UAV to Launch Simultaneously (i.e., 2, 5, 10, 20) x 2 scenario case (i.e., best case, worst case) for the RMSD workload measures are provided in

Table 67, Table 68, and Table 69 for Ramp up, Steady state, and Ramp down shift states, respectively.

While four row factors are statically significant for Ramp up, the effect size is greater than 0.02 for only the scenario case factor (see the effect size marked with the bold "*" in

Table 67). The box plots for the best-and worst-case scenarios are provided in Figure 20.

Table 67. RMSD Overall Workload ANOVA results for Mid-air collision UEs: Ramp up.

Factor	**df**	**F**	**p**	**Effect Size**

Max # of Active UAVs (Max UAVs)	3, 3124	5.097	.002	.0049
Max # of UAV to Launch Simultaneously (Wave size)	3, 3124	7.527	< .001	.0072
Scenario Case	1, 3124	1801.807	< .001	**.3658***
Max UAVs x Wave size	9, 3124	2.108	.026	.0060

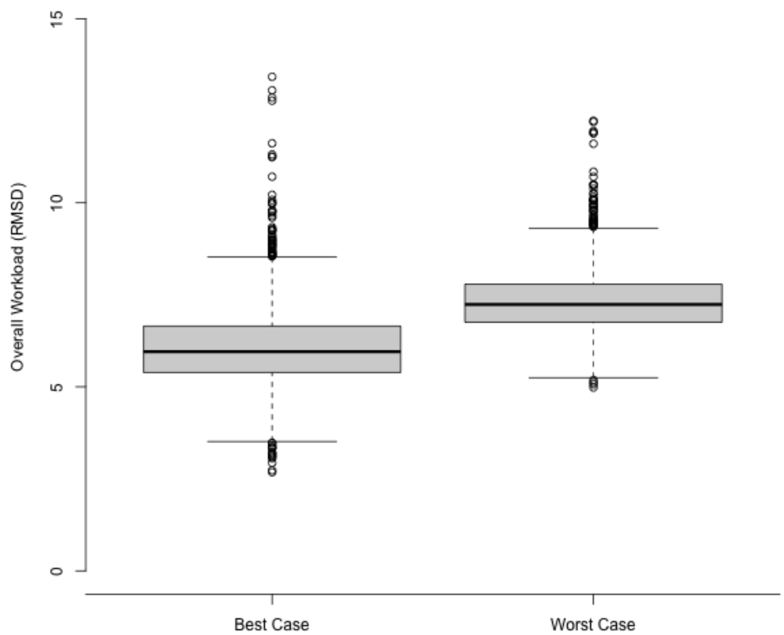


Figure 20. ANOVA results: RMSD Overall Workload box plots for Mid-air collision UEs: Ramp up trials by Scenario case.

Three Steady state row factors are significant (Table 68); however, only the scenario case's effect size is greater than 0.02. While the mean RMSD Overall Workload in the best-case scenario was 6.009, it was 7.351 in the worst case (Figure 21).

Table 68. RMSD Overall Workload ANOVA results for Mid-air collision UEs: Steady state.

Factor	df	F	p	Effect Size
Max # of Active UAVs (Max UAVs)	3, 3134	5.079	.002	.0048
Time to Launch a Wave of UAV(s)	1, 3134	6.204	.013	.0020
Scenario Case	1, 3134	1450.180	< .001	**.3163***

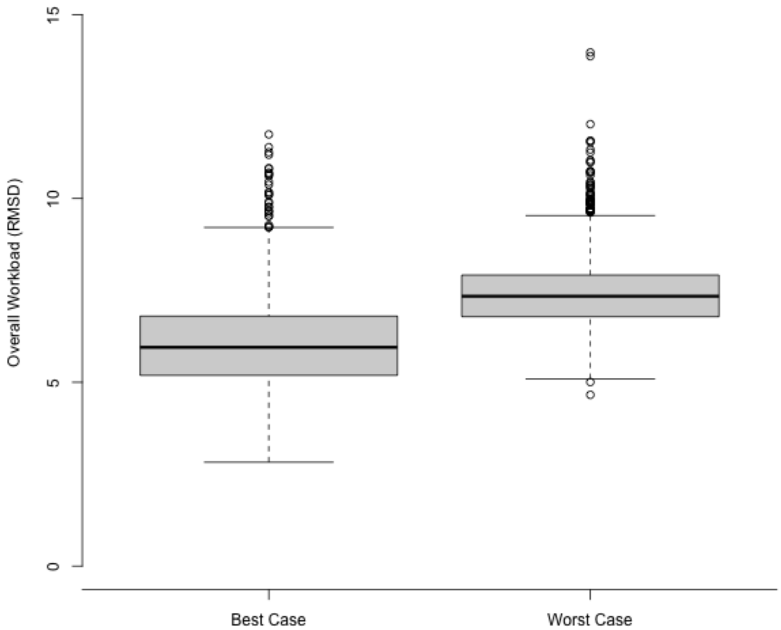


Figure 21. ANOVA results: RMSD Overall Workload box plot for mid-air collision UEs' Steady state trials by scenario case.

Six Ramp down row factors are significant; however, only scenario case has an effect size greater than 0.02 (Table 69). While the mean RMSD Overall Workload in the best-case scenario was 6.692, it was 8.368 in the worst case (Figure 22).

Table 69. RMSD Overall Workload ANOVA results for Mid-air collision UEs: Ramp down.

Factor	**df**	**F**	**p**	**Effect Size**
Max # of Active UAVs (Max UAVs)	3, 3124	8.509	< .001	.0081
Scenario Case	1, 3124	237.366	< .001	**.0706***
Max UAVs x Time to Launch a Wave of UAV(s)	3, 3124	2.642	.048	.0025
Time to Launch a Wave of UAV(s) x Max # of UAV to Launch Simultaneously (Wave size)	3, 3124	6.104	< .001	.0058
Time to Launch a Wave of UAV(s) x Wave size x Case	3, 3124	3.909	.008	.0037
Max UAVs x Time to Launch a Wave of UAV(s) x Wave size x Scenario Case	9, 3124	2.537	.007	.0073

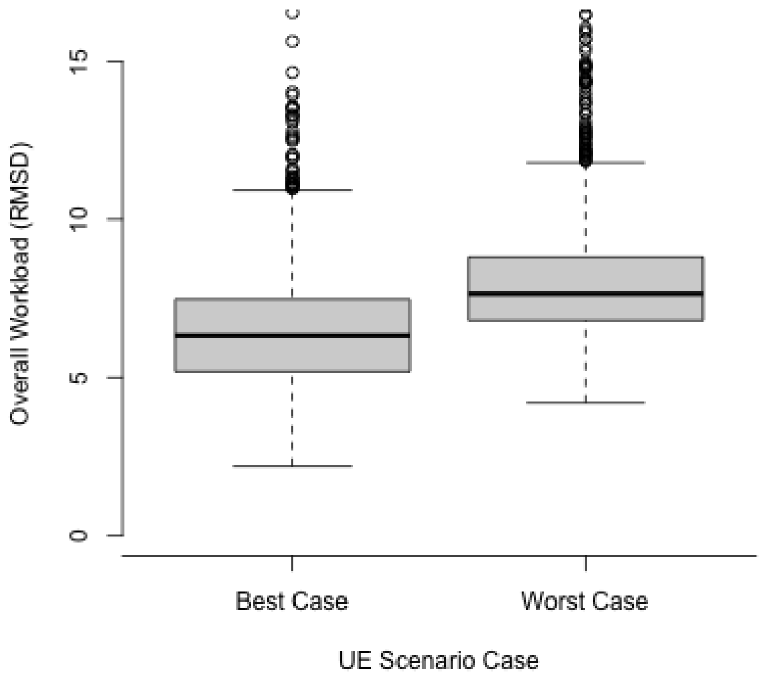


Figure 22. ANOVA results: RMSD Overall Workload box plot for mid-air collision UEs Ramp down trials by scenario case.

16.3.4.3. C² Link Loss (decision support system is unavailable)

Although the planned Max # of UAV(s) to Launch Simultaneously included 5 values (i.e., 1, 2, 5, 10, and 20), the Max # of UAV(s) Launched Simultaneously when set to 1 data were removed from the analysis, as trials for the combination of Time to Launch a Wave of UAV(s) set to 60 seconds and the Max # UAVs set to 100 were not valid and were removed. Additionally, as the Steady state trials and the Ramp up/Ramp down trials were executed separately, different trials were cleansed for the shift state analyses. The RMSD Overall Workload measures were available for 3200 Steady state and 2874 Ramp up and Ramp down events. There were 2874 Ramp up, 3200 Steady state, and 2874 Ramp down RMSD Overall Workload measures included in the data analysis.

The RMSD Overall Workload and each workload channel descriptive statistics for Ramp up, Steady state and Ramp down shift states are presented in Table 70, Table 71, and Table 72, respectively. Generally, the Overall Workload was driven by the cognitive and visual workload channels; auditory and fine motor channels were not the main contributors. The descriptive statistics for standard deviation and Levene's test for homogeneity of variance indicate a lack of meeting the assumptions of the use of ANOVA analyses. Thus, ANOVA analyses are conducted on the RMSD Overall Workload measure to provide insights into the results, but need to be interpreted with care.

Table 70. Descriptive statistics for RMSD Workloads in C^2 link loss UEs: Ramp up.

	Overall	Auditory	Cognitive	Fine Motor	Visual
Mean	7.591	0.279	4.028	1.081	3.345
Median	7.672	0.258	4.084	0.945	3.413
Standard deviation	1.674	0.156	0.679	0.485	0.668
Range	3.422-12.512	0.000-0.588	2.127 -5.793	0.000-2.327	1.467-5.685

Table 71. Descriptive statistics for RMSD Workloads in C^2 link loss UEs: Steady state.

	Overall	Auditory	Cognitive	Fine Motor	Visual
Mean	7.699	0.288	4.060	1.094	3.404
Median	7.803	0.263	4.128	0.942	3.472
Standard deviation	1.757	0.155	0.724	0.485	0.701
Range	3.426-13.446	0.000-0.609	2.133-6.325	0.036-2.233	1.626-6.248

Table 72. Descriptive statistics for RMSD Workloads in C^2 link loss UEs: Ramp down.

	Overall	Auditory	Cognitive	Fine Motor	Visual
Mean	8.379	0.279	4.330	1.154	3.748
Median	7.905	0.258	4.158	0.979	3.490
Standard deviation	3.452	0.157	1.404	0.527	1.577
Range	2.075-45.600	0.000-0.612	1.770-19.387	0.076-4.060	1.502-22.243

Three Ramp up row factors are significant; however, only the scenario case's effect size is greater than 0.02 (Table 73). While the mean RMSD Overall Workload in the best-case scenario was 6.093, it was 9.100 in the worst case (Figure 23).

Table 73. RMSD Overall Workload ANOVA results for C^2 link loss UEs: Ramp up.

Factor	df	F	p	Effect Size
Max # of UAV to Launch Simultaneously (Wave size)	3, 2810	13.015	<0.001	.0137
Scenario Case	1, 2810	12207.48	<0.001	**.8129***
Max # of Active UAVs (Max UAVs) x Wave size	9, 2810	1.909	0.046	.0061

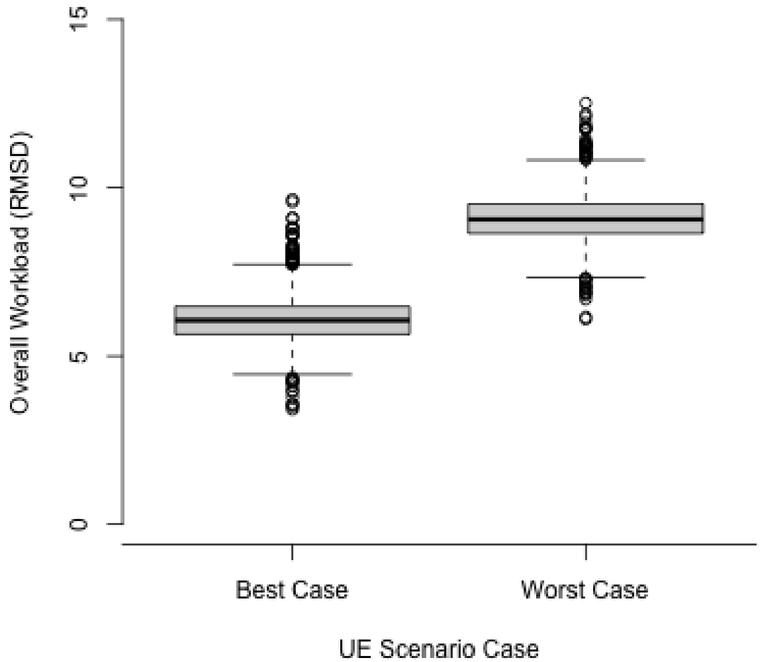


Figure 23. ANOVA results: the RMSD Overall Workload box plot for C2 link loss UEs Ramp up trials by scenario case.

During Steady state, four row factors are significant; however, only the scenario case factor has an effect size greater than 0.02 (

Table 74). The mean RMSD Overall Workload in the best-case scenario was 6.203 and was 9.195 in the worst case (Figure 24).

Table 74. RMSD Overall Workload ANOVA results for C2 link loss UEs: Steady state.

Factor	**df**	**F**	**p**	**Effect Size**
Max # of Active UAVs (Max UAVs)	3, 3136	16.562	<0.001	.0156
Time to Launch a Wave of UAV(s) (Launch)	1, 3136	4.860	0.027	.0015
Scenario case	1, 3136	8565.276	<0.001	**.7320***
Launch x Max # of UAV to Launch Simultaneously (Wave size) x Scenario case	3, 3136	2.644	0.048	.0025

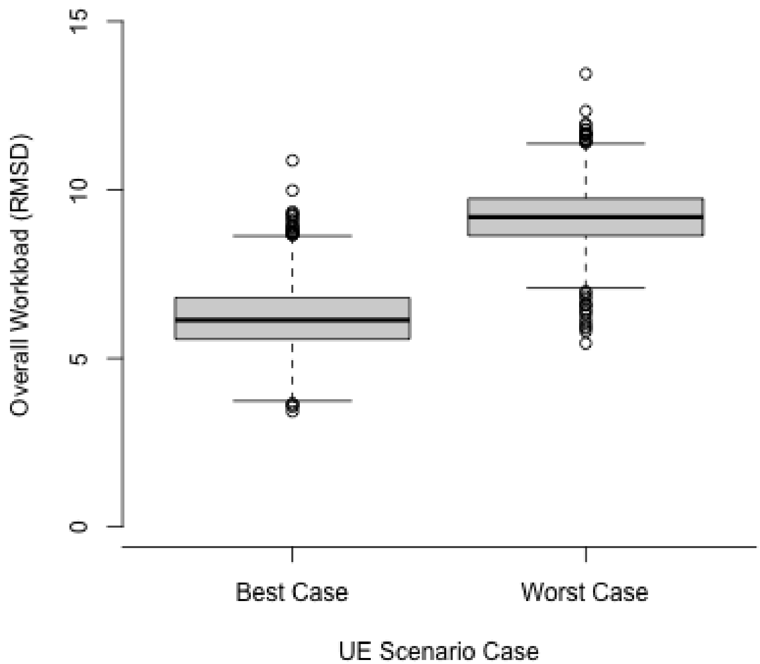


Figure 24. ANOVA results: the RMSD Overall Workload box plot for C^2 link loss UEs Steady state trials by scenario case.

Four Ramp down row factors are significant, but only the scenario case factor has an effect size greater than 0.02 (

Table 75). While the mean RMSD Overall Workload in the best-case scenario was 6.826, it was 9.944 in the worst case (Figure 25).

Table 75. RMSD Overall Workload ANOVA results for C^2 link loss UEs: Ramp down.

Factor	**df**	**F**	**p**	**Effect Size**
Max # of Active UAVs (Max UAVs)	3, 2180	6.979	<0.001	.0074
Scenario case	1, 2180	737.314	<0.001	**.2079***
Time to Launch a Wave of UAV(s) (Launch) x Scenario case	1, 2180	7.645	0.006	.0027
Max # of UAV to Launch Simultaneously (Wave size) x Scenario case	3, 2180	3.223	0.022	.0034

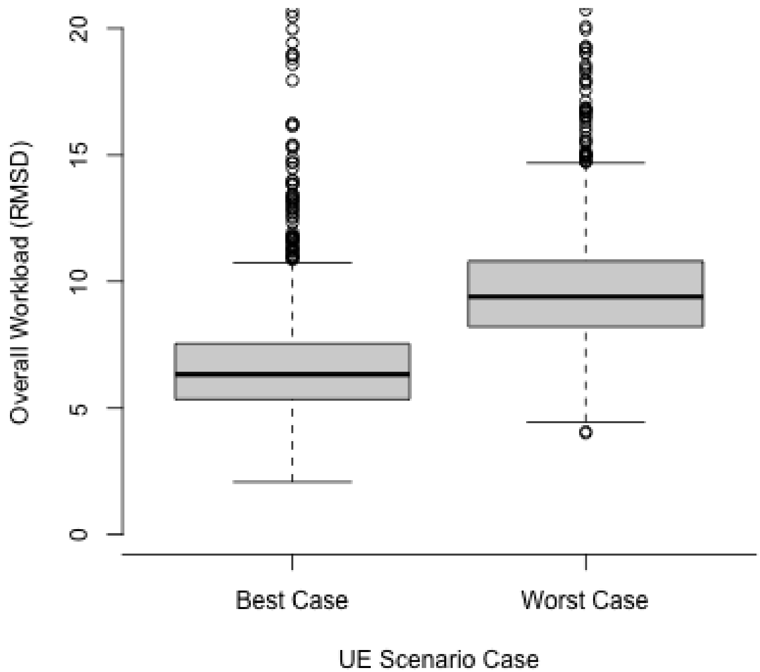


Figure 25. ANOVA results: the RMSD Overall Workload box plot for C^2 link loss UEs Ramp down trials by scenario case.

16.4. Distraction Event Use Cases

Ten distraction event use cases were developed by the A26 team as part of Task 3 (see the Task 3 report, Appendix B). It is infeasible within the scope of the A26 effort to model and fully analyze all ten distractions. As a result, and based on industrial and FAA feedback, the team developed decision trees for four distractions and further narrowed the distractions that will be modeled:

- Mindwandering
- Fatigue

16.4.1. Use Case Summaries

All decision trees for the modeled distractions use case decision trees are provided in Appendix A.

16.4.1.1. Mindwandering (Supervisor unaware)

The example Mindwandering distraction demonstrates a Supervisor who is Mindwandering, but is unaware of their Mindwandering or its effects on their task performance. The Supervisor is experiencing significant Mindwandering, which degrades the Supervisor's performance; however, the Supervisor is unaware of their Mindwandering, and they continue to attempt to perform their job duties as normal. Although the Watch Supervisor is responsible for acknowledging the effects of distraction on the Supervisor, the modeled example assumes the Watch Supervisor remains unaware of the distraction's effects. The effects of the Mindwandering distraction on the Supervisor are active for a finite period of time. Once the distraction ends, so do its effects on the Supervisor's workload and the Supervisor continues working as normal.

Regarding the impact of Mindwandering on workload, a few predictions can be made. The Overall Workload level experienced due to Mindwandering is expected to decrease. This Overall

Workload decrease is directly tied to disengagement from the task, and a shedding of expended effort. Similarly, this Overall Workload reduction is often accompanied by a corresponding reduction in task performance, which research suggests being between 10-20% for Mindwandering (Gourad et al, 2018; Yanko & Spalek, 2014). Shorter Mindwandering periods (~30 secs), for example, are expected to have negligible impacts on Overall Workload or performance; however, longer Mindwandering durations (~120s) are expected to create a natural backlog of task duties and require the Supervisor to 'catch-up' on task performance. Further, such lengthy task disengagement naturally will prolong the amount of time required to complete a task given the amount of time the Supervisor is working at sub-optimal levels.

16.4.1.2. Fatigue (Supervisor unaware)

The Fatigue (Supervisor unaware) distraction demonstrates a Supervisor under cognitive fatigue, who is unaware of their fatigue level and its effect on their task performance. The Supervisor is experiencing excessive fatigue, but given that they are unaware of their fatigue level and its associated impact on performance, the Supervisor continues to attempt to perform their job duties as normal. Although the Watch Supervisor is responsible for acknowledging the effects of fatigue on the Supervisor, the modeled example assumes the Watch Supervisor remains unaware of the fatigue's effects on the Supervisor. The effects of the Fatigue distraction on the Supervisor are active from the beginning of their shift until the shift ends. The SAFTE model gradually effects fatigue over the course of the shift.

Fatigue appears to be synonymous with increases in experienced workload, likely tied to the increased levels of effort or stress experienced during normal duties or because of external factors (Hancock & Verwey, 1997). Similarly, while low levels of fatigue may have a limited impact on overall performance or workload, higher or longer levels of experienced fatigue are expected to make these effects more pronounced and detectable.

16.4.2. Model Development

The distraction event use case models leverage a majority of nominal use case model and incorporate the looping linear scanning task introduced for the UE use case model.

16.4.2.1. Mindwandering

The Mindwandering use case was developed based on the characteristics noted in Section 16.4.1.1. The model's implementation generally required the same elements, atomic tasks with associated timings and workload component values, as the nominal use case model.

Table 76. Usage of distributions within the Mindwandering distractions event use case models.

Distribution Purpose	Distribution Type & Parameter Values	Min Value	Max Value
Selection of Distraction Event Occurrence Clock in the 2nd and 4th Ramp Up, Steady State, or Ramp Down Shift State	DiscreteUniform (1st sec, Nth sec)	1st sec	N^{th} sec

The Mindwandering distraction was implemented as a togglable event that randomly occurs during the Ramp up state, Steady state, or Ramp down state. The distraction events were implemented to occur during the Supervisor's 2nd and 4th shift working periods. No Mindwandering events occurred during the shift's 1st and 3rd working periods. Given that the model does not degrade the Supervisor's performance over time, the occurrence of distraction events within a trial, either a single event across the entire trial or a single type of event within a work period, does not change the model outcomes. As a result, multiple distraction events with unique independent variables can be generated within a trial, based on different work periods. The clocks at which the distraction events occur were selected by the discrete uniform distribution, shown in Table 76. The same distribution was used to for all Mindwandering distraction events in each shift state.

Two model variations were implemented. One version has Mindwandering events that occur once during the Ramp up shift state and once in the same work period's Ramp down shift state for two work periods (i.e., 2^{nd} and 4^{th}) during a trial. The second Mindwandering event variant occurs once in two of the Steady state shift work periods (i.e., 2^{nd} and 4^{th}). The two versions prevent the occurrence of back-to-back distraction events. For example, if both versions were combined, one distraction event may be randomly selected to occur at the end of Ramp up, while another is selected to occur at the beginning of Steady state, which can result in overlapping distraction events or an abnormally long event.

Generally, the distraction model, shown in Figure 26, is very similar to the nominal use case model with the exception of the Linear Scanning task group node, looping Event Checker node, and the Mindwandering nodes that represent the two Mindwandering implementations, long and short. The Event Checker node's primary function is to continuously check whether the current simulation clock is equal to the distraction occurrence clock selected by the discrete uniform distribution at the start of the simulation run. If the current simulation clock is equal to the distraction occurrence clock, the appropriate Mindwandering event node (short or long) is activated.

The activation of either Mindwandering node causes a decrease in Supervisor workload and an increase in the linear scanning task duration, for a period of time. A short Mindwandering event lasts 30 secs, while a long mind-wandering event lasts 2 mins (i.e., 120 secs). Supervisor workload is decremented by 10% during both short and long Mindwandering events; however, during short Mindwandering, the duration of the linear scan task is increased by 10%, whereas the duration of the linear scan task is increased by 50% during a long Mindwandering event.

Distraction events do not result in any change to the Supervisor's assigned or to be assigned UAVs. This model assigns UAVs to the Supervisor in the same manner as the nominal model. A distraction does not result in UAVs being unassigned to the Supervisor. As a result, there is no visible change in the number of active UAVs en-route, as shown in Figure 27(a) and (c). The predominate phenomenon from a distraction is a decrease in the Supervisor's workload due directly to the distraction event. This decrement in Overall Workload is visible for long and short duration Mindwandering distractions, during the 2^{nd} and 4^{th} work periods, in Figure 27(b) and (d). An example of Mindwandering during the Ramp up and Ramp down shift periods are provided in Appendix B. The modeling assumptions associated with the Mindwandering distraction are provided in Table 77.

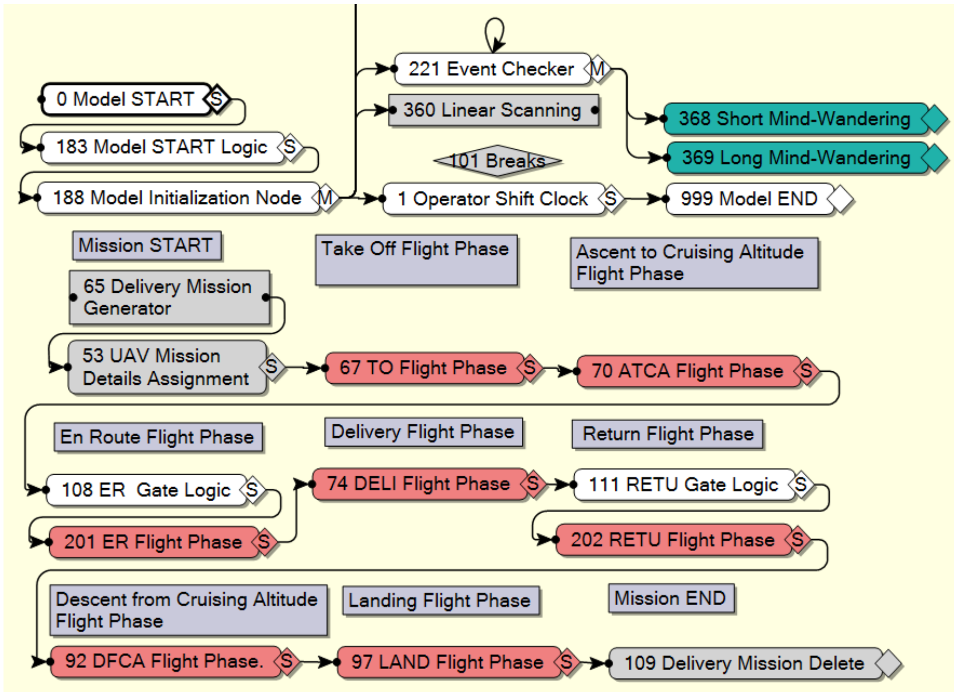
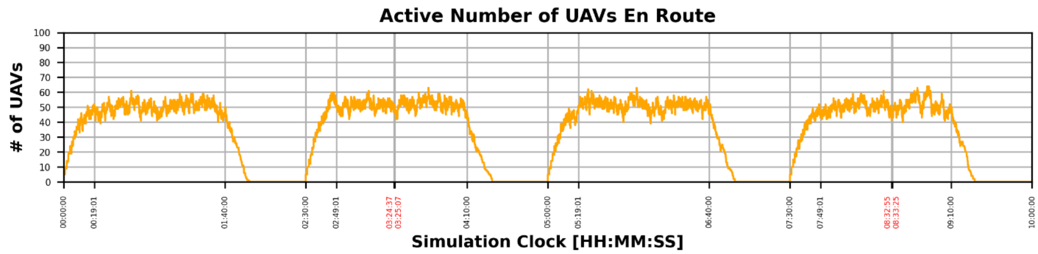
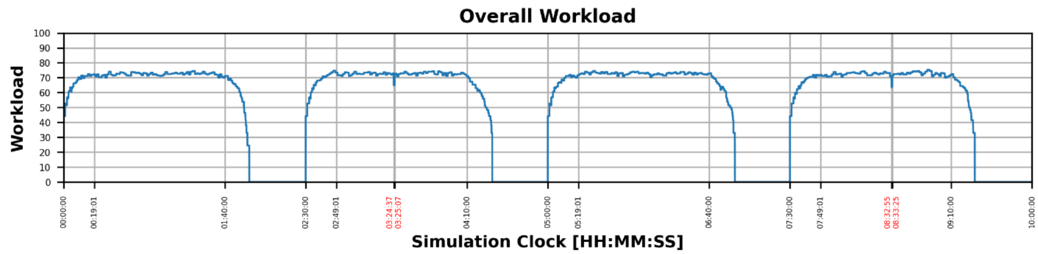


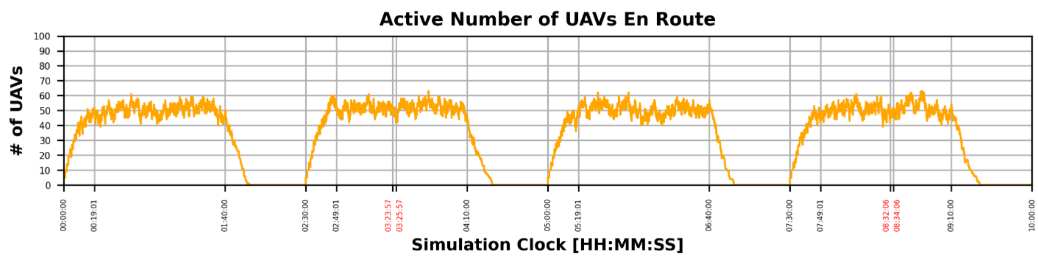
Figure 26. Screenshot of the Distraction Use Case Model within IMPRINT Pro.



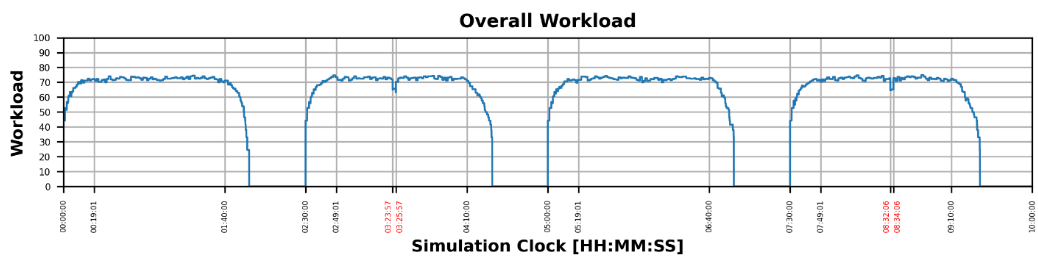
(a) The number of UAVs monitored during two short Steady state Mindwandering distraction events (see red clock times on the x-axis) in the 2nd and 4th work periods.



(b) The Overall Workload the Supervisor experiences during two short Steady state Mindwandering distraction events in the 2nd and 4th work periods.



(c) The number of UAVs monitored during two long Steady state Mindwandering distraction events in the 2nd and 4th work periods.



(d) The Overall Workload the Supervisor experiences during two long Steady state Mindwandering distraction events in the 2nd and 4th work periods.

Figure 27. Example Mindwandering distraction trials with short and long Steady state events. Red time stamps mark each distractions' start and end during the 2nd and 4th work periods. Number of assigned UAVs with (a) short and (c) long events and Overall Workload with (b) short and (d) long events.

Table 77. Mindwandering distraction event use case modeling assumptions.

Subject Matter Expert-Based Assumptions
Supervisor's shift includes mandatory breaks.
Supervisors manage UAV systems in a shared work environment, simultaneously occupied by other personnel.
Distractions derive from the external work environment, or from within the Supervisor themselves.
Supervisors have some limited access to personal devices and may receive communications.
Distractions are comprised of various components, and can be auditory, speech-based, visual, cognitive, or haptic in nature.
There exists a *Watch Supervisor*, responsible for broad oversight of Supervisor performance.
Mindwandering Use Case Model Assumptions
Two Mindwandering distraction durations exist: short (30 seconds) and long (120 seconds).
The Supervisor is unaware that they are Mindwandering, and continues to attempt to do the normal job duties.
The distraction does not impact the Supervisor's assigned or to be assigned UAVs.
The Mindwandering distraction is discrete and finite with regard to their impact on the Supervisor's performance.
The Supervisor's shift is composed of four work periods, for all modeled trials and Mindwandering events, no Mindwandering events occur during the 1st or 3rd work periods. Mindwandering events only occur during the 2nd and 4th work periods.
The Ramp up Mindwandering events assume that the event ends prior to the start of the Steady state period.
The Steady state Mindwandering events are completed prior to the start of the Ramp down period.
The Ramp down Mindwandering events are completed prior the end of the work period or shift.
A single Steady state Mindwandering distraction occurs during the trials' 2nd and 4th work periods.
The Ramp up and Ramp down Mindwandering event trials are combined into a single trial, with a single Mindwandering instance occurring during the 2nd and 4th work periods' for both the Ramp up and Ramp down stages.

The Mindwandering distraction model was developed to reuse the nominal model and UE model. The Mindwandering distraction model introduces about 30 unique lines of code. The new code is responsible for the initialization and activation of the Mindwandering distractions and the logging of the distraction's effects on Supervisor performance. The exact number of unique lines of code that compose the distraction model is difficult to estimate, as only a portion of the UE model's code was reused.

16.4.2.2. Fatigue

The Fatigue distraction event use case was developed based on the characteristics provided in Sections 16.2.1 and 16.4.1.2. The SAFTE algorithm is an IMPRINT Pro plugin that predicts changes in human performance based on the number of hours slept each of the last four nights. The SAFTE algorithm plugin creates fatigue-related degradations in performance over the course of the Supervisor's shift. The algorithm incorporates quantitative information related to circadian rhythms, sleep inertia, and recovery and decay rates in order to predict human performance [Alion S&T 2012]. The model permits specifying 8, 6, 4 or 2 hours of sleep each of the last four nights in order to understand the corresponding implications.

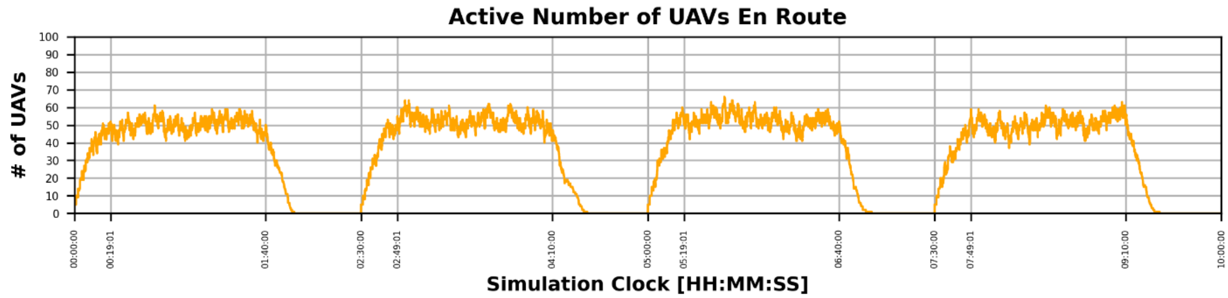
The SAFTE algorithm is an IMPRINT Pro plugin; thus, no changes were required to operate the plug with on the nominal use case model. The SAFTE algorithm generally is applied to an entire trial, and is not a discrete event (e.g., Mindwandering, Emergency in the air space) that occurs randomly throughout a trial for a period of time. Rather, the algorithm is enabled at the start of a trial with a specified number of hours of sleep for the preceding four nights. As such, there is an expected decrement in the Supervisor's effectiveness throughout the shift. This decrement in effectiveness impacts the time to complete tasks, which also impacts Overall Workload.

The Fatigue distraction event does not change the Supervisor's assigned or to be assigned UAVs. This model assigns UAVs to the Supervisor in exactly the same manner as the nominal model. A high-level of fatigue does not result in UAVs being unassigned to the Supervisor. As a result, there is no visible change in the number of active UAVs en-route, as shown in Figure 30(a). Since the modeled Supervisor slept eight hours each of the last four nights, the Overall Workload is relatively unchanged, as shown in Figure 30(b). An example of the Fatigue distraction's SAFTE plugin results for the number of sleep hours equivalent to four and two are provided in Appendix B.

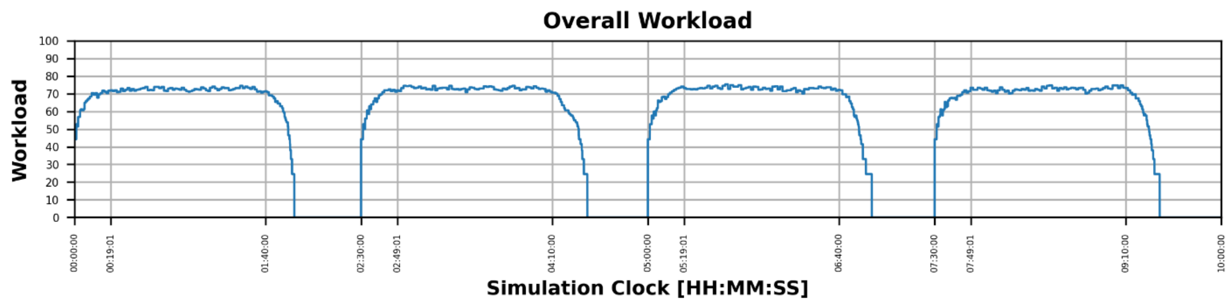
The SAFTE plugin provides all the necessary code to support the Fatigue distraction. The nominal and UE models are leveraged as is for the Fatigue distraction. The SAFTE plugin requires specifying parameter values (e.g., number of hours slept each of the last four nights) and indicating to which model nodes the SAFTE plugin is to be applied (e.g., checking a parameter box within the nominal model's nodes for the Supervisor's tasks). Integration of the plugin does add to the developed code base, but that code was not developed by the A26 team. The Fatigue distraction event's model relies on many of the general assumptions from the Nominal use case and the Mindwandering use case, but also includes some specific assumptions provided in Table 78.

Table 78. Fatigue distraction event use case modeling assumptions.

Fatigue Use Case Model Assumptions
The SAFTE model plugin provides the fatigue model.
The SAFTE model is enabled at the start of the trial and remains enabled throughout the entire trial.
The Fatigue distraction event does not change the Supervisor's assigned or to be assigned UAVs.
A high-level of fatigue does not result in UAVs being unassigned to the Supervisor.



(a) Number of UAV a Supervisor monitors during an example Fatigue distraction trial when the modeled Supervisor slept for 8 hours each night for the last 4 nights.



(b) Overall Workload of Supervisor during an example fatigue distraction trial when the modeled Supervisor has slept for 8 hours each night for the last 4 nights.

Figure 28. Example Fatigue distraction trial where the Supervisor slept for 8 hours each night for the last 4 nights.

16.4.3. Experimental Design

The Distraction Use case scenarios are intended to explore how the presence of distractions of various types may influence performance beyond nominal conditions in an en-route monitoring task. Distractions pull the Supervisor's attention and focus from the assigned tasks, but the actual demands of the tasks do not change, as such the Supervisor's objective workload, or cognitive demands, directly derived from the assigned tasks will decrease given that the Supervisor is less engaged with the assigned tasks. Specifically, experiencing a distraction will cause the Supervisor to reallocate attention, and the associated mental resources towards resolving the distraction, which reduces the Supervisor's engagement with the assigned tasks. As the Supervisor will be focusing less on the assigned tasks, if left unchecked, the reallocation of attention is likely to produce observable deficiencies in task performance and the workload associated with the tasks. The impact of distractions was only evaluated for the best-case scenario. The worst-case distraction event scenarios involve the removal of the Supervisor from the C^2 station to go on an early break, and naturally this will effectively end the data collection based on the length of a normal break. Further, the magnitude of distraction was varied. Short and long distraction event instances (conceptualized as two cycles of the distraction within the Mindwandering model) were considered. The short and long distraction events do not apply to the Fatigue distraction, as the SAFTE model is enabled for the entire trial.

Three additional research questions were generated:

4. Do distractions reduce Overall Workload relative to normal baseline values, both overall and channel?
    c. What is the impact of a short vs. long Mindwandering event?
    d. What is the impact of reduced numbers of hours of sleep over the last four days?
5. Does the type of distraction differentially influence any observed impact on Overall Workload?
6. Do distractions interact with the current state of UAV operation (Ramp up, Steady state, Ramp down)?

16.4.3.1. Independent Variables

The Distractions use case experiments used specified values for some of the parameters and varied others. The Supervisor's overall shift was set to 10 hours, with a 120 mins working period. The Supervisor break was set at 30 mins. The distraction-specific use case independent variables are presented in Table 79. The distractions varied across shift state, as did their observed impact during the Ramp up, Steady state, and Ramp down portions of en-route operation. The Time to Launch a Wave of UAV(s), and the Max # of UAVs to launch simultaneously variables use the same values as the nominal and UE experiments. The lowest number of maximum UAVs (10) was omitted, as was the case with the UE use cases. The Mindwandering distraction was evaluated for two lengths, while the Fatigue distraction was evaluated for three values of the number of hours slept by the Supervisor each of the last four days. It is noted that the nominal use case did not incorporate Supervisor performance degradation due to fatigue; thus, the 8 hour of sleep each of the last four nights was evaluated in the Fatigue distraction evaluations, as it is a more ecologically valid representation of predicted Supervisor performance over a typical shift.

Table 79. Distraction experiments independent variables.

Independent Variable	**Tested Values**
Distraction type	Mindwandering, Fatigue
Shift State	Ramp Up, Steady State, Ramp Down
Max # of Active UAVs	25, 50, 75, 100
Time to Launch a Wave of UAV(s)	30, 60
Max # of UAVs to Launch Simultaneously	1, 2, 5, 10, 20
Mindwandering: Distraction length	Short (30 secs), Long (120 secs)
Fatigue: # Hours slept each night for the last 4 days	4, 6, 8 (hours)

16.4.3.2. Dependent Variables

The dependent variables for the distractions use case evaluation were similar to those for the nominal use case evaluation, provided in

Table 80. The SAFTE model, used for the Fatigue distraction use
case trials only, provides an Effectiveness value that represents how effective the Supervisor is based on the number of hours slept each of the last four nights.

Table 80. Distraction use case dependent variables.

Dependent Variables	Minimum	Maximum
Cognitive Workload	10.2	33.69
Fine Motor Workload	2.2	7.27
Visual Workload	12.1	39.96
Overall Workload	24.5	80.91
# of UAV En-route ($N_{En\text{-}route}$)	1	100
Fatigue: Effectiveness	0.775	1.006

16.4.3.3. Simulation Methodology

16.4.3.3.1. Mindwandering Distraction Methodology

A total of 160 independent variable combinations are possible for the Mindwandering distraction; however, 24 variable combinations do not result in valid trials because they result in Ramp up or Steady state phases that are shorter than 2 mins. The short and long duration Mindwandering distractions in these problem instances cause the distraction to continue into the next shift state. As a result, 136 independent variable combinations were evaluated. A total of twenty-five trials were completed for each valid variable combination. Examining distractions over these specific shift states once again ensures that appropriate data and results are generated that capture the impact of the Mindwandering distraction on the Supervisor.

The consolidation of independent variable values by initiating a Mindwandering distraction in the Ramp up and Ramp down for the same work period reduces the 240 possible independent variable combinations to 160. As indicated, these discrete events do not influence one another and permit reducing the number of required trials while still generating the same amount of data. The distraction event occurred during the same trial for both the Ramp up and Ramp down shift state occurrences during the 2nd and 4th work periods. No distraction event occurred during the 1st or 3rd working periods.

The distraction events during the Steady state trials were also consolidated as there were no direct implications on a distraction in an earlier work period on later work periods. No distraction event occurred during the 1st or 3rd Steady state working period. The Mindwandering distraction occurred during each of the 2nd and 4th Steady state working periods. These consolidations of the Mindwandering distraction events into condensed trials reduced the number of trials from 160 to 136. A total of 25 trials were run for each combination, resulting in a total of 3,400 trials run (136 x 25 = 3,400).

16.4.3.3.2. Fatigue

A total of 120 independent variable combinations are possible for the Fatigue distraction model, for which 25 trials were completed per relevant independent variable combination provided in Table 79. The SAFTE model was enabled at the start of each trial and has a continuous impact on the Supervisor's performance, as a result, it is applied to each shift state for a single trial.

The Fatigue model trials' independent variables closely mimic those of nominal model trials; however, the Max Shift Duration, Duration of the Supervisor's Working Period, and Duration of the Supervisor's Breaks independent variables were fixed to 10 hours, 120 minutes, and 30 minutes, respectively. The number of possible values for the Max # of Active UAVs and Max #

of UAV to Launch Simultaneously were reduced, as indicated in Table 79. The Fatigue trials do not include UE or distraction events (i.e., Mindwandering) that may impact workload.

A total of 25 trials were run for each of the 120 variable combinations, resulting in a total of 3,000 completed trials (120 x 25 = 3,000).

16.4.3.4. Data analysis Methodology

The dependent measure used for the Mindwandering distraction data was the same as for the UEs, RMSD Overall Workload. The Fatigue distraction model's use of the SAFTE model, to represent the Supervisor's efficiency based on the number of hours slept each of the last four nights, results in effects that are cumulative over a simulation trial; thus, the analysis methodology was different for these data. Since the Fatigue model applies to the entire trial, the work periods were treated as a within subject variable. Rather than use the RMSD Overall Workload, the mean Overall Workload for the respective shift state and work period was the dependent variable. Thus, a 4 Max # of Active UAVs (Max UAVs) (i.e., 25, 50, 75, 100) x 2 Time to Launch a Wave of UAV(s) (i.e., 30, 60 secs) x 5 Max # of UAV to Launch Simultaneously (i.e., 1, 2, 5, 10, 20) x 3 Hours of Sleep (i.e., 8, 6, 4) x 4 Work Period (i.e.,1, 2, 3, 4) Mixed ANOVA was conducted.

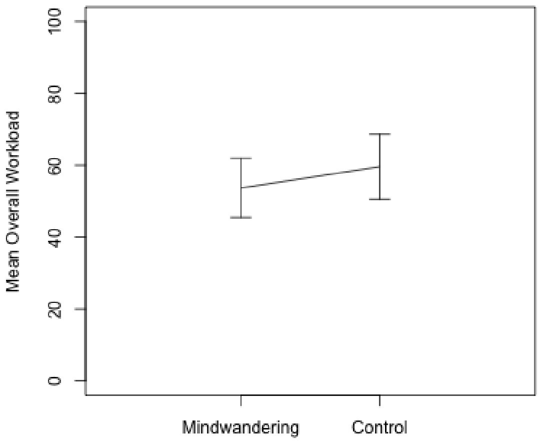
16.4.4. Results

16.4.4.1. Mindwandering Distraction Results

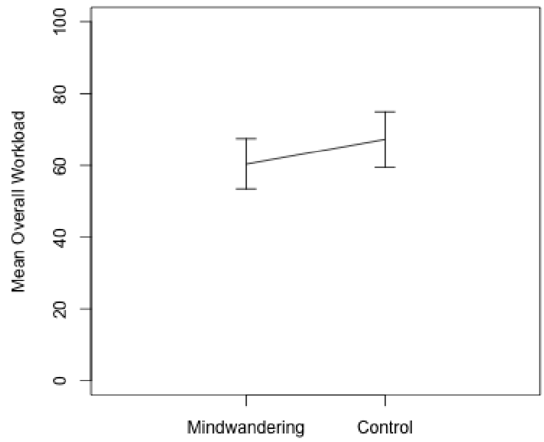
The descriptive statistics for Overall Workload for all the Mindwandering distraction trials are presented in Table 81. The decrease in mean Overall Workload during the period when Mindwandering is occurring is highlighted in Figure 29.

Table 81. Summary of the Overall Workload descriptive statistics – mean (standard deviation) - for Mindwandering distraction trials by shift state.

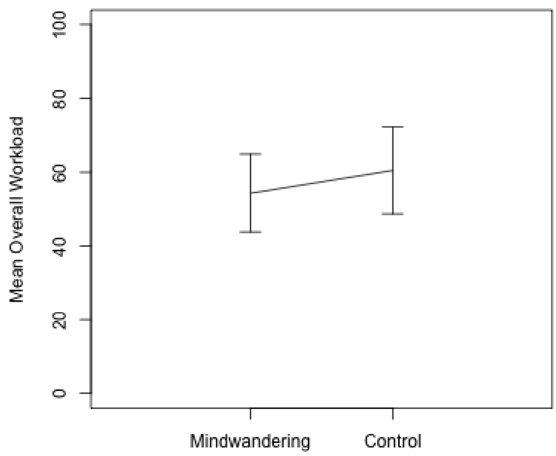
Ramp up	Steady state	Ramp down
53.67 (8.23)	60.40 (6.95)	54.34 (10.55)



(a) Ramp up



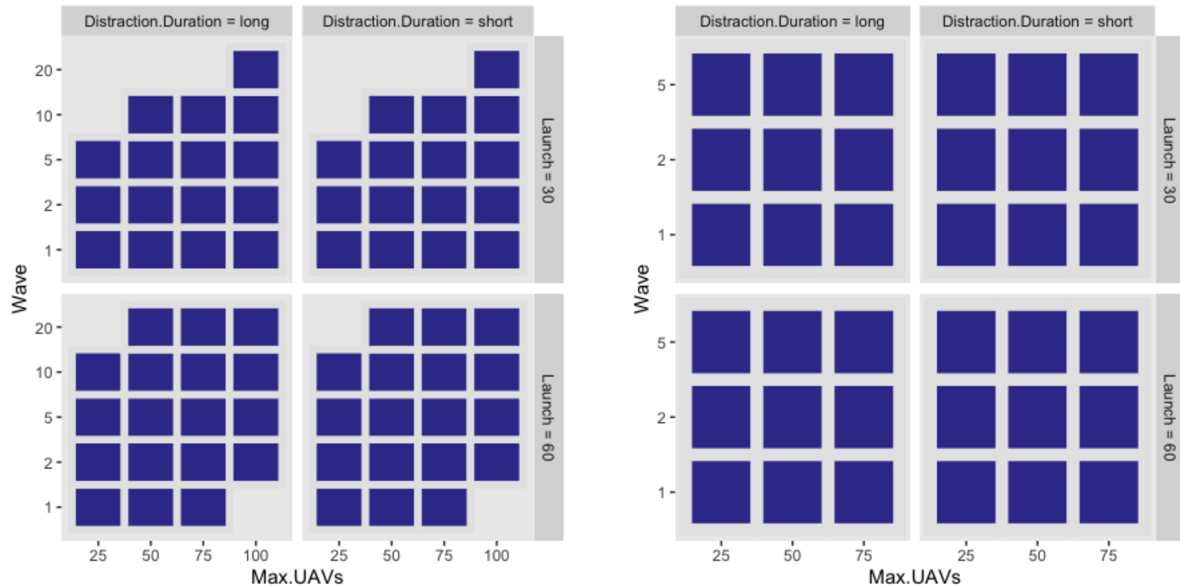
(b) Steady state



(c) Ramp down

Figure 29. Mean Overall Workload for Mindwandering distraction events trials during periods when Mindwandering was occurring and not occurring (control): (a) Ramp up, (b) Steady state, (c) Ramp down

Not all the independent variables combinations were simulated (see Figure 30a), as explained in Section 16.4.3.3.1. The ANOVA analysis attempted to incorporate as many independent variable values and the associated data as possible. The analysis used a 3 Max # of UAVs (i.e., 25, 50, 75) x 3 Max # of UAV(s) to Launch Simultaneously (i.e., 1, 2, 5) x 2 Time to Launch a Wave of UAV(s) (i.e., 30, 60) x 2 Distraction Duration (i.e., short, long) between subjects design (see Figure 30b).



(a) (b)

Figure 30. Visualization of the mindwandering data with respect to the (a) planned experimental design and (b) complete factorial design (ANOVA analyses). Blue cells indicate data was available for a particular combination of independent variables, while empty gray cells indicate no data was available. The Max # of UAVs (bottom X axis), the Max # of UAV(s) to Launch Simultaneously (left y-axis), Distraction Duration (top x-axis), and Time to Launch a Wave of UAV(s) (Launch; right y-axis).

There were 1800 observations for each shift state after removing levels to form a complete factorial design. The RMSD descriptive statistics for Overall Workload and each workload channel for the Ramp up, Steady state, and Ramp down shift states are provided in Table 82,

Table 83, and Table 84, respectively. As with the unexpected events, the cognitive and visual workload channels were the large contributors to RMSD Overall Workload. Levene's test for homogeneity of variance indicated a violation of constant variance assumptions for the use of ANOVA analyses. Thus, ANOVA analyses are conducted on the RMSD Overall Workload measure to provide insights into the results, but need to be interpreted with care due to the lack of conformance with the underlying assumptions of ANOVA.

Table 82. Descriptive statistics for RMSD Overall Workload in Mindwandering distraction event cases: Ramp up.

	Overall	Cognitive	Fine Motor	Visual
Mean	5.746	2.392	0.516	2.838
Median	5.756	2.396	0.517	2.843
Standard deviation	1.658	0.690	0.149	0.819
Range	0.527- 13.856	0.219- 5.769	0.047- 1.244	0.260-6.843

Table 83. Descriptive statistics for RMSD Overall Workload in Mindwandering distraction event cases: Steady state.

	Overall	Cognitive	Fine Motor	Visual
Mean	6.462	2.690	0.580	3.191
Median	6.600	2.748	0.593	3.260
Standard deviation	1.747	0.727	0.157	0.863
Range	0.736-12.349	0.307-5.141	0.066- 1.109	0.364-6.099

Table 84. Descriptive statistics for RMSD Overall Workload in Mindwandering distraction event cases: Ramp down.

	Overall	Cognitive	Fine Motor	Visual
Mean	6.592	2.744	0.592	3.256
Median	6.439	2.681	0.578	3.180
Standard deviation	3.780	1.574	0.339	1.867
Range	0-41.625	0-17.330	0-3.738	0-20.558

The Ramp up results show that six row factors (main effects, two-way interactions, three-way interactions) are significant (

Table 85). However, four row factors have effect sizes below the small threshold, including the distraction length as well as a three-way interaction with distraction length. Another two row factors only involve, singly or in combination, the Max # of UAVs, the Time to Launch a Wave of UAV(s) and the Max # of UAVs to Launch Simultaneously, known to have an effect on Overall Workload due to the nominal analysis (see

Table 52).

Table 85. RMSD Overall Workload ANOVA results for Mindwandering distraction event: Ramp up.

Factor	df	F	p	Effect Size
Max # of Active UAVs (Max UAVs)	2,1764	30.808	<0.001	.0337*
Time to Launch a Wave of UAV(s) (Launch)	1,1764	5.187	0.023	.0029
Max # of UAV to Launch Simultaneously (Wave Size)	2,1764	21.368	<0.001	.0236*
Distraction length	1,1764	25.901	<0.001	.0145
Launch x Wave size	2,1764	5.284	.005	.0060
Launch x Wave size x Distraction length	2,1764	8.673	<0.001	.0097

Five Steady state row factors are significant (Table 86), but three have effect sizes below the small threshold. The other two significant row factors only involve the Max # of UAVs, and the Max # of UAVs to Launch Simultaneously, known to have an effect on Overall Workload due to the nominal analysis.

Table 86. RMSD Overall Workload ANOVA results for Mindwandering distraction event: Steady state.

Factor	df	F	p	Effect Size
Max # of Active UAVs (Max UAVs)	2,1764	23.297	<0.001	.0257*
Time to Launch a Wave of UAV(s) (Launch)	2,1764	15.939	<0.001	.0090
Max # of UAV to Launch Simultaneously (Wave Size)	2,1764	77.942	<0.001	.0812*
Max UAVs x Wave size	4,1764	4.735	<0.001	.0106
Launch x Wave size	2,1764	6.704	0.001	.0075

The Ramp down analysis indicated that two row factors are significant (Table 87). However, both row factors have effect sizes well below the small threshold.

Table 87. RMSD Overall Workload ANOVA results for Mindwandering distraction event: Ramp down.

Factor	df	F	p	Effect Size
Time to Launch a Wave of UAV(s) (Launch) x Max # of UAV to Launch Simultaneously (Wave Size)	2,1764	6.837	0.001	.0077
Wave size x Distraction length	2,1764	7.432	<0.001	.0084

16.4.4.2. Fatigue Distraction Results

There were 12,000 observations of Overall Workload measures for the Ramp up, Steady state, and Ramp down shift states (25 replications x 4 levels of Max # of UAVs x 2 Time to Launch a Wave of UAV(s) x 5 levels of Max # of UAV(s) to Launch Simultaneously x 4 Work Periods x 3 Hours slept each of the last four nights) available for the analysis. The Overall Workload and each workload channel descriptive statistics for Ramp up, Steady state, and Ramp down shift states are provided in Table 88,

Table 89, and Table 90, respectively. Generally, the Overall Workload was driven by cognitive and visual workload channels; the fine motor channel was not a main contributor. Mauchly's test for sphericity indicated a violation of the assumptions for the use of ANOVA analyses. Thus, ANOVA analyses are conducted on the Overall Workload measure to provide insights into the results, but need to be interpreted with care.

Table 88. Descriptive statistics for the workloads in Fatigue distraction event cases: Ramp up.

	Overall	**Cognitive**	**Fine Motor**	**Visual**
Mean	59.774	24.885	5.367	29.521
Median	60.176	25.053	5.4036	29.720
Standard deviation	5.958	2.480	0.535	2.942
Range	45.212-70.100	18.823-29.184	4.060-6.295	22.329-34.621

Table 89. Descriptive statistics for the workloads in Fatigue distraction event cases: Steady State.

	Overall	Cognitive	Fine Motor	Visual
Mean	66.557	27.709	5.977	32.871
Median	69.203	28.811	6.214	34.178
Standard deviation	7.663	3.190	0.688	3.785
Range	47.463-78.424	19.760-32.650	4.262-7.042	23.441-38.732

Table 90. Descriptive statistics for the workloads in Fatigue distraction event cases: Ramp down.

	Overall	Cognitive	Fine Motor	Visual
Mean	43.406	18.071	3.898	21.437
Median	43.508	18.113	3.907	21.487
Standard deviation	8.024	3.340	0.720	3.963
Range	18.030-61.945	7.506- 25.789	1.619-5.562	8.904-30.593

The Ramp up analysis found 24 row factors (main effects, two-way interactions, three-way interactions, and four-way interactions) are significant (

Table 91). However, ten row factors have effect sizes below the small threshold. Another seven row factors only involve, singly or in combination, the Max # of UAVs, the Time to Launch a Wave of UAV(s), and the Max # of UAV(s) to Launch Simultaneously, known to have an effect on Overall Workload due to the nominal use case analysis (

Table 52). The effect of the working period was not a contributor, either alone or in a combination of factors, to significant effects that crossed the small effect size threshold. Seven significant row factors involve the Hours slept. While the main effect of hours of sleep was significant with an effect size above the small threshold, the means were similar from a practical perspective: 59.792 for 4 hours of sleep, 59.952 for 6 hours and 59.577 for 8 hours (Figure 31). The interaction of Hours slept with the Max # of UAVs, the Time to Launch a Wave of UAV(s), and the Max # of UAV(s) to Launch Simultaneously were each significant, with the interaction with Time to Launch a Wave of UAV(s) had a large effect size (Figure 32). Three three-way interactions were also significant with an effect size crossing the small threshold; however, only two involved Hours slept (Figure 33 and Figure 34). The three-way interaction of Hours of sleep x Time to Launch a Wave of UAV(s) x Max # of UAV(s) to Launch Simultaneously (Figure 34) highlights an interesting result as at the 20 wave size, the Overall Workload is higher for the largest # of UAVS to launch simultaneously and shorter time launch a UAV wave, the model suggests that sleeping 8 hours each of the last four nights reduces Overall Workload compared to 6 Hours slept.

Table 91. Overall Workload ANOVA results for Fatigue distraction event cases: Ramp up.

Factor	**df**	**F**	**p**	**Effect Size**
Hours of sleep	2, 2878	1008.024	<0.001	**.1387***
Max # of Active UAVs (Max UAVs)	3, 2878	382716.0	<0.001	.9892*
Time to Launch a Wave of UAV(s) (Launch)	1, 2878	54132.14	<0.001	.8121*
Max # of UAV to Launch Simultaneously (Wave size)	4, 2878	385706.2	<0.001	.9919*
Work period	3, 8634	43.659	<0.001	.0115
Hours of sleep x Max UAVs	6, 2878	50.087	<0.001	**.0234***
Hours of sleep x Launch	2, 2878	282.216	<0.001	**.0431***
Max UAVs x Launch	3, 2878	3241.972	<0.001	.4372*
Hours of sleep x Wave size	8, 2878	552.744	<0.001	**.2610***
Max UAVs x Wave size	12, 2878	8221.080	<0.001	.8874*
Launch x Wave size	4, 2878	29863.98	<0.001	.9051*
Hours of sleep x Work period	6, 8634	17.889	<0.001	.0095
Launch x Work period	3, 8634	5.684	<0.001	.0015
Wave size x Work period	12, 8634	8.827	<0.001	.0094
Hours of sleep x Max UAVs x Launch	6, 2878	5.737	<0.001	.0027
Hours of sleep x Max UAVs x Wave size	24, 2878	80.420	<0.001	**.1336***
Hours of sleep x Launch x Wave size	8, 2878	92.947	<0.001	**.0561***
Max UAVs x Launch x Wave size	12, 2878	1545.607	<0.001	.5970*
Hours of sleep x Launch x Work period	6, 8634	6.440	<0.001	.0034
Hours of sleep x Wave size x Work period	24, 8634	5.474	<0.001	.0116
Max UAVs x Wave size x Work period	36, 8634	1.531	0.022	.0049
Launch x Wave size x Work period	12, 8634	3.257	<0.001	.0035
Hours of sleep x Max UAVs x Launch x Wave size	24, 2878	21.846	<0.001	**.0402***
Hours of sleep x Launch x Wave size x Work period	24, 8634	4.686	<0.001	.0099

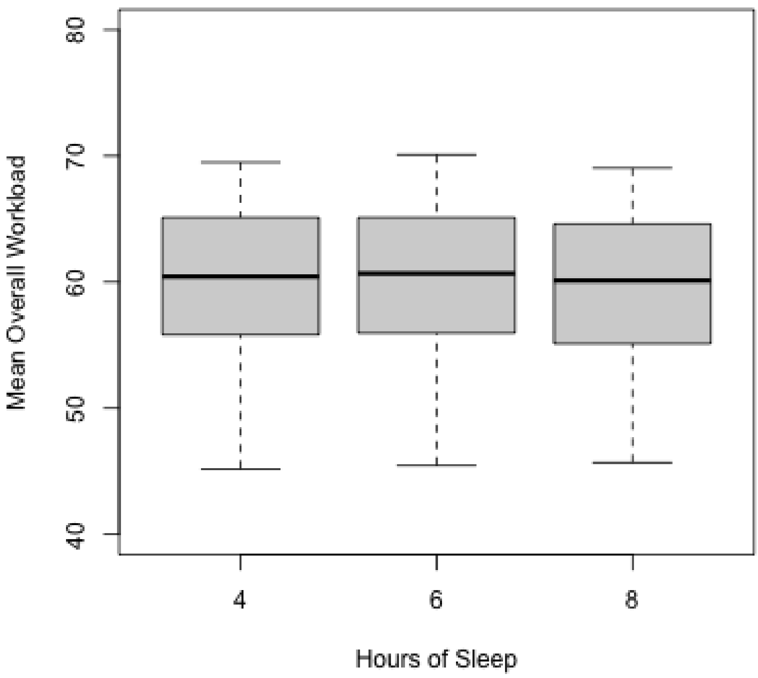
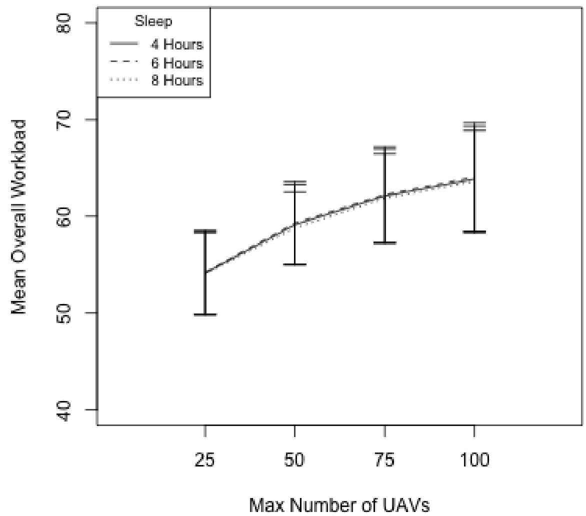
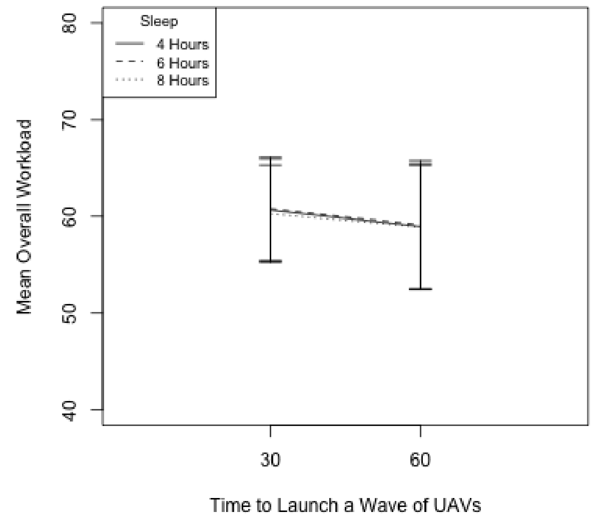


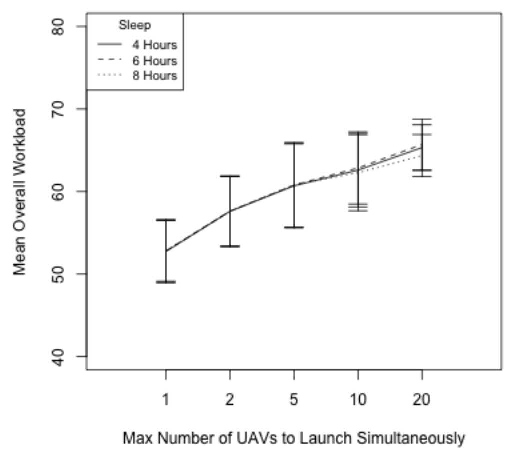
Figure 31. ANOVA results: the Overall Workload box plot for the Fatigue distraction Ramp up trials by hours of sleep.



(a) Max # of active UAVs

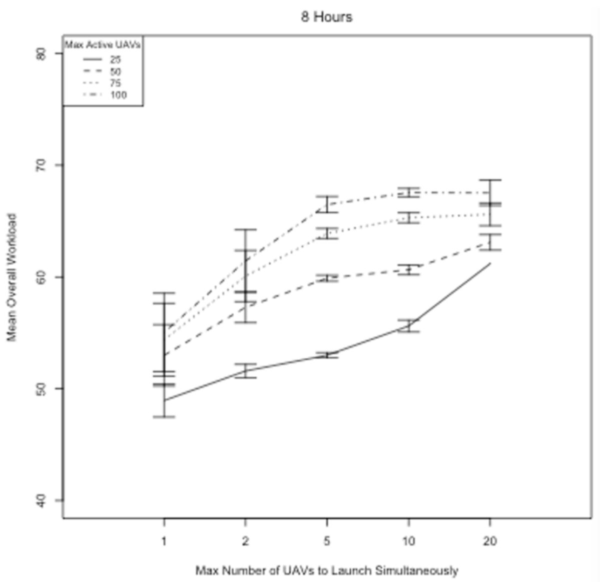


(b) Time to Launch a Wave of UAV(s)

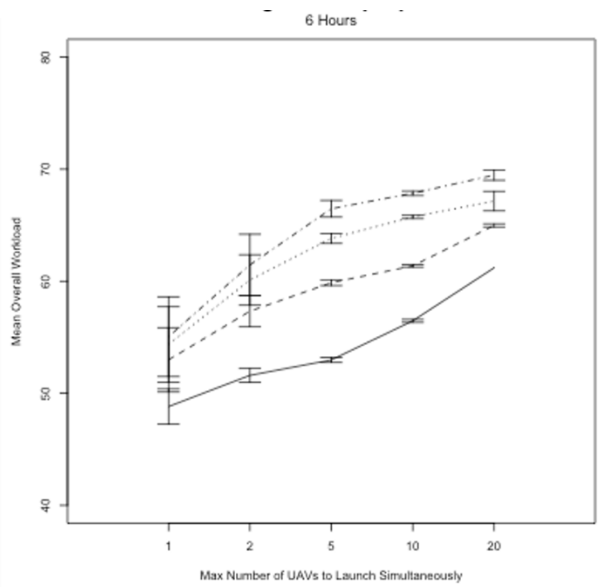


(c) Max X of UAVs to launch simulatenously

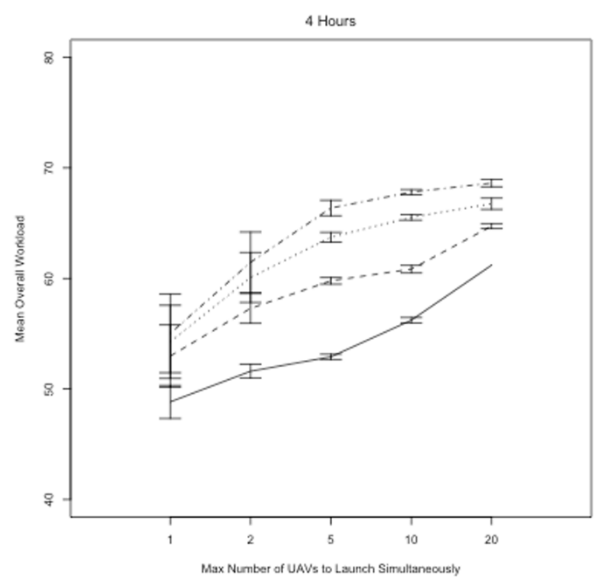
Figure 32. ANOVA results: two-way interaction plots of Overall Workload (with one standard deviation error bars) for the Fatigue distraction Ramp up trials (a) Max # of UAVs, (b) Time to Launch a Wave of UAV(s), and (c) Max # of UAV(s) to Launch Simultaneously.



(a) 8 hours of slept the last four nights

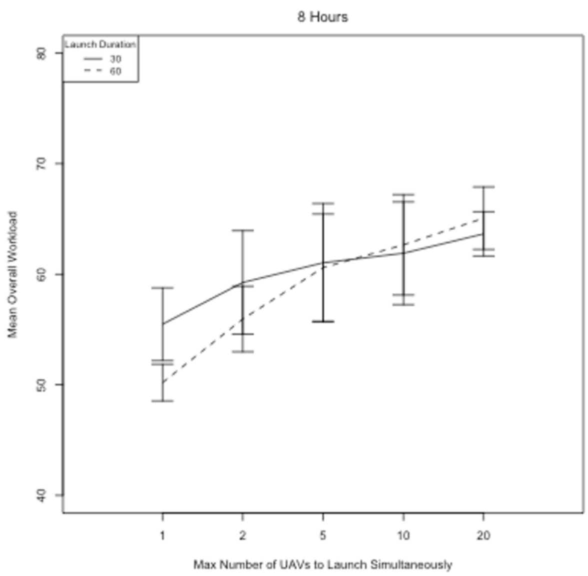


(b) 6 hours slept the last four nights

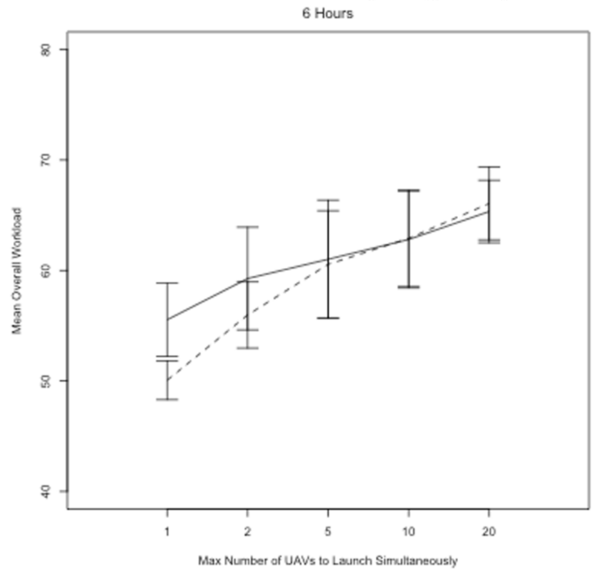


(d) 4 hours slept the last four nights.

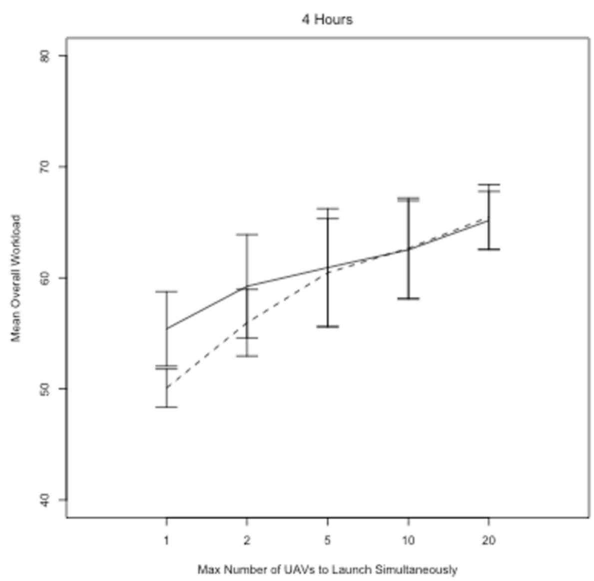
Figure 33. ANOVA results: three-way interaction plots of Overall Workload (with one standard deviation error bars) for the Fatigue distraction Max # of UAVs x Max # of UAV(s) to Launch Simultaneously Ramp up trials (a) 8 hours, (b) 6 hours, and (c) 4 hours slept each of the last four nights.



(a) 8 hours slept each of the last four nights.



(b) 6 hours slept each of the last four nights.



(c) 4 hours slept each of the last four nights.

Figure 34. ANOVA results: three-way interaction plots of Overall Workload (with one standard deviation error bars) for the Fatigue distraction Launch duration x Max # of UAV(s) to Launch Simultaneously Ramp up trials (a) 8 hours, (b) 6 hours, and (c) 4 hours slept each of the last four nights.

The Steady state analysis found ten row factors are significant (Table 92); however, three have effect sizes below the small threshold. The other seven only involve, singly or in combination, the Max # of UAVs, the Time to Launch a Wave of UAV(s), and the Max # of UAV(s) to Launch Simultaneously, known to have an effect on Overall Workload due to the nominal use case analysis (

Table 52).

Table 92. Overall Workload ANOVA results for Fatigue distraction event cases: Steady state.

Factor	**df**	**F**	**P**	**Effect Size**
Max UAVs	3, 2878	335188.7	<0.001	.9892*
Time to Launch a Wave of UAV(s) (Launch)	1, 2878	1.788594	<0.001	.9421*
Max # of UAV to Launch Simultaneously (Wave size)	4, 2878	438860.2	<0.001	.9938*
Work period	3, 8634	11.987	<0.001	.0031
Max UAVs x Launch	3, 2878	4990.93	<0.001	.5767*
Max UAVs x Wave size	12, 2878	33089.57	<0.001	.9731*
Launch x Wave size	4, 2878	41108.03	<0.001	.9374*
Wave size x Work period	12, 8634	2.648	0.002	.0027
Hours of sleep x Launch x Wave size	8, 2878	2.652	0.007	.0019
Max UAVs x Launch x Wave size	12, 2878	2430.29	<0.001	.7263*

Fourteen Ramp down row factors are significant (

Table 93), but seven have effect sizes below the small threshold. The other seven factors only involve, singly or in combination, the Max # of UAVs, the Time to Launch a Wave of UAV(s), and the Max # of UAV(s) to Launch Simultaneously, known to have an effect on Overall Workload due to the nominal use case analysis (

Table 52).

Table 93. Overall Workload ANOVA results for Fatigue distraction event cases: Ramp down.

Factor	**df**	**F**	**P**	**Effect Size**
Max UAVs	3, 2878	5573.773	<0.001	.5929*
Time to Launch a Wave of UAV(s) (Launch)	1, 2878	3372.424	<0.001	.2271*
Max # of UAV to Launch Simultaneously (Wave size)	4, 2878	6750.970	<0.001	.7017*
Work period	3, 8634	5.128	0.002	.0013
Max UAVs x Launch	3, 2878	118.111	<0.001	.0299*
Hours of sleep x Wave size	8, 2878	2.346	0.002	.0016
Max UAVs x Wave size	12, 2878	512.980	<0.001	.3490*
Launch x Wave size	4, 2878	724.146	<0.001	.2015*
Launch x Work period	3, 8634	4.868	0.002	.0013
Wave size x Work period	12, 8634	2.228	0.008	.0023
Max UAVs x Launch x Wave size	12, 2878	38.789	<0.001	.0390*
Max UAVs x Wave size x Work period	36, 8634	1.826	0.002	.0057
Launch x Wave size x Work period	12, 8634	2.017	0.002	.0021
Max UAVs x Launch x Wave size x Work period	36, 8634	1.528	0.022	.0047

16.5. Discussion

The analysis of the three types of UEs (C2 link loss, Emergency in the airspace, Mid-air collision) yielded task factor results for the Max # of active UAVs, Max # of UAV(s) to Launch Simultaneously, and Time to Launch a Wave of UAV(s), as did the analysis of the nominal use case. These results for both the nominal UE scenarios found that many of the effect sizes were small to non-existent; thus, even though the actual Overall Workload differences were significant, they were not always interesting in a practical sense.

What is more interesting is that the analysis of the three types of UEs all showed that the protocols used to address the UEs have a great impact on Overall Workload. The best-case scenarios for all UEs do not require the Supervisor complete any UE-related tasks, since the affected UAV(s) is handed off immediately to the UE Supervisor. The worst-case C^2 link loss and Mid-air collision UEs increased Overall Workload, because the Supervisor completes additional tasks to address the UE, while still performing their nominal duties (e.g., visual monitoring). As a result of the UE related tasks, the Supervisor experiences a greater increase in Overall Workload compared the best-case UE scenario The Emergency in the airspace UE had a qualitatively opposite effect on Overall Workload compared to the other two UEs. Generally, the Supervisor experiences a short, small increase in Overall Workload from handing off UAVs to the UE Supervisor, the Supervisor experiences a much longer and larger decrease in Overall Workload from having fewer UAVs to monitor. The best-case scenario's outcome is relative, the more UAVs for which the Supervisor is responsible, the greater their Overall Workload will decrease. These outcomes occur due to the fact that the Emergency in the airspace UE requires UAVs to be grounded; thus, reducing the number of UAVs for which the Supervisor is responsible. Specifically, the Emergency in the airspace worst-case UE requires the Supervisor to ground the impacted aircraft, while maintaining responsibility for any UAVs unaffected by the emergency. After the Supervisor grounds UAV(s), responsibility for the grounded UAV(s) is handed off to the ground recovery team. However, the Supervisor is still responsible for UAVs that were not grounded, which means the decrement in workload is not a great as in the best-case scenario. Generally speaking, the Supervisor's Overall Workload is related directly to the number of UAVs the Supervisor monitors; thus, grounding UAV(s) reduces the experienced Overall Workload. This result indicates that UE protocols are worthy of deeper investigation and that addressing the UAV(s) differently based on features, such as proximity for Emergencies in the airspace, may require additional autonomy and decision support in order to allow the Supervisor to address the situation.

Comparing the mean Overall Workload for three types of UE trials during periods when the UEs occurred and when they were not (Figure 14) also highlighted that differences in UE type can have an impact even when they are not occurring. As Figure 14 shows, the Overall Workload during the non-event control periods were lower for the Emergency in the airspace trials than for C^2 link loss and Mid-air collision UEs during Ramp down. This result is likely an artifact of the analysis caused by differences in the durations of the three UE types. The C^2 link loss and Mid-air collision UEs are relatively short in duration, resulting in the control intervals to which the UEs are compared being fairly consistent in terms of Overall Workload. However, when the Emergency in the airspace UE occurs during Ramp down, the UAVs are always handed off to the UE Supervisor, as the UE frequently lasts longer than the Ramp down period and the time remaining in the Supervisor's shift. The Overall Workload when averaged over the entirety of the Ramp down period will tend to be less than when averaged over a shorter interval earlier in Ramp down. Future work needs to explore alternative operational definitions for the shift states to eliminate this confound.

The change in Overall Workload caused by the Mindwandering distraction was smaller than expected. As a result, future work needs to investigate additional methods for modeling this type of distraction.

The Fatigue distraction results did not yield the expected effects based on the number of hours slept each of the last four nights and the work period. While the main effect and some interaction effects were significant, the effect sizes were negligible. Future work consisting of additional analyses of other measures, such as time to complete tasks, may be needed to see the effect of the built-in IMPRINT Pro models. This additional analysis is relevant, as the SAFTE model assumes additional fatigue makes the Supervisor less efficient; thus, the Supervisor will take longer to complete tasks. While the SAFTE model is common, additional different fatigue models also need to be investigated in future work.

It is noted that A26 only modeled three unexpected and two distraction events, some of which only apply to a single UAV. Further, the modeling did not investigate either cascading or simultaneous events. The A26 Task 3 final report provided an extensive, although not exhaustive, list of potential unexpected and distraction events that remain to be analyzed. It cannot be assumed that the results identified in the A26 simulation results directly represent any of these types of situations.

As presented in Section 15.2, the IMPRINT Pro model assumes a linear model of workload, which is not a representative model of workload for a single human supervising multiple UAVs. No other accurate models of workload for this scenario were identified in the literature. The A26 team went to extensive efforts to derive an appropriate model of workload, which was used for these simulation experiments; however, it is noted that this model and the reported results have not yet been verified via human subject experiments.

One of the stated goals of A26 was to inform future human subject experiments. The results herein highlight the value of the use of simulation to compare protocols to inform future human subject experiments.

17. TIGHTLY COUPLED (AERIAL IGNITION) USE CASE MODEL

The Tightly Coupled use case was modeled for an exemplar nominal situation that assumes the Supervisor sleeps eight hours each of the preceding four nights. The Fatigue distraction was further modeled assuming six and four hours of sleep each of the preceding four nights. The Fatigue distraction is the only distraction event modeled. Further, none of the exemplar unexpected events were modeled. The models focus on the ignition mission deployment portion of the use case only.

17.1. Workload Model Information

As noted in Section 15.2, it was necessary to define an appropriate workload model. The workload equation (Eq. 2) was used for model development, but requires the specification of the log rate. The team conducted an analysis of various log rates using the nominal use case (eight hours of sleep the last four nights), as shown in Figure 35. Based on Adams' prior objective workload estimation work (Harriott et al. 2015, Heard et al. 2019), her efforts with the DARPA OFFSET program (Atherton 2022), and her prior first response research, including field exercises, the logarithmic rate for the Tightly Coupled task model trials was set to 0.5.

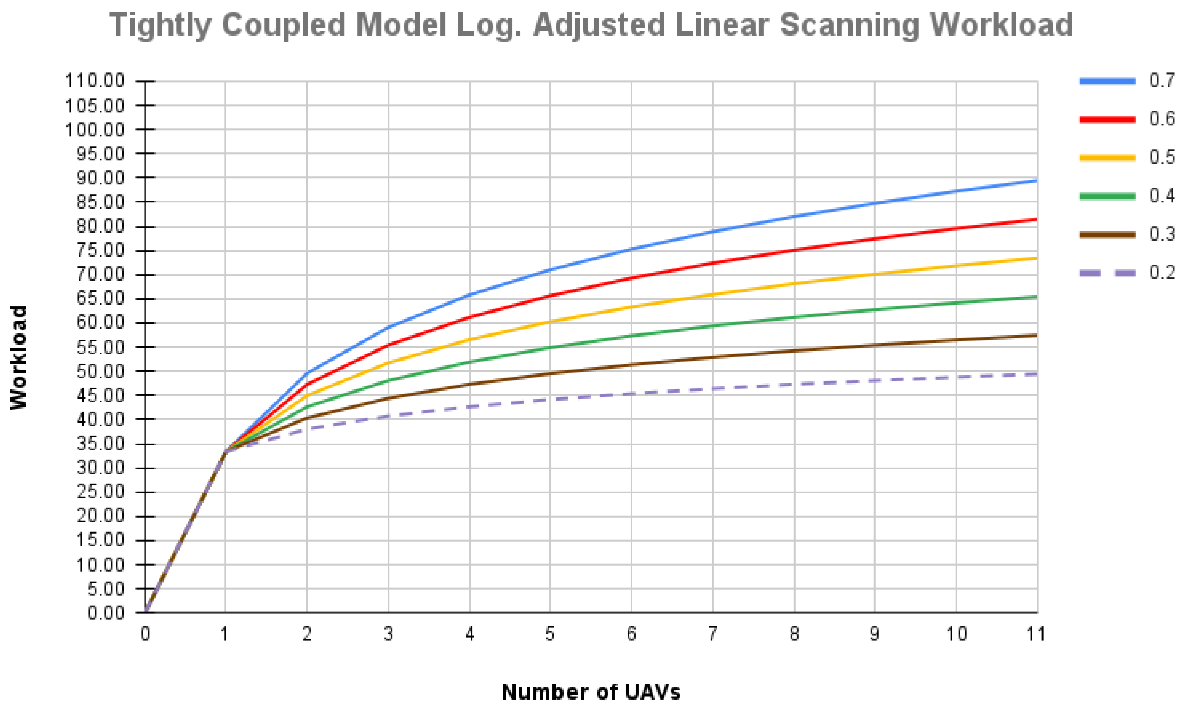


Figure 35. An analysis of resulting workload by the number of UAVs for the nominal Tightly Coupled use case using the logarithmic workload model with potential rates from 0.2 to 0.7.

17.2. Use Case Model

The nominal use case was developed using feedback from industrial partners, the U.S. Forestry Service and publicly available documents. The nominal use case decision tree is provided in Appendix B.

17.2.1. Model Development

The model represents the Supervisor's tasks for monitoring multiple Ignition and Surveillance UAVs conducting a ridgeline aerial ignition mission. The nominal use case model assumes that a single Supervisor is responsible for managing multiple UAVs during the aerial ignition mission. The nominal use case model incorporates examples of common mission activities (e.g., adjusting ignition sphere drop density, verifying surveillance areas), but does not incorporate any unexpected events or distraction use cases. The nominal use case enables the SAFTE fatigue plugin, assuming that the Supervisor has slept 8 hours each of the last four nights.

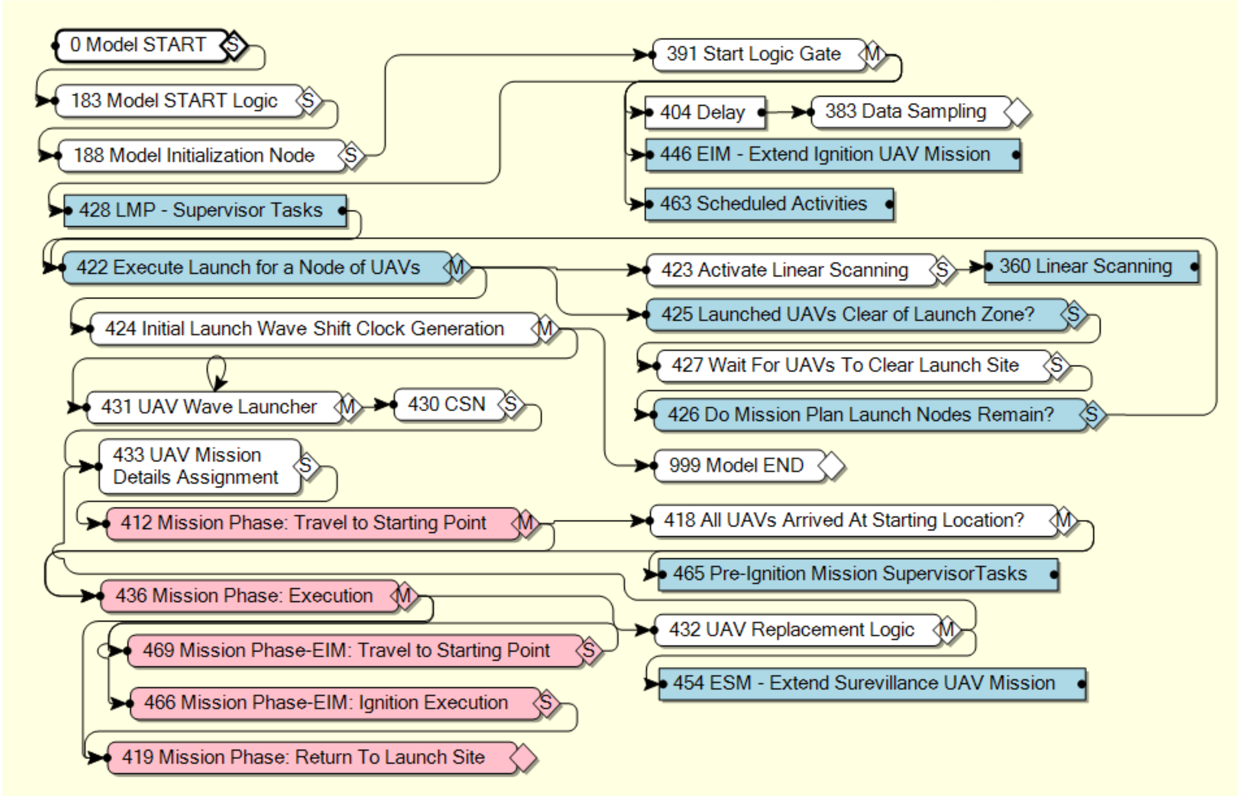


Figure 36. Screenshot of the Tightly Coupled nominal use case model within IMPRINT Pro.

Similar to the Loosely Coupled use case models, the nominal use case was decomposed into atomic tasks with a specified task completion time and associated workload values for the required workload components (i.e., cognitive, visual, speech, auditory, gross motor, fine motors and tactile). The IMPRINT Pro high-level nominal use case model is provided in Figure 36. The UAVs are simulated from the start of the mission, including selecting the mission plan nodes to execute that launch UAVs, progressing through the mission, and the mission completion. The designated mission time is intentionally longer than the UAVs' power supply, which means the UAVs are modeled to identify a point at which they must stop their current task, return to the launch area and request a replacement UAV. The replacement UAV launches and flies to the depleted power UAV's last location and recommences the mission and navigation plans; this behavior is called a swap. It is assumed in the model that no tasks are persistent tasks, and all UAVs can leave their task at any time due to power depletion and request a replacement UAV as soon as beginning to return to the launch area.

The A26 modeling effort incorporates the enroute flight to the location to commence mission execution, the execution of a UAV's navigation path as part of the mission, return to the launch area, descent from cruising altitude, and landing flight phases. Only the descent from cruising altitude and landing has a pre-defined time of 30 secs.

The Tightly Coupled use case incorporates a single use case specific probability distribution for the UAVs' power levels or available fuel for each UAV. This distribution is intended to accurately model the variability found in common UAV batteries. As such, during initialization, the UAV's fuel level is set to a value between 15 and 20 mins using the discrete uniform Fuel Duration distribution, as provided in Table 94.

Table 94. The Tightly Coupled use case model distribution.

Distribution Purpose	Distribution Type & Parameter Values	Min Value	Max Value
UAV Fuel Duration	DiscreteUniform (900, 1200)	900 secs (15 mins)	1200 secs (20 mins)

A number of typical activities can occur during the Tightly Coupled nominal use case, as indicated in the use case description provided in the final Task 3 report. These activities require the Supervisor to either take action or converse with the Communications lead about actions to be taken. A summary of these activities is provided in Table 95, along with general task descriptions. After the Supervisor executes a task change, the mission plan updates, the UAV(s) is notified, and the UAV(s) plan new deconflicted navigation path(s).

Table 95. Tightly Coupled use case model's typical Supervisor activities.

Task Activity	Description
Launch Mission Plan (LMP)	The mission plan was developed and reviewed previously. The team is ready for the mission deployment, and upon verification the Supervisor launches the mission plan. Launching the mission plan results in the first set of UAVs taking off, planning deconflicted navigation paths to their designated start locations and proceeding to their designated areas to begin conducting the mission. This activity is completed once at the start of the model.
Verify Surveillance UAV(s) coverage Area (VSA).	This activity requires the Supervisor to verify that the Surveillance UAV(s) are in their designated position, if hovering, or on their designated navigation path in order to provide appropriate sensor coverage of the area. The first instance of this activity occurs once the Surveillance UAV(s) arrive at their initial mission start positions in order to verify the mission plan. After this initial instance, the activity occurs every 10 mins, up to 40 mins into the mission.
Communications Lead Request Supervisor review Surveillance UAV(s) sensor feed (CLR).	The Communications lead asks the Supervisor to review a Surveillance UAV's sensor feed. This task requires a conversation between the two, as well as the Supervisor reviewing relevant information, such as displaying a camera feed, on the Supervisor's handheld C^2 station, looking for information that the Communications lead has indicated, and having a conversation with the Communications lead.

Task Activity	Description
Change a Surveillance UAV(s) monitoring Area (CSA).	This activity requires the Supervisor to either modify the navigation path, the orientation, altitude, etc. of Surveillance UAV(s) in order to adjust the area covered by the associated sensors. Once the changes are verified, the Supervisor executes a command to make the change, the mission plan is updated, the UAV receives the command, the UAV plans any deconflicted navigational changes, and executes those changes.
Switch a Navigating Surveillance UAV to a Hover surveillance task (SNH).	The Supervisor selects a navigating Surveillance UAV, designates a location and orientation at which the UAV is to hover, and executes the command. Execution of the command results in the mission plan being updated, the UAV receiving the command, the UAV planning a deconflicted navigation path to the hover point, and the UAV traveling to that point to commence hovering.
Switch a Hovering Surveillance UAV to a Navigating surveillance task (SHN).	The Supervisor selects a hovering Surveillance UAV, indicates resumption of the prior navigation plan or provides a new set of waypoints for navigation planning, and executes the command. Execution of the navigation command results in the mission plan being updated, the UAV receiving the command, and the UAV planning a deconflicted navigation path, the UAV possibly traveling to the start location at which to commence the navigation path, and executing the navigation path plan.
Adjust Ignition UAV(s)' Drop Density (ADD)	The density (i.e., distance between ignition sphere drops) is either increased/decreased by the Supervisor based on feedback from the Communications lead. Once the density change is verified, the command is sent to the UAV(s), the mission plan is updated, the UAV(s) plan deconflicted navigation paths with the designated drop waypoints, and commence executing the change.

Task Activity	Description
Extend Ignition UAV(s)' Mission (EIM)	The first Ignition UAV that has completed its mission assignment is selected by the Supervisor for an extended mission. If the UAV does not have enough fuel to execute the extension, a replacement UAV is launched to take its place. Once the ignition mission extension is executed, the mission plan is updated, the UAV receives the command and plans a deconflicted navigation path to the designated region, navigates to that region, and executes the drop pattern. The new region is of the same width as the ignition mission subregions, and is designated as the area to the right of the last ignition mission subregion, see Figure 38. The UAV must begin the ignition drops at the top left corner of the region. A single swamp is permitted to occur, therefore, at most two UAVs will drop spheres on this region. This activity completes once the second Ignition UAV's battery/spheres are depleted and it returns to the launch area. The longest that this activity can last is 40 mins (20 mins maximum battery life x 2); however, in practice, this activity last significantly less than 40 mins.
Extend Surveillance UAVs' Mission (ESM)	The Surveillance UAVs can have an extended monitoring mission after the original ignition mission plan has been completed. Note, if the Ignition mission is extended, the Supervisor begins the Surveillance UAV(s)' mission extension when the last Ignition UAV completes its original mission assignment. The Supervisor extends the monitoring mission for 30 mins. When the mission extension command is sent, the mission plan is updated, the Surveillance UAV(s) may replan deconflicted navigation paths (not modeled currently), and continue (or begin) the navigation path for monitoring. Surveillance UAVs are replaced until the intended replacement UAV is unable to fly to its surveillance starting waypoint, surveil for a sensible amount of time, and return to the launch site before the 30th minute. All Surveillance UAVs return to the launch area by the 30th min, at which point the mission is considered complete.

A timeline representing the order and times when the nominal use case's Supervisor activities from Table 95 begin in sequence as presented in Figure 37. The nominal use case assumes that the Supervisor is completing the visual linear scan at the same time as the Supervisor's activities, otherwise the activity timeline assumes each activity occurs independently, with no overlap with the others activities in Table 95. The IME (orange in the Figure) and SME (green in the Figure) activities begin based on the UAVs' mission progress, which means these times vary slighting across trials for a specific number of UAVs due to the cited UAV related distribution in Table 94. The Tightly Coupled use case is scheduled to last approximately 1 hour and 30 mins. Specifically, the mission completes 30 mins after the SME task begins; therefore, mission completion times will be, on average, less than 60 mins for the 4 and 6 UAV trials and approximately 95 mins for the 11 UAV Team size cases.

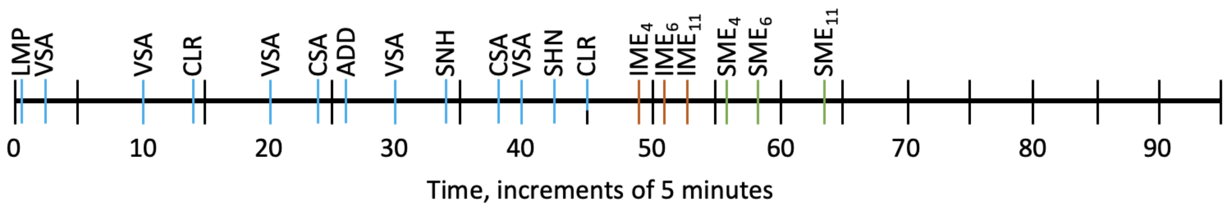


Figure 37. The Tightly Coupled use case model timeline. The Supervisor activities are listed in order of occurrence, see Table 95 for acronyms. Blue items occur at the same time irrespective of the number of UAVs, red and green items represent approximate start time based on the number of UAVs. Mission end time is 30 mins after SME start.

The Fatigue distraction SAFTE model parameters cause the Supervisor to be less effective as the number of hours of slept over the last four nights decreases. As such, the Supervisor's activities take slightly longer to perform. While the modeled activities take longer to complete during the Fatigue distraction trials, the activities occur in the same order at the same scheduled times as presented in Figure 37. However, extended activity completion times can result in some activities' steps occurring simultaneously, or overlapping.

The modeled Tightly Coupled example aerial ignition use case makes a large number of assumptions, as detailed in Table 96. The assumptions are decomposed into sections related to the deployment mission planning, UAV related items, as well as Supervisor, Communication lead, and Logistics coordinator related items.

Table 96. Tightly Coupled use case modeling assumptions.

Mission Plan Assumptions
The mission requires two types of UAVs, Ignition UAVs that drop the ignition spheres and Surveillance UAVs that provide coverage of the deployment area with relevant sensors (e.g., cameras).
The mission occurs along a remote mountain ridge. Radio communications between the team members exists, and may exist with other response teams in the area. It is assumed that communications with incident command and other organizations that are outside of radio frequency range are not available.
The maximum tree height is assumed to be 250 feet, which is based on the height of trees in the Lake Tahoe region of the United States.
The ridge incline is an average of the Sierra Nevada Mountain area affected by the 2021 Lake Caldor Fire, 20 degrees.
The Ignition UAVs generally fly at 137.16 meters (450 feet) Above Ground Level (AGL).
The Surveillance UAVs generally fly at 182.88 meters (600 feet) AGL.
The area of operation contains an ignition area that, when the number of Ignition UAVs > 1, is divided into equal-sized subregions, where each subregion is assigned to a single Ignition UAV in order to address one aspect of deconfliction.

Mission Plan Assumptions: Continued
The mission plan is designed such that when initiated, the UAVs launch in groups, with the UAVs, both Ignition and Surveillance, that must transition to the furthest subregion launching first. The number of launch groups varies by UAV Team size. An 11 UAV team launches in three groups, where the first group launched contains two Ignition and one Surveillance UAVs, while the second and third group each contain one Ignition and one Surveillance UAVs. The 6 UAV team launches in two groups of one Ignition and one Surveillance UAVs, while the four UAV team launches as a single group of one Ignition and one Surveillance UAVs. The launch group to which an UAV is assigned is based on the distance between the launch site and the UAV's assigned subregion. UAVs with the further assigned subregions are assigned to groups that launch earlier than the UAVs with closer assigned subregions.
The Surveillance UAVs are assigned to navigation paths or waypoints at which to hover in the area of operation. The assigned surveillance routes/locations are deconflicted from one another and are generally associated with Ignition UAV areas.
Each Ignition UAV is assigned to a designated area and will have a planned deconflicted navigation path along which ignition spheres are dropped.[3]
The Ignition UAVs begin dropping spheres at the top of the ridge and move down the mountain, inside the assigned ignition sections, using a lawnmower pattern.
The lawnmower pattern assumes that the Ignition UAVs complete a path across the area, at the end of the path across, the UAVs move down 10 meters before resuming a path across the assigned area.
There is a 5 meter buffer between each ignition subregion, when the number of UAVs > 1.
The ignition mission is approximately 60 minutes long, but the Supervisor extends the Surveillance UAVs' mission by 30 minutes.
The number of spheres that the UAV can hold is sufficient to drop spheres at the requested density equivalent to the available battery supply for this portion of the mission.
The simulation begins with the Ignition UAVs dropping ignition spheres every 10 meters, but is adjusted about half way through the modeled mission to every 5 meters.
The mission activities that require Supervisor actions do not occur simultaneously in the nominal case (i.e., Supervisor has slept eight hours each of the last four nights). It is possible, that with the Distraction cases some mission activities that require Supervisor actions may partially or completely overlap.
UAV Specific Assumptions
All UAVs are highly autonomous, with, for example, on-board processing that plans deconflicted navigation paths and the ability to automatically return to launch when the battery is low (i.e., swap).
All UAVs have a battery duration of 15-20 minutes.
All UAVs must return to and reach the launch area with 10% of their battery level remaining, called a swap behavior. As such, UAVs at a longer distance from the launch area will begin returning with a high remaining battery level.
All UAVs that have returned to the launch area hover for 30 secs before landing in order to simulate congestion in the launch site.
The swapping of a UAVs' battery is instantaneous once a UAV with a depleted battery has landed in the launch area.
The refilling of an Ignition UAV's ignition spheres is instantaneous once an Ignition UAV has landed in the launch area.
When flying between the launch/landing area, after take-off and transitioning to flying attitude, and the UAVs' mission waypoint, either to commence the mission or last point during the mission, the UAVs fly at 15 meters per second.

[3] Examples of the mission are detailed in Figure 38. Additionally, Appendix B provides additional details.

UAV Specific Assumptions: Continued
Ignition UAVs and Surveillance UAVs that are conducting their respective mission tasks fly at 5 meters per second.
The Surveillance UAV has a camera with a 58.2 degrees field of view, based on the Drone Amplified thermal and visual camera.
Supervisor Assumptions
The Supervisor is generally stationary (i.e., not walking) or making other gross motor movements during the mission.
The Supervisor uses a handheld (e.g., tablet) C^2 station.
The Supervisor is located in close proximity and communicates with the Communication lead (i.e., sensor monitor) using normal speaking voices.
The Supervisor is not required to monitor the Surveillance UAVs' sensor feeds, rather that is the responsibility of the Communication lead.
The Supervisor and Communication lead are located far enough from the Logistics coordinator that shouting or a radio is required for communication. The Communication lead does the vast majority of any required communication with the Logistics coordinator.
The Supervisor's C^2 system provides the ability to develop a new mission plan (not modeled).
The Supervisor's C^2 system provides the ability to modify and validate the mission plan (not modeled).
The Supervisor's C^2 system provides the ability to execute sections of the mission plan as groups.
The Supervisor's C^2 system provides a map-based interface that provides the ability to display various pieces of important information (e.g., mission plan, ignition regions).
The Supervisor's C^2 system provides the ability to monitor the deployed and reserve UAVs' locations and health status, including remaining Ignition UAV spheres and Surveillance sensor payloads.
The Supervisor's C^2 system provides the ability to display sensor feeds when required.
The Supervisor activities are completed as outlined in Table 95.
The Supervisor can hear directly the audible sounds of the UAVs, which do provide information related to take off, commencing flight out to the subregion, returning and landing. This aspect can provide additional information pertaining to mission progress and low battery swaps.
The Supervisor can visually see directly (if looking up from the C^2 system) UAVs taking off, commencing flight out to the subregion, returning and landing. This aspect can provide additional information pertaining to mission progress and low battery swaps.
Communications Lead Assumptions
The Communications lead remains in close proximity of the Supervisor throughout the entire mission deployment.
The Communications lead is responsible during the mission for all communications with any personnel not within normal speaking voice range.
The Communications lead is responsible for monitoring all Surveillance UAV sensor feeds.
Logistics Coordinator Assumptions
The Logistics coordinator is responsible for ensuring all UAVs are properly prepared for the mission deployment.
The Logistics coordinator is responsible for swapping all UAV batteries and refilling ignition sphere reservoirs, which is modeled as happening instantaneously.

A general depiction of the implemented example use case is provided in Figure 38, by the number of mission UAVs. These example depictions are intended to provide valuable context and are not to scale.

The depiction shows the three human wildland fire response team members, with their corresponding roles: Supervisor, Communications lead (and sensor feed monitor), and the

Logistics coordinator. All human team members are located a safe distance from the designated ignition area. The Supervisor and Communications lead are in close proximity to one another so that they can talk to one another directly (i.e., not using a radio). The Communications lead is responsible for monitoring the UAV's sensor feeds. The rectangular area in the lower left corner represents a designated UAV launch/landing area. This area is a safe distance from the Supervisor and Communications lead, such that they are unable to speak at a normal voice level with the Logistics coordinator. Shouting or radio communications may be needed to talk to the Logistics coordinator. The logistics coordinator is "responsible" for ensuring all UAVs are set up and ready to commence the mission (i.e., all required systems checks are completed), swapping UAVs' the batteries, and refilling their ignition sphere reservoirs, packing up the UAVs upon mission completion, etc. Note that the Logistics coordinator is not modeled at all, the Communications lead is generally not modeled, but communications with the Supervisor (i.e., information coming to the Supervisor, or the Supervisor communicating information) are modeled.

The Ignition UAVs (black) and Surveillance UAVs (gray) are represented in Figure 38 as either part way through the assigned mission plan or as reserve vehicles in the launch/landing area. The smallest mission has four UAVs, two Ignition and two Surveillance UAVs each, with one primary ignition area (long grey rectangle with flame indicators of where ignition spheres have been dropped in Figure 38(a)). The Ignition UAV begins its mission at the top of the ridge (top left of the ignition area) and works down the ridge within the mission region, using a lawn mower pattern. The Surveillance UAV has a navigation path that provides sensor coverage of the ignition area and any of the surrounding environment included in the mission plan specification. The two UAVs fly their planned navigation paths until a low battery situation occurs. Once a UAV has a low battery signal, a variable threshold based on how far the UAV is from the current location to the launch/landing area and the time to permit a safe land. The Ignition UAV will simultaneously be out of ignition spheres, which is noted as a modeling simplification assumption. The low battery threshold triggers the *swap* behavior, and as the UAV begins its return, it simultaneously requests a replacement UAV. Assuming a replacement UAV of the proper type (e.g., an Ignition UAV cannot be replaced by a Surveillance UAV) is available, the replacement UAV launches, flies to the waypoint at which the prior UAV stopped executing its mission navigation path, and the replacement UAV continues with the mission navigation path, including dropping Ignition spheres.

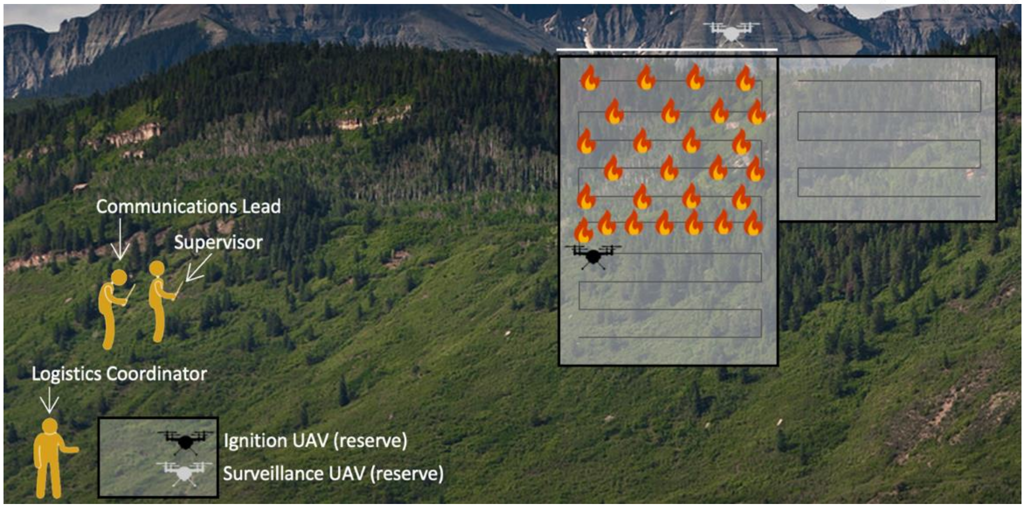
During the modeled example use case mission, the Supervisors adjusts the ignition sphere drop density by reducing the space between drops. This adjustment is visible in the primary (Figure 38(a)) and first ignition subregions of the remaining subfigures, as the fire symbols being depicted closer together.

The modeled example use case mission also incorporates the Supervisor extending the Ignition UAV's mission to continue to drop spheres on the smaller rectangle depicting the lawnmower pattern. This extension occurs as the Ignition UAV completes the primary ignition subregion, but has not yet returned to the launch/land area. The extended mission requires the Ignition UAV to fly to the upper left corner of the smaller area and begin dropping spheres. At most two Ignition UAVs, assuming the low battery swap behavior, will drop spheres in this additional subregion. The additional subregion is modeled as always being to the right of the final mission ignition subregion, when the model incorporates multiple Ignition UAVs, Figure 38(b) and (c), the first Ignition UAV to finish its assigned ignition subregion is the UAV that has its mission extended.

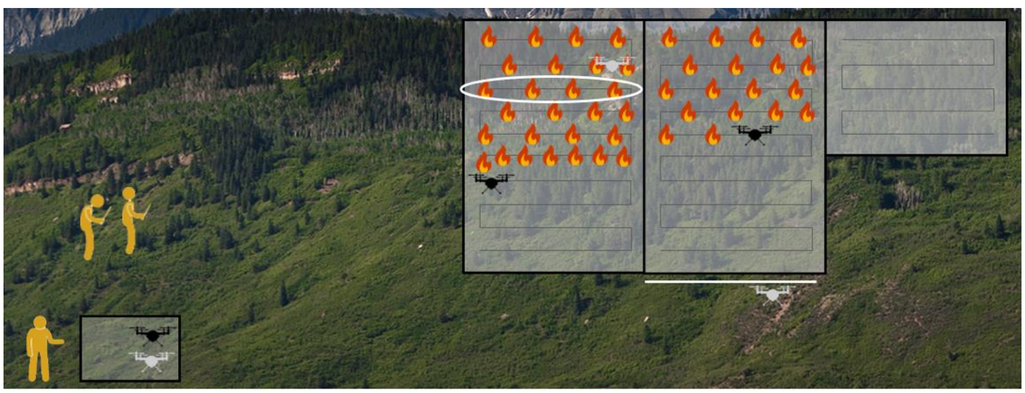
The deployed Surveillance UAVs fly their designated navigation paths
that are generally deconflicted, even in the modeled versions with multiple deployed Surveillance UAVs that overlap the mission ignition subregions that they cover.

The models with six and eleven UAVs, Figure 38(b) and (c), demonstrate the assumed layout of ignition subregions. It is important to note that the mission plan launches the UAVs at approximately the same time, using waves for the larger team sizes. The UAVs fly at the same speeds along their respective deconflicted navigation paths, planned by reach respective UAV; however, the travel distance to the start of the Ignition UAVs' mission subregion and the Surveillance UAVs' mission starting waypoint will cause the UAVs to arrive at different times. An Ignition UAV flying to the furthest ignition subregion will not commence dropping Spheres until after an Ignition UAV that is assigned the ignition subregion closest to the launch/landing area. The depictions provide example representations of these differences.

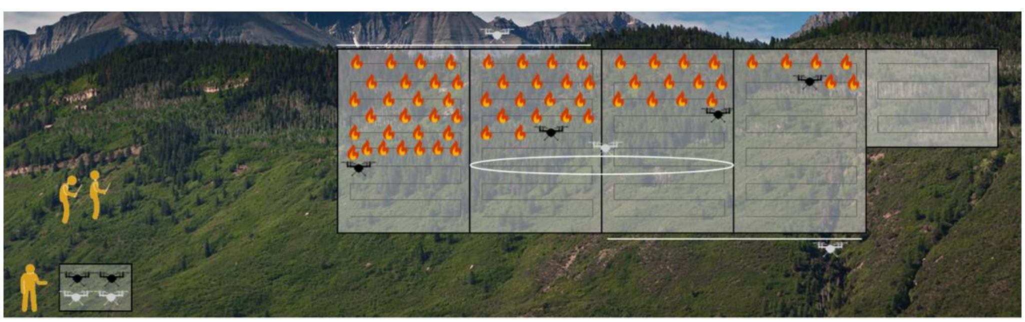
The total ignition mission area size, the area in which ignition spheres are dropped by the Ignition UAVs, is a function of the number of the number of simultaneously deployed Ignition UAVs. Each Ignition UAV's subregion is 1,920 meters x 305 meters. The ignition subregions are aligned horizontally across the ridgeline, as shown in Figure 38; therefore, the size of the total area covered ranges between a single subregion with the four UAV team (i.e., a 1,920 meters x 305 meters area), to an area covering four subregions (i.e., a 7,680 meters x 305 meters area) with the 11 UAV team composition. The width of the extended mission area is identical to that of an ignition subregion. Surveillance UAVs have an identical size surveillance area above the ignition UAVs, except under a 11 UAV team composition where the number of Surveillance UAVs is smaller than the number of ignition subregions. The Surveillance UAVs, in this case are assigned surveillance areas that encompass two ignition subregions, with some of the Surveillance UAVs' areas overlapping.



(a) Aerial ignition conducted by the UAV Supervisor, Communication lead (sensor monitor) and Logistics Coordinator with 4 UAVS, 2 Ignition UAVs (black) and 2 Surveillance UAVs (gray). One of each UAV type is held in reserve to swap when the deployed UAVs' power is depleted. The ignition mission area (left) is depicted along with the extended mission area (right).



(b) Aerial ignition mission conducted using 6 UAVS, 3 Ignition UAVs and 3 Surveillance UAVs.



(c) Aerial ignition mission conducted using 11 UAVS, 6 Ignition UAVs and 5 Surveillance UAVs.

Figure 38. Depictions of the Tightly Coupled aerial ignition use case with (a) 4 UAVs, (b) 6 UAVs, and (c) 11 UAVs.[4]

[4] The aerial ignition depictions were developed using imagery from the Worldwide Web. Please see Appendix C for a list of sources.

The Tightly Coupled model leverages 37% percent of the code developed for the Loosely Coupled model. 2,494 unique lines of code were introduced for the Tightly Coupled model. The new code is responsible for necessary Tightly Coupled model features, such as generating the simulation mission plan, executing the mission, the low power UAV swap behavior (Table 96), and the Supervisor's activities (Table 95) logic.

17.2.2. Experimental Design

The nominal use case experiments focused on the UAVs' mission deployment (i.e., UAVs conducting ignition and surveillance tasks) and supervision of the UAVs without any disruptions from unexpected events or distractions. The Fatigue distraction use case experiments used the exact same model and simply adjusted the SAFTE model's number of hours slept over the last four nights parameter. The basic research questions were the same for both sets of experiments:

- Do any specific independent variables dramatically impact the Overall Workload the Supervisor can manage?
- How do the modeled Supervisor activities during the mission deployment impact the dependent variables?
- As the number of UAVs supervised increases, does Overall Workload increase?
- Given that Overall Workload is expected to increase as the number of UAVs increases, is there a significant difference in the conditions impact on Overall Workload?

17.2.2.1. Independent Variables

The number of UAVs, along with the number of Ignition and Surveillance UAVs in the total team, represent the primary independent variable, as shown in

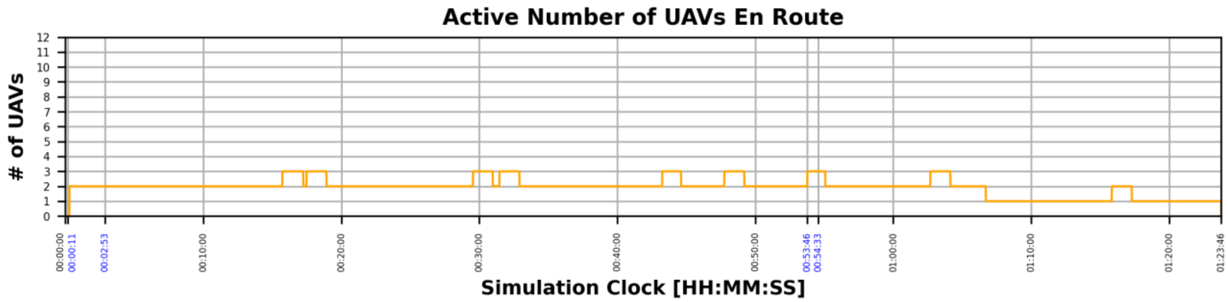
Table 49. Each presented team size includes two categories of UAV groups, deployed UAVs and Reserve UAVs. The deployed UAVs represent the UAVs deployed to execute the aerial ignition related tasks, while the reserve UAVs represent the extra vehicles available to swap with the respective deployed vehicle(s) when the power supply is depleted. The UAV Team size implies an adjustment to the total area covered, as explained in Section 17.2.1.

This independent variable was the same across the nominal and Fatigue distraction trials.

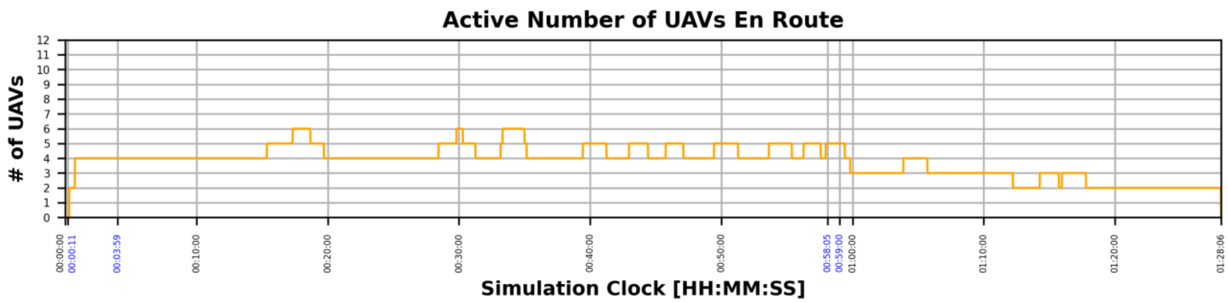
Table 97. Nominal use case independent variables.

Team Size	Mission Active UAVs		Reserve (Swap) UAVs	
	Ignition UAVs	Surveillance UAVs	Ignition UAVs	Surveillance UAVs
4	1	1	1	1
6	2	2	1	1
11	4	3	2	2

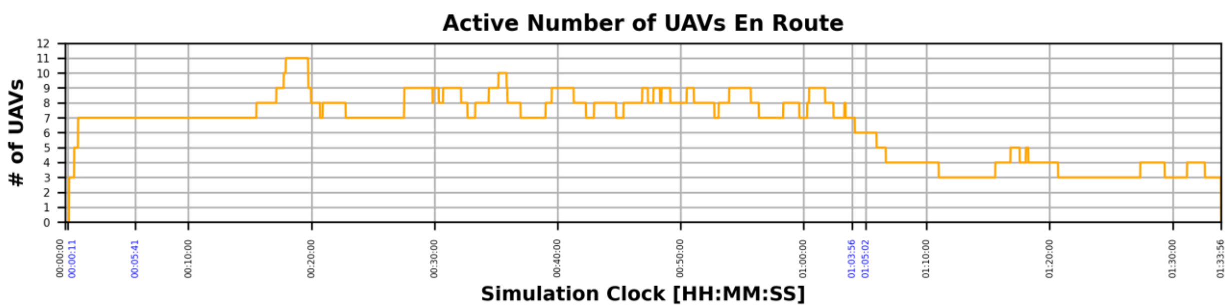
The number of deployed UAVs throughout a trial will vary. After the initial mission plan launches, the lowest number of deployed UAVs will correspond to the Mission Active UAVs column in Table 97. However, as the mission active UAVs' power supplies become low and the replacement swap behavior is enabled, the number of deployed vehicles will increase until the returning UAV(s) lands. As the overall UAV team size increases, there will be an increased number of replacement swap behavior instances, which increases the number of deployed vehicles, as shown in Figure 39. The number of deployed UAVs for the Fatigue distraction trials are provided in Appendix B.



(a) The 4 UAV team size.



(b) The 6 UAV team size.



(c) The 11 UAV team size.

Figure 39. The number of deployed UAVs throughout the nominal use case (the Supervisor has slept 8 hours each of the last four nights) mission by UAV team size: (a) 4 UAVs, (b) 6 UAVs, and (c) 11 UAVs. The increases above the number of Mission Active UAVs (see Table 97) are due to the UAV low power swap behavior. The blue time points represent, in order: mission plan execution, the start of the Ignition phase of the mission plan, the end of the mission's planned Ignition phase, and the extension of the Surveillance UAVs.

The SAFTE mode's number of hours slept each of the last four nights variable represents the independent variable that distinguishes the nominal and distraction use case trials. The nominal use case assumes that the Supervisor had 8 hours of sleep each of the last four nights. The distraction trials investigate the impact of fatigue on Supervisor performance and workload. The number of hours the Supervisor slept each of the last four nights in these trials was set to either 6 or 4 hours.

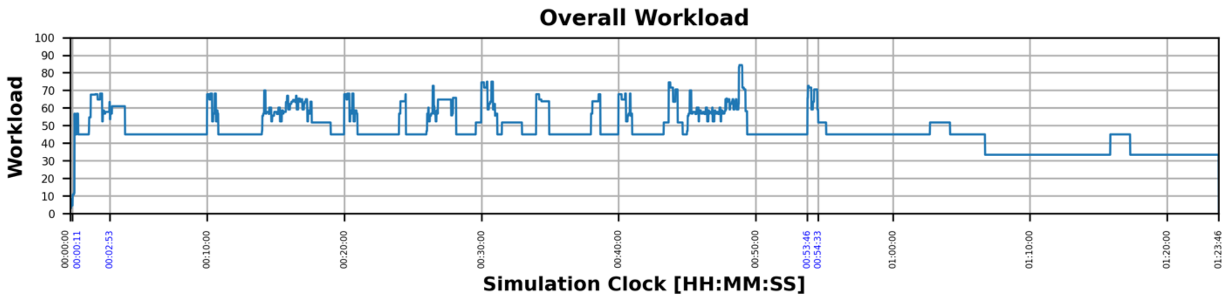
17.2.2.2. Dependent Variables

The Overall and component Workload metrics represent the primary dependent variables. The remaining dependent variables are related to the Supervisor's Effectiveness based on the fatigue level, the number (#) of UAV swaps during the mission trial, and the Overall time to run a mission trial. Almost all dependent variables are listed in Table 98; a measurement of Supervisor Efficiency is also a dependent variable. The dependent variables were recorded at three different timings: 1 sec, 5 secs and 10 secs. The purpose of these times was to determine what is a fine-grained enough scale at which to see the variations in the results, but not be so fine grained to hinder data analysis.

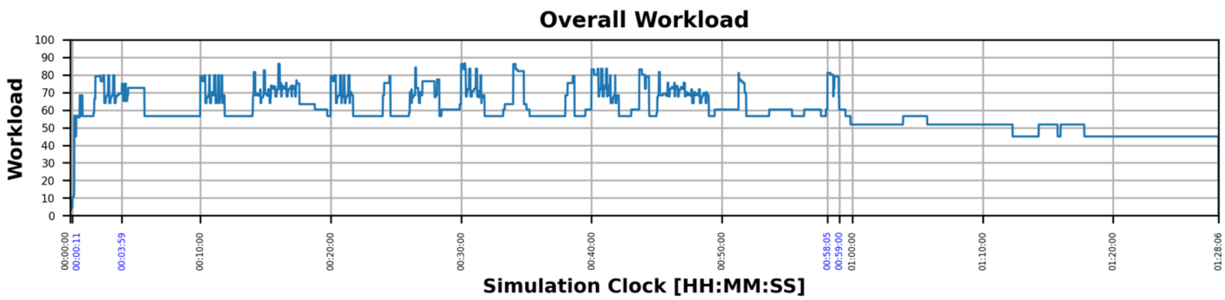
Table 98. The Tightly Coupled use case's dependent variables.

Dependent Variables	Minimum	Maximum
Auditory Workload	3	26.46
Cognitive Workload	4.6	34.93
Fine Motor Workload	2.2	13.26
Gross Motor Workload	1.5	3.30
Speech Workload	1.5	10.32
Tactile Workload	1	2
Visual Workload	4	26.86
Overall Workload	3	99.44
Effectiveness	0.806	1.0
# of UAV swaps (total)	9	37
# of Ignition UAV swaps	4	18
# of Surveillance UAV swaps	5	19
Overall Mission Duration	01:23:35	01:38:58
VSA Activity Duration	00:00:29	00:03:23
CLR Activity Duration	00:03:20	00:04:36

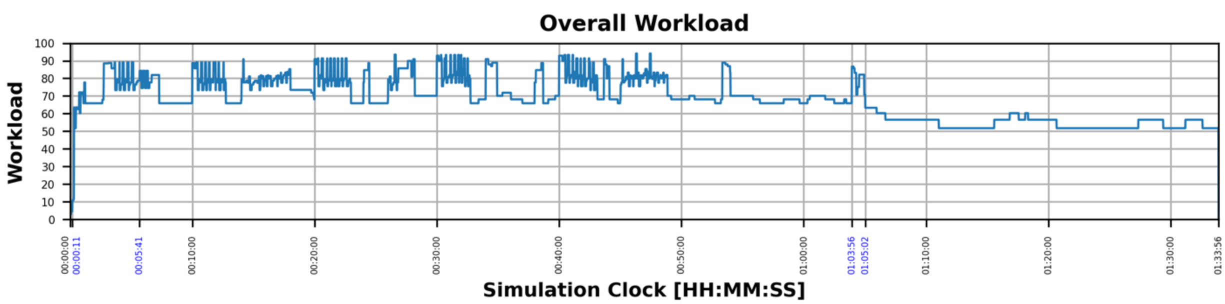
The maximum and minimum workload values are based on the IMPRINT Pro channel scales, as shown in Table 50. As a reminder, IMPRINT Pro considers a value above 60 to be overloaded. Workload is expected to be impacted the most by the number of UAVs in the team (an independent variable) and the Supervisor's mission activities, which were identical across all experimental trials. An example of the Overall Workload results for each team size during the nominal use case are provided in Figure 40. Corresponding figures for the Fatigue distraction cases are provided in Appendix B.



(a) The 4 UAV team size.



(b) The 6 UAV team size.



(c) The 11 UAV team size.

Figure 40. The Overall Workload results for a single nominal use case (the Supervisor has slept 8 hours each of the last four nights) trial by UAV team size: (a) 4 UAVs, (b) 6 UAVs, and (c) 11 UAVs. The increases in Overall Workload indicate Supervisor activities, which occurred as indicated in Figure 37. The blue time points represent only four of the Supervisor's activities, in order: mission plan execution, the start of the Ignition phase of the mission plan, the end of the Ignition phase, and the extension of the Surveillance UAVs.

The SAFTE model provides an *effectiveness* value based on the associated number of hours slept over the last four nights. The base effectiveness value is 1.0 when the Supervisor has slept 8 hours each of the last four nights, 0.923 with 6 Hours slept, and 0.806 with 4 Hours slept. Figures representing the effectiveness across the independent variables are provided in Appendix B.

The *# of UAV swaps* was recorded by UAV type, Ignition or Surveillance. The number of swaps will vary depending on the UAV team size and the distributions (e.g., power supply) in Table 94. The minimum number of swaps occur with the smaller Team sizes. The number of swaps based

on UAV type is similar. The average number of Ignition UAVs across
all trials was 11.12, while the average number of Surveillance UAV swaps was 9.523. The Ignition UAVs had a minimum number of swaps equal to 4, which occurred for the 4 UAV Team size, and 18 maximum swaps that occurred with the 11 UAV Team size. The Surveillance UAVs had a minimum of 5 swaps with the 4 UAV Team size, and 19 maximum swaps occurred with the 11 UAV Team size.

The *Overall mission duration* ranged from a minimum of 1 hour, 23 minutes and 35 seconds for the 4 UAV Team size to a maximum of 1 hour, 38 minutes and 58 seconds for the 11 UAV Team size. The Overall mission duration was fairly consistent across the trails. This information was recorded, but is not reported in detail.

The *VSA* and *CLA Activity duration* represent how long the Supervisor took to complete a specific type of activity. The range of VSA activity Durations was 29 seconds to 3 minutes and 23 seconds, and is impacted by the number of deployed UAVs. The CLR activity Duration range was tighter, with a minimum of 3 minutes and 20 seconds and a maximum of 4 minutes and 36 seconds.

The final dependent variable, *Efficiency* represents the simple ratio of Overall Workload/time to complete the task. Higher ratios, or Efficiency, are indicative of more workload per a given unit of time. Efficiency was calculated during the data analysis and is not a direct output of the model.

17.2.2.3. Simulation Methodology

A total of 3 independent variable combinations are possible for the nominal use case (8 hours of sleep). Each combination of independent variables was run for 25 trials in order to account for variability in the model distributions provided in Table 94. A total of 75 trials were run (3 x 25 = 75).

The Fatigue distraction use case trials incorporate a total of 9 independent variable combinations. Each combination of independent variables was run for 25 trials in order to account for variability in the model distribution provided in Table 94. A total of 225 trials were run (9 x 25 = 225), of which 75 trials are the nominal use case trials noted in the prior paragraph.

17.2.2.4. Data Analysis Methodology

An initial set of analyses focuses on examining the influence of the independent variables (e.g., hours slept and team size) on Overall Workload and the # of swapped UAVs across the duration of the mission. Given that the mission trials overall durations differ based on the UAV team size, a time period of 83 minutes was selected for the overall mission analysis, as this preserved the largest amount of time data across trials. This 83 minute time period was segmented into 1 minute increments. These time points were used as a within factor in a mixed factorial ANOVA, which included Hours slept and UAV Team size as between groups factors. Data for each of the 25 trials for each combination of the independent variables was analyzed.

The overall mission analysis does not focus on the Supervisor's activities, thus, a similar overall analysis that considers the Supervisor's activity type during the mission was conducted across the 14 activities in the order that they occurred during the missions. This set of analyses has five dependent variables: activity Effectiveness, Overall Workload, activity Duration, # of swapped UAVs, and Efficiency. The Efficiency dependent measure represents the simple ratio of Overall Workload/activity Duration. Higher ratios are indicative of more Overall Workload per a given unit of time. All of these dependent measures were analyzed using a mixed factorial ANOVA.

This initial analysis provides an overall conceptualization of Supervisor activity performance, which is expanded in additional analyses.

A more nuanced analysis of the data focuses on the Supervisor's activities, listed in Table 95 (excluding the LMP activity) is provided. The effects of the two independent variables (e.g., Hours slept the last four days and UAV Team size) were used to analyze the outcomes for the eight Supervisor activities modeled in the Tightly Coupled task. The analyzed dependent variables for each activity are Overall Workload, activity Duration, and activity Efficiency. The *Efficiency* dependent measure represents the simple ratio of Overall Workload/activity Duration. Higher ratios are indicative of more workload per a given unit of time. Three activities (e.g., Visual Scanning, Communication, and Adjustment of Surveillance area) occurred multiple times during a given work period, allowing for a more closely examination of effects over time. VSA activity provided the best analysis opportunity, as it occurred five times during a given mission, whereas the CLR and CSA activities only occurred twice each. The repeated activity instances were added to the analysis as a within groups factor in order to examine any changes over activity occurrence during the mission deployment.

Analyses for the activities that occurred only once during a mission deployment were analyzed with a factorial ANOVA, while those activities that did occur multiple times were analyzed using a mixed-factorial ANOVA.

All analyses were evaluated for significance at an $\alpha < 0.05$, and standardized effect sizes were reported (η^2).

17.2.3. Results

The Tightly Coupled Task's results are divided into three sections. The first section focuses on validating the SAFTE model's results. The second section presents overall results and the final section presents results based on the Supervisor's activities.

17.2.3.1. Validation of the SAFTE Model

Supervisor fatigue was modeled using the SAFTE model's plugin within IMPRINT PRO. An initial analysis was conducted for the overall mission, agnostic to the Supervisor's activities (i.e., the activities in Table 95, excluding LMP), in order to validate that Fatigue impacted the model in appropriate ways. The SAFTE model implements a manipulation of task effectiveness, which scales task performance based on effectiveness values. Nominally, without fatigue (i.e., 8 hours slept each of the last four nights), this effectiveness value rests at 1.0. A mixed-factorial ANOVA on model effectiveness was conducted evaluating the two between groups independent variables (Hours slept and UAV Team size), and the Supervisor's activities, excluding LMP, in the order they occurred during a mission trial (see Figure 37) as the within factor. Note that these activities are each unique in their composition and demands; however, the SAFTE plugin does modify them consistently via the effectiveness adjustment, regardless of their nature. This analysis serves as a manipulation check to confirm that effectiveness did in fact vary as intended with the utilization of the SAFTE model plugin. These ANOVA results are provided in

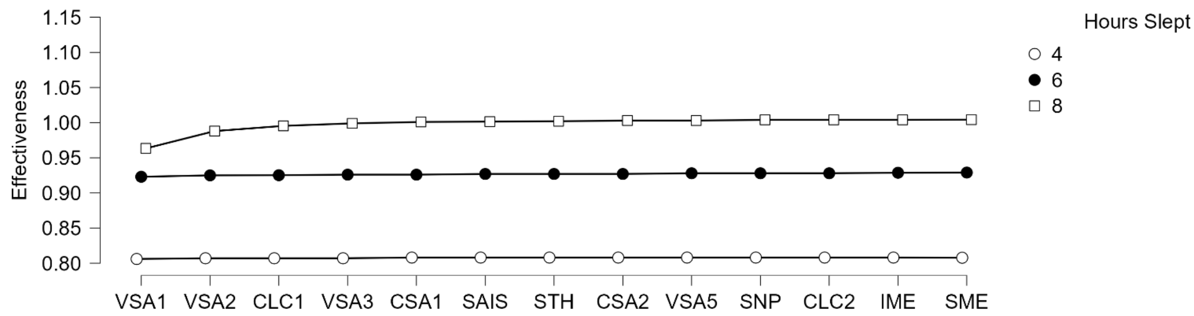
Table 99.

Table 99. ANOVA table for task effectiveness by independent variables and over task position.

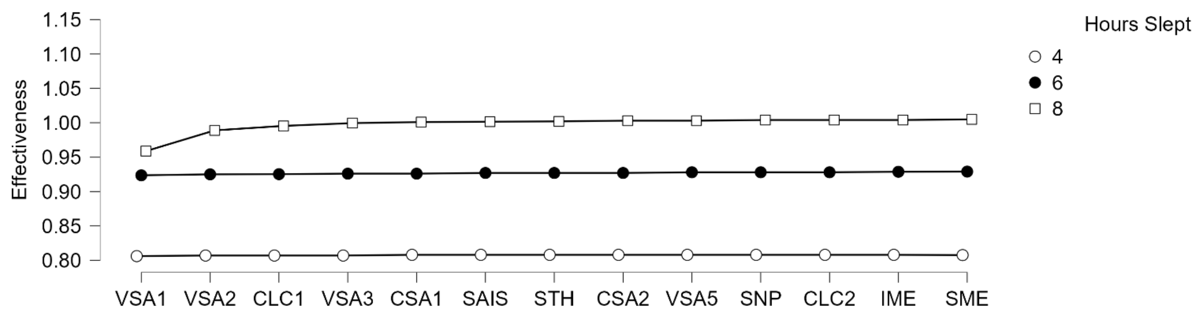
Factor	***df***	***F***	η^2	α
Hours slept	2, 216	3.58 e+7**	0.99	<.001
Team size	2, 216	68.06**	<.001	<.001
Activity occurrence location	13, 2808	15619.92**	<.01	<.001
Hours slept x Team size	4, 216	43.22**	<.001	<.001
Activity occurrence location x Hours slept	26, 2808	9885.93**	<.01	<.001
Activity occurrence location x Team size	26, 2808	42.94**	<.001	<.001
Activity occurrence location x Hours slept x Team size	52, 2808	32.55**	<.001	<.001
***p*<.001				

Activity Effectiveness did vary by all the independent variables, as visible in

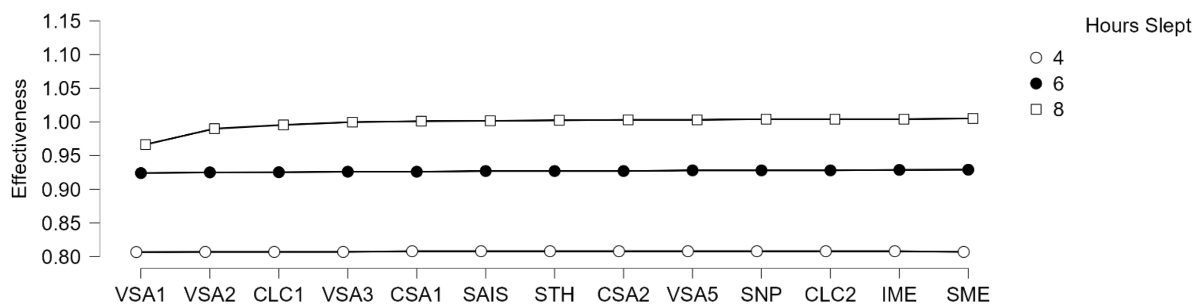
Table 99, such that both Hours slept and UAV Team size did significantly impact Effectiveness, as did the order of the activities. Fewer Hours slept (i.e., 4 or 6 hours) resulted in lower levels of Effectiveness than when the Supervisor slept 8 hours each of the last four nights, where this difference was a large reliable effect ($\eta^2 = 0.99$). Both the UAV team size, and activity order also impacted Effectiveness, but these effect sizes approach zero, and likely are statistical artifacts of the large sample size. All two-way and the three-way interactions were likewise significant, but also produced trivial effect sizes. These effects are graphically displayed in Figure 41, where there are stark differences in Effectiveness based on Hours slept, but fundamentally no difference as a result of either UAV Team size, or across the activities as they occur within a mission deployment. As the SAFTE model is triggered by the adjustment of Hours slept, it was fully expected that this independent factor results in differences in Effectiveness, which was borne out by the current analysis. It is important to note that Effectiveness appears to plateau across a mission's duration, and while fewer Hours slept does lower overall Effectiveness, working a mission deployment does not appear to exacerbate this Effectiveness value in a substantial way.



(a) UAV Team size equal to 4.



(b) UAV Team size equal to 6.



(c) UAV Team size equal to 11.

Figure 41. Task Effectiveness by Hours slept and UAV Team size over each activity within a mission deployment with Team size equal to (a) 4 UAVs, (b) 6 UAVs, and (c) 11 UAVs.

17.2.3.2. Overall Results Analysis: Mission

The Overall Workload was analyzed across the first 83 minutes of the mission (segmented into 1 minute intervals), using Hours slept and UAV Team size as between group factors. The ANOVA results are presented in Table 100. The results indicate that Overall Workload does significantly vary over time ($\eta^2 = 0.81$), and that both Hours slept ($\eta^2 = 0.004$) and UAV Team size ($\eta^2 = 0.81$) were both significant factors in predicting Overall Workload, although there was no significant interaction between Hours slept and UAV Team size. Larger UAV Team sizes, and fewer Hours slept both increased the Supervisor's experienced Overall Workload. However, it must be noted that the effect size of Hours slept was trivial, while UAV Team size was a very large effect, suggesting that UAV Team size is the main driver of Overall Workload in general.

Table 100. ANOVA results for Overall Workload and # of swapped UAVs over mission duration.

Factor	*df*⁺	*F*	η^2	*α*
Overall Workload				
Hours slept	1.77, 42.49	62.93**	<.01	<.001
UAV Team Size	1.49, 35.65	9034.78**	0.81	<.001
Time (minute)	82, 1968	534.68**	0.81	<.001
Hours slept x UAV Team Size	3.51, 84.14	0.81	<.001	0.51
Time x Hours slept	164, 3936	5.71**	0.03	<.001
Time x UAV Team Size	164, 3936	24.05**	0.27	<.001
Time x Hours slept x UAV Team Size	328, 7872	3.25**	0.04	<.001
# of Swapped UAVs				
Hours slept	1.85, 44.35	1.51	<.001	0.23
UAV Team Size	1.88, 45.08	1098.49**	0.18	<.001
Time (minute)	82, 1968	33.62**	0.3	<.001
Hours slept x UAV Team Size	2.63, 63.00	0.64	<.001	0.57
Time x Hours slept	164, 3936	1.84**	0.01	<.001
Time x UAV Team Size	164, 3936	8.26**	0.15	<.001
Time x Hours slept x UAV Team Size	328, 7872	1.30**	0.01	<.001

⁺ Greenhouse-geisser corrections applied as needed
*p<.05, **p<.001

The Hours slept ($\eta^2 = 0.03$; Figure 42) and UAV Team size ($\eta^2 = 0.27$; Figure 43) did interact with time, but while the effect size of the UAV Team size interaction was very large, the interaction with Hours slept was small. Finally, there was also a 3-way interaction between the independent variables and time ($\eta^2 = 0.04$; Figure 44). Larger UAV Team sizes produce higher levels of Overall Workload across the mission, although more Hours slept slightly alleviated these higher levels of Overall Workload. This result has a small/medium sized effect.

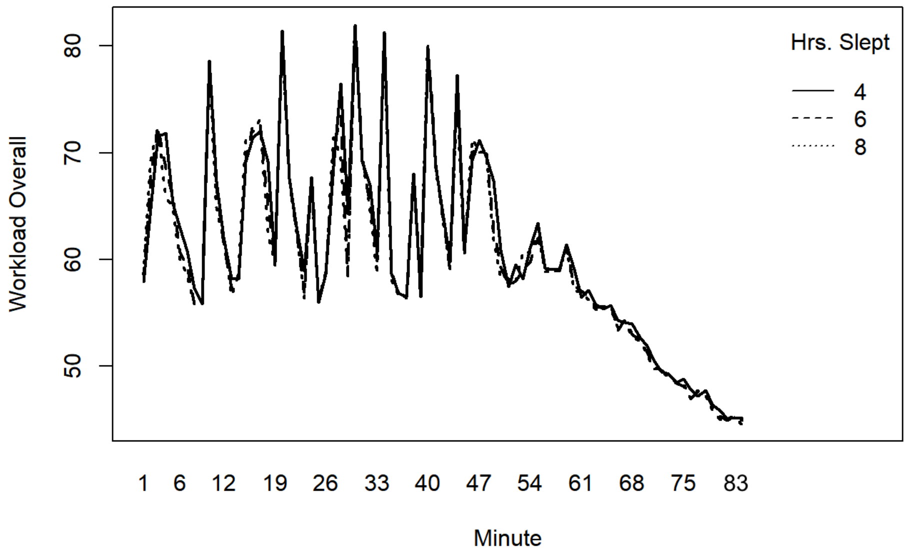


Figure 42. The impact of Hours slept on Overall Workload over the first 83 minutes of the mission.

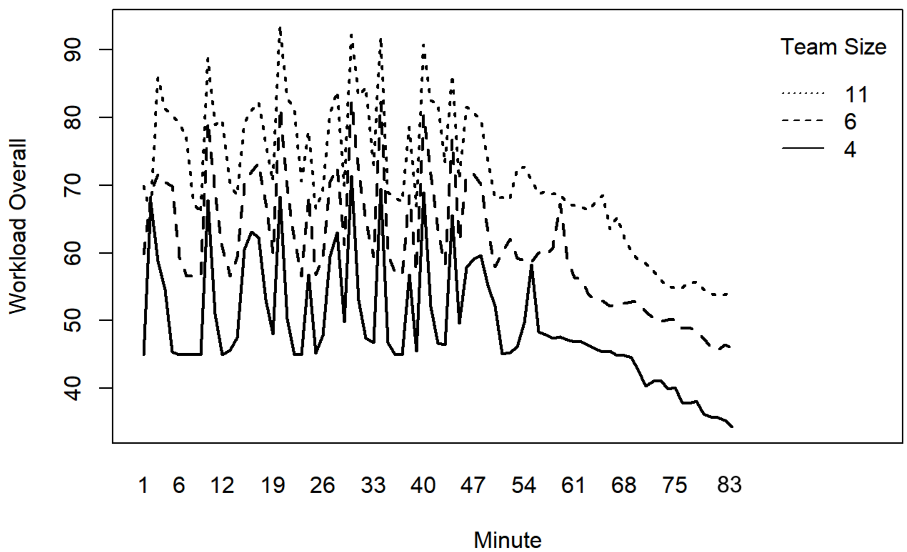
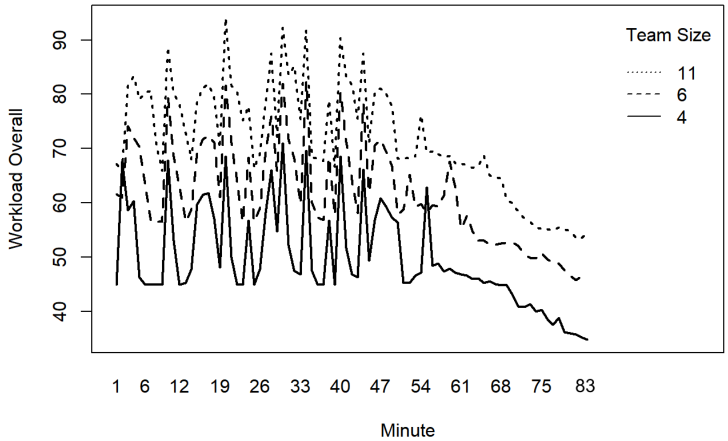
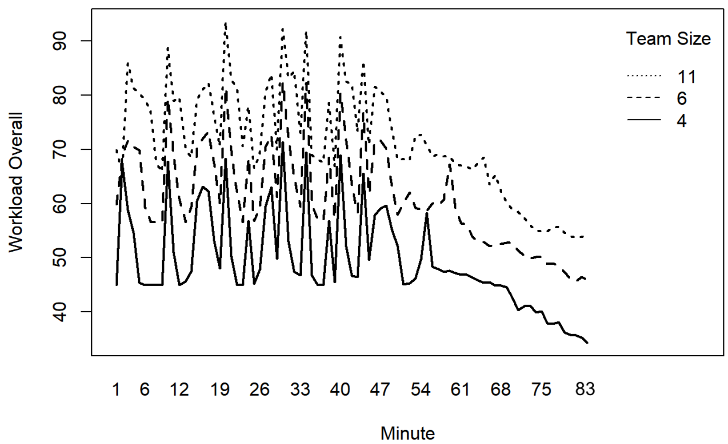


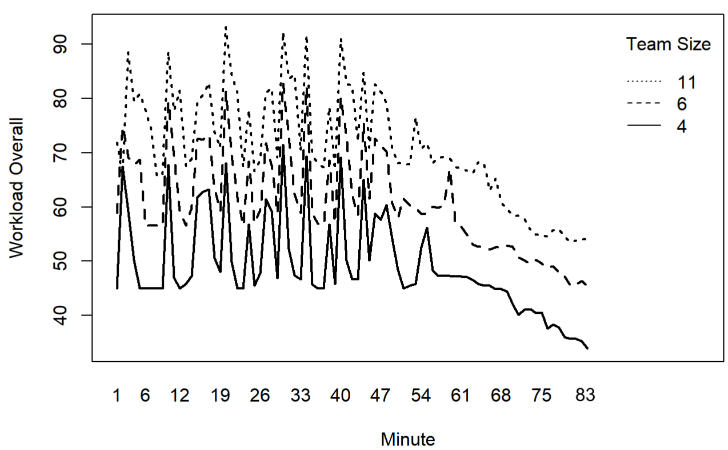
Figure 43. The impact of UAV Team size on Overall Workload over the first 83 minutes of the mission.



(a) Four Hours slept.



(b) Six Hours slept.



(c) Eight Hours slept.

Figure 44. The interaction between UAV Team size and Hours slept over the first 83 minutes of the mission: (a) four, (b) six, and (c) eight Hours slept.

This same analyses over the first 83 minutes of the mission were repeated with the # of swapped UAVs. The Hours slept and UAV Team size served as between groups factors. The Results are presented in Table 100. While the # of swapped UAVs did significantly change over time (η^2 =

0.30), only UAV Team size significantly impacted the # of swapped UAVs (η^2 = 0.18; Figure 45), with large effect. Unsurprisingly, the larger UAV Team size mandated a higher # of swaps over the mission. The Hours slept did not impact the # of swapped UAVs ($\eta^2 < 0.001$), and there was no interaction between Hours slept and UAV Team size. There was a significant interaction between Hours slept and time (η^2 = 0.01), and UAV Team size and time (η^2 = 0.15), but only the UAV Team size interaction was of any notable effect size. Finally, there was a 3-way interaction between Hours slept, UAV Team size and time (η^2 = 0.01), but the size of this effect seems to suggest that this is a trivial result.

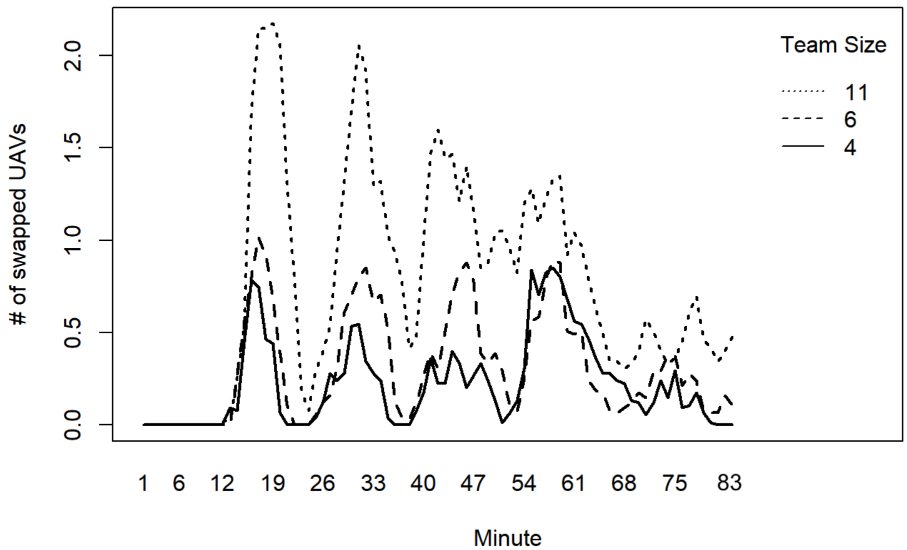


Figure 45. The impact of UAV Team size on the # of swapped UAVs during the first 83 minutes of the mission.

17.2.3.3. Overall Results Analysis: Supervisor Activities Only

The remaining data analysis focuses on the Supervisor activities. An analysis of the Overall Workload, Activity duration, Efficiency and # of swapped UAVs was conducted. All relevant ANOVA results are provided in Table 101.

Table 101. ANOVA table for overall activity results.

Factor		df^{+}	F	η^2	α
Overall Workload					
	Hours slept	2, 216	0.66	<.001	0.52
	Team Size	2, 216	58881.54**	0.89	<.001
	Activity Occurrence Location	6.39, 1379.29	424.24**	0.07	<.001
	Hours slept x Team Size	4, 216	0.13	<.001	0.97
	Activity Occurrence Location x Hours slept	12.77, 1379.29	0.9	<.001	0.61
	Activity Occurrence Location x Team Size	12.77, 1379.29	32.27**	0.01	<.001
	Activity Occurrence Location x Hours slept x Team Size	25.54, 1379.29	0.25	<.001	1
Activity Duration					
	Hours slept	2, 216	436.33**	<.01	<.001
	Team Size	2, 216	5624.35**	0.05	<.001
	Activity Occurrence Location	7.31, 1578.35	13089.21**	0.83	<.001
	Hours slept x Team Size	4, 216	3.13*	<.001	0.02
	Activity Occurrence Location x Hours slept	14.61, 1578.35	16.88**	<.01	<.001
	Activity Occurrence Location x Team Size	14.61, 1578.35	748.84**	0.1	<.001
	Activity Occurrence Location x Hours slept x Team Size	29.23, 1578.35	1.16	<.001	0.25
Efficiency					
	Hours slept	2, 216	242.17**	0.01	<.001
	Team Size	2, 216	28.59**	<.01	<.001
	Activity Occurrence Location	6.42, 1385.65	2577.69**	0.8	<.001
	Hours slept x Team Size	4, 216	1.64	<.001	0.17
	Activity Occurrence Location x Hours slept	12.83, 1385.65	18.56**	0.01	<.001
	Activity Occurrence Location x Team Size	12.83, 1385.65	169.93**	0.11	<.001
	Activity Occurrence Location x Hours slept x Team Size	25.66, 1385.65	1.87*	<.01	0.01
# of Swapped UAVs					
	Hours slept	2, 216	1.05	<.001	0.35
	Team Size	2, 216	1971.36**	0.17	<.001
	Activity Occurrence Location	6.50, 1403.31	407.98**	0.43	<.001
	Hours slept x Team Size	4, 216	0.55	<.001	0.7
	Activity Occurrence Location x Hours slept	12.99, 1403.31	0.49	<.01	0.99
	Activity Occurrence Location x Team Size	12.99, 1403.31	75.09**	0.16	<.001
	Activity Occurrence Location x Hours slept x Team Size	25.99, 1403.31	0.25	<.01	1

[+] Greenhouse-geisser corrections applied as needed
*p<.05, **p<.001

Mirroring the Effectiveness analysis in Section 17.2.3.1, Overall Workload was examined across the Supervisor's activity sequence, using the Hours slept and UAV Team size to predict Overall Workload. UAV Team size (η^2 = 0.89) and activity occurrence location (η^2 = 0.07) did significantly predict Overall Workload across the mission deployment, but Hours slept did not. There was also a significant interaction between UAV Team size and activity occurrence location, but this effect produced a small effect size (η^2 = 0.01). No other interactions were significant. These results suggest that during the overall mission deployment, the main driver of Overall Workload was UAV Team size (Figure 46), such that larger team sizes increase Overall Workload. Hours slept and activity occurrence location were less important for influencing Overall Workload.

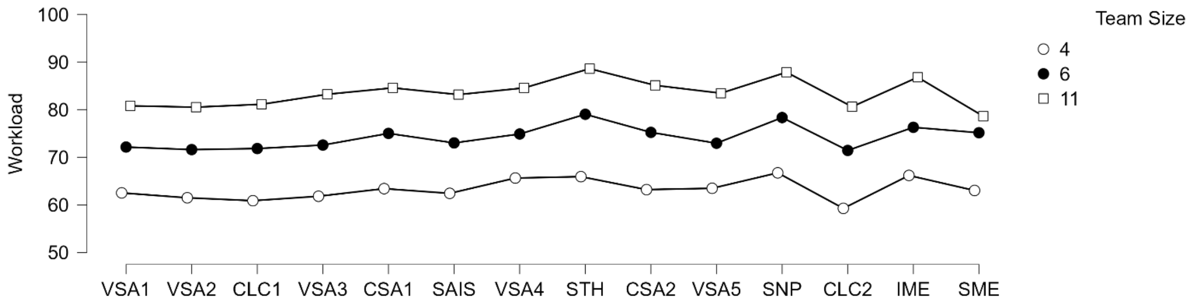


Figure 46. Overall Workload across activity occurrence location by UAV Team size.

The analysis by Activity duration found that both Hours slept (η^2 = 0.004) and UAV Team size (η^2 = 0.05) were significant predictors; however, Hours slept had a very small effect, while UAV Team size had a small/medium effect on time. Activity occurrence location; however, was significant and produced a very large effect (η^2 = 0.83). Activity occurrence location did also significantly interact with both Hours slept and UAV Team size, but the interaction with Hours slept was a very small effect. while the interaction with UAV Team size was a medium/large effect (η^2 = 0.10). As is visible in Figure 47, larger UAV Team sizes generally inflated Activity duration, although this did appear to vary with each activity.

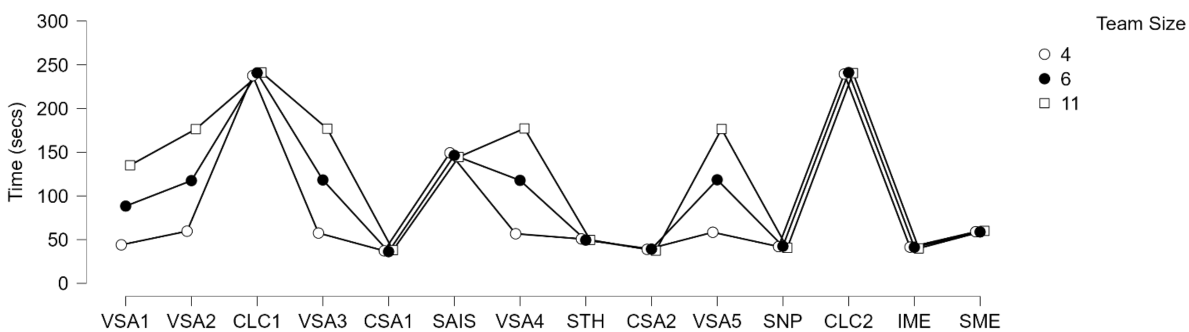


Figure 47. Activity duration across activity occurrence location and UAV Team size.

The Efficiency, UAV Team size, Hours slept and Activity duration all had significant main effects, although only activity occurrence location produced a non-trivial effect size (η^2 = 0.80). Activity occurrence location did interact with both Hours slept (η^2 = 0.01) and UAV Team size (η^2 = 0.11; Figure 48), but there was no 3-way interaction. Once again, as is visible in Figure 48, larger UAV

Team sizes produced higher values generally speaking, although this does appear to vary by activity.

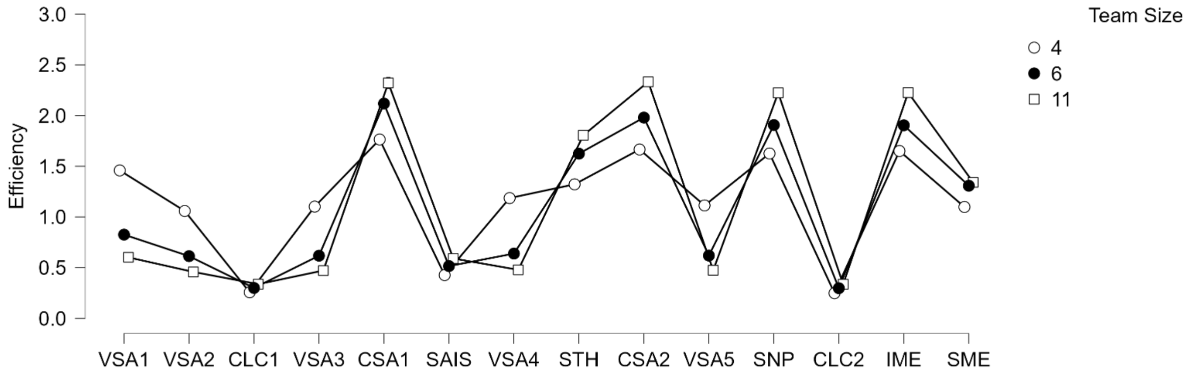


Figure 48. Efficiency across activity position by UAV Team size.

Finally, in an effort to explain the increases in both Overall Workload, Activity duration, and Efficiency, the # of swapped UAVs was analyzed. Hours slept did not impact the # of swapped UAVs, but UAV Team size ($\eta^2 = 0.17$) and activity occurrence location ($\eta^2 = 0.43$) both had large effects on # of swapped UAVs. There was also an interaction between activity occurrence location and UAV Team size ($\eta^2 = 0.16$; Figure 49). As is visible in Figure 49, larger UAV Team sizes increased the # of swapped UAVs, and this likewise did vary across activity occurrence location, with generally more swaps occurring towards the end of the mission. This effect is not surprising as more UAVs equates to more necessity for swapping, and as time progresses, UAVs are more likely to need to be swapped out as their battery levels are depleted.

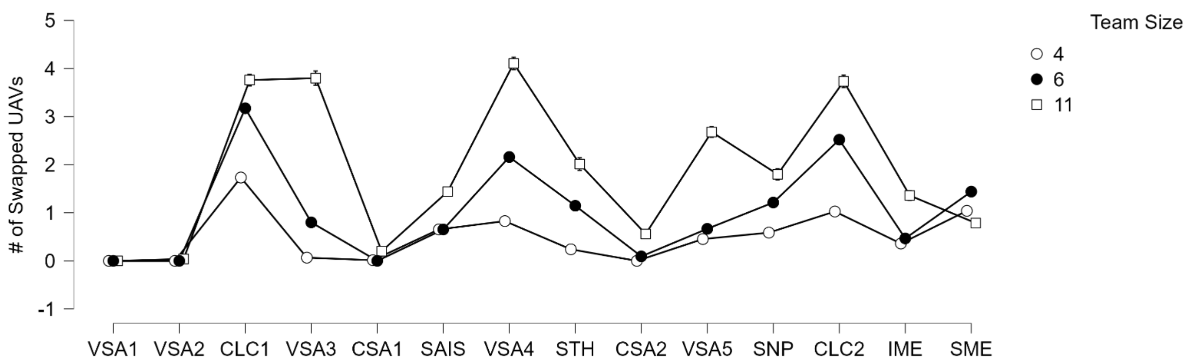


Figure 49. The # of swapped UAVs across activity occurrence location by UAV Team size.

17.2.3.4. Analysis by Supervisor Activity

17.2.3.4.1. Verify Surveillance UAV(s) Coverage Area Activity

During a given mission deployment, there are five VSA activity instances that occur. The first instance occurs when the UAVs reach the waypoints at which they commence the mission, the remaining instances occur every ten minutes, as indicated in Figure 37. The repetition of this activity provides a good opportunity to examine the influence of the independent variables on the same activity over the duration of a mission. A mixed-factorial ANOVA was conducted examining the influence of the between factors (i.e., Hours slept and UAV Team size) across the within factor of VAS activity at the five timepoints during a shift for the four dependent variables of interest (i.e., Overall Workload, # of swapped UAVs, Activity duration, and Efficiency). The ANOVA values are presented in Table 102.

Table 102. ANOVA table for the Supervisor's VSA activities analysis.

Factor		df^{+}	F	η^2	α
Overall Workload					
	Hours slept	2, 216	6.77**	<.001	<.001
	Team size	2, 216	22149.33**	0.94	<.001
	Activity occurrence location	2.19, 473.57	194.5**	0.03	<.001
	Hours slept x Team size	4, 216	0.26	<.001	0.9
	Activity occurrence location x Hours slept	4.39, 473.57	1.38	<.001	0.24
	Activity occurrence location x Team size	4.39, 473.57	13.17**	<.01	<.001
	Activity occurrence location x Hours slept x Team size	8.77, 473.57	0.29	<.001	0.98
Activity Duration					
	Hours slept	2, 216	82.5**	<.01	<.001
	Team size	2, 216	19480.71**	0.9	<.001
	Activity occurrence location	4, 864	474.71**	0.06	<.001
	Hours slept x Team size	4, 216	5.96**	<.001	<.001
	Activity occurrence location x Hours slept	8, 864	1.51	<.001	0.15
	Activity occurrence location x Team size	8, 864	38.26**	<.01	<.001
	Activity occurrence location x Hours slept x Team size	16, 864	0.82	<.001	0.67
Efficiency					
	Hours slept	2, 216	26.48**	<.01	<.001
	Team size	2, 216	4563.56**	0.78	<.001
	Activity occurrence location	3.62, 782.78	164.8**	0.08	<.001
	Hours slept x Team size	4, 216	4.94**	<.01	<.001
	Activity occurrence location x Hours slept	7.25, 782.78	4.19**	<.01	<.001
	Activity occurrence location x Team size	7.25, 782.78	14.56**	0.01	<.001
	Activity occurrence location x Hours slept x Team size	14.50, 782.78	2.28*	<.01	<.01
# of Swapped UAVs					
	Hours slept	2, 216	0.49	<.001	0.61
	Team size	2, 216	1023.93**	0.27	<.001
	Activity occurrence location	2.41, 521.49	528.48**	0.36	<.001
	Hours slept x Team size	4, 216	0.06	<.001	0.99
	Activity occurrence location x Hours slept	4.83, 521.49	1.17	<.01	0.32
	Activity occurrence location x Team size	4.83, 521.49	145.15**	0.2	<.001
	Activity occurrence location x Hours slept x Team size	9.66, 521.49	0.23	<.001	0.99

$^{+}$ Greenhouse-geisser corrections applied as needed

*$p<.05$, ** $p<.001$

The Overall Workload results found that both of the between factors produced reliable effects; however, the Hours slept produced a trivial effect size (i.e., ~0), whereas the UAV Team size produced a very large effect ($\eta^2 = 0.94$, Figure 50). The position of the VSA activity occurrence within the mission was also statistically reliable, such that later instances produced higher levels of Overall Workload; however, this result had only a small effect ($\eta^2 = 0.02$, Figure 50). The only significant interaction was between the UAV Team size across the VSA activity instances, but again only a negligible effect size ($\eta^2 = 0.003$) existed. The UAV Team size appears to be the primary driver of increases in Overall Workload for the VSA activity, regardless of the Hours slept or the activity's occurrence timing during the mission.

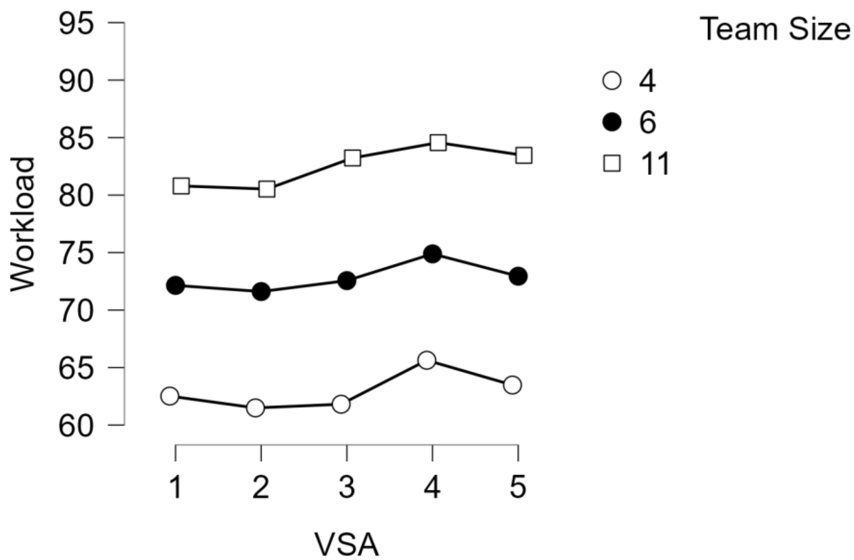


Figure 50. Overall Workload during VSA activity across the UAV Team sizes and occurrence timing within the mission.

Both the Hours slept, and the UAV Team size were significant predictors of the VSA's activity durations; however, the Hours slept produced a trivial effect size (η^2=0.004), whereas the UAV Team size was a very large effect ($\eta^2 = 0.90$, Figure 51). As expected, larger UAV Team sizes significantly increased the VSA's activity durations. The VSA occurrence location during the mission was likewise significant, and produced a small to medium effect on time ($\eta^2 = 0.06$, also visible in Figure 51). Similarly, while there was a significant interaction between Hours slept and UAV Team size, and also between the UAV Team size and VSA activity occurrence location during the mission, these were again negligible effects (η^2s < 0.00). Thus, as with Overall Workload, it appears that the main determinant of VSA Activity duration was driven by the UAV Team size, and less so by Hours slept or the VSA activity occurrence location during the mission.

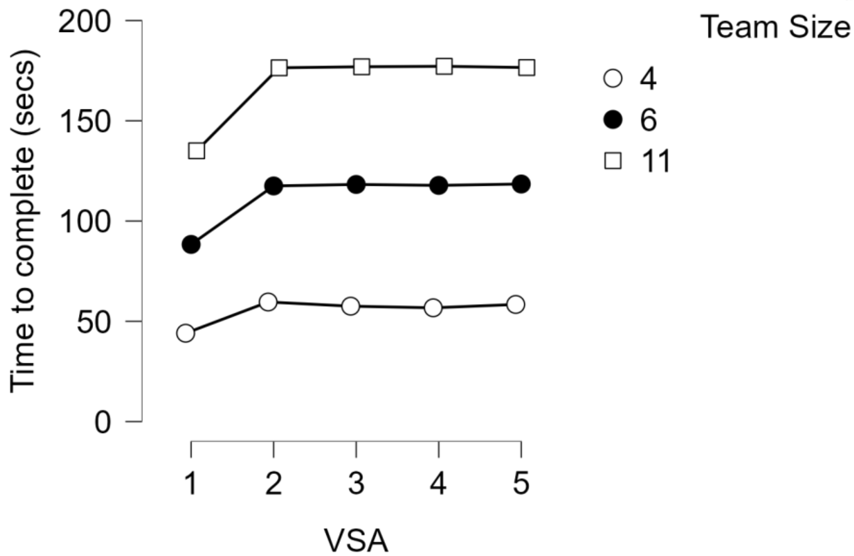
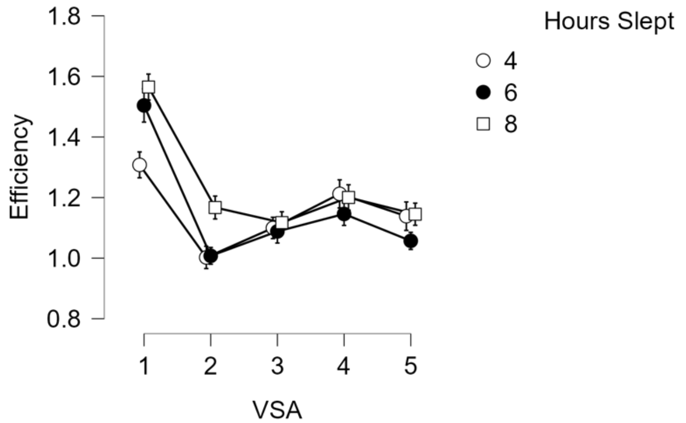
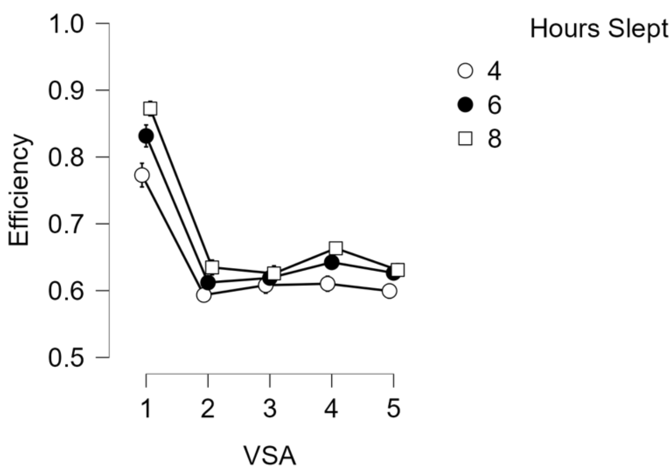


Figure 51. VSA Activity duration across UAV Team size and activity occurrence location within the mission.

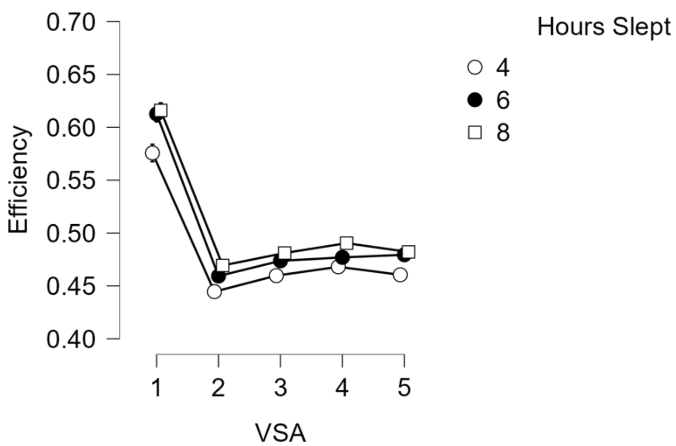
Task Efficiency was evaluated with a mixed-factorial ANOVA, comparing the independent variables of Hours slept and UAV Team size over the VSA activity instances throughout the mission. Remember that this Efficiency variable represents the workload for a given activity/Activity duration, and serves as a proxy for estimating Efficiency across instances. Note this variable is a completely abstract value, there is no set expectation or value for 'nominal' Efficiency, and this variable is included simply to integrate and illustrate how the Overall Workload and Activity duration data covary. Higher values indicate more Efficiency, essentially a higher amount of work being conducted over the period it takes to conduct. Results indicated that all main effects (i.e., Hours slept, UAV Team size and activity occurrence location within the mission) and interactions were significant, with activity occurrence location producing a medium sized effect ($\eta^2 = 0.08$) and UAV Team size producing a very large effect ($\eta^2 = 0.78$), all other effects were very small or negligible (η^2s < 0.01). These results are presented in Figure 52, such that Efficiency does appear to drop during a mission, but reaches its lowest levels with higher UAV Team size.



(a) UAV Team size equal to 4.



(b) UAV Team size equal to 6.



(c) UAV Team size equal to 11.

Figure 52. VSA activity Efficiency by Hours Slept and UAV Team size, over the activity instances within a mission by UAV team size equal to (a) 4, (b) 6, and (c) 11.

Finally, in an effort to clarify the later surge in Overall Workload (Figure 50), Activity duration, and reduced Efficiency, the # of UAVs swapped during each VSA activity was analyzed with a mixed factorial ANOVA, and compared across levels of each independent variable (i.e., Hours slept, UAV Team size, and activity occurrence location). Consistent with the prior results, especially those of Overall Workload, there were main effects of UAV Team size on swaps (η^2 = 0.27), VSA activity occurrence location (η^2 = 0.36), and an interaction between activity occurrence location and UAV Team size (η^2 = 0.20). As is visible in Figure 53, larger UAV Team size produced more swaps, which began occurring earlier in the shift the more UAVs were flying. These outcomes all represent very large effects. There were no other significant effects or interactions on the number of swapped UAVs. This effect is perhaps unsurprising, as the more UAVs are flying the more UAVs need to return, and naturally the likelihood of returning increases during the mission as the battery drains over time. However, these results do shed some light on increases in Overall Workload, as it must be noted that the average correlation between the number of swaps and Overall Workload was on average very high, especially during the last three VSA activities (r = -.85, p < 0.001), and seems to suggest that more UAV swapping can significantly increase the Supervisor's Overall Workload.

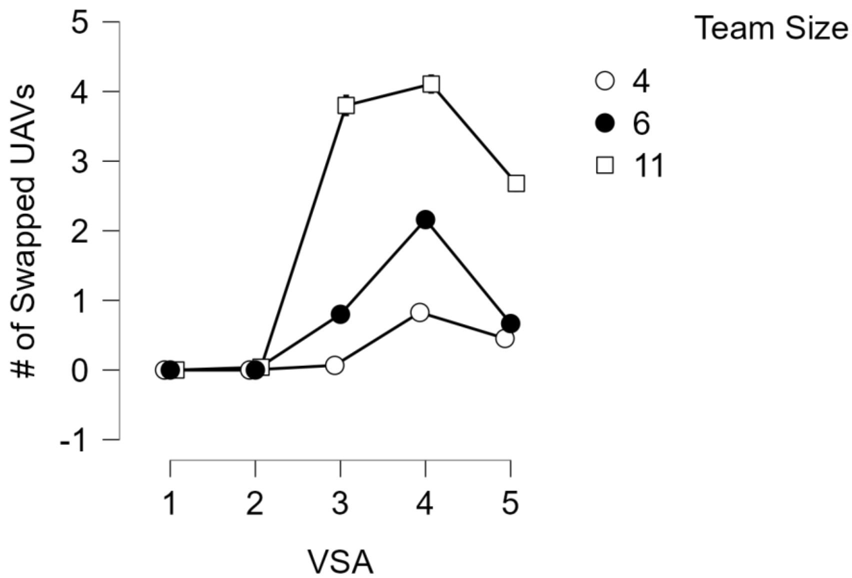


Figure 53. Number of swapped UAVs by UAV Team size and VSA activity occurrence position.

17.2.3.4.2. Communications Lead Request Supervisor Review Surveillance UAV(s) Sensor Feed

The CLR activity, where the Communication lead contacts the Supervisor and requests the Supervisor view the camera feed, and a subsequent conversation about this viewing ensues, occurred twice during mission deployment. Just as with the VSA activity, a mixed factorial ANOVA examined the two independent variables (i.e., Hours slept and UAV Team size) across these two activity instances. Overall Workload, Activity duration, and Efficiency were all analyzed. The ANOVA results are presented in Table 103.

Table 103. ANOVA results for CLR activity.

Factor	*df*	*F*	η^2	α
Overall Workload				
Hours slept	2, 216	1.82	<.001	0.16
Team size	2, 216	14398.06**	0.98	<.001
Activity occurrence location	1,216	45.7**	<.01	<.001
Hours slept x Team size	4, 216	0.07	<.001	0.99
Activity occurrence location x Hours slept	2, 216	1.6	<.001	0.2
Activity occurrence location x Team size	2, 216	9.61**	<.01	<.001
Activity occurrence location x Hours slept x Team size	4, 216	0.52	<.001	0.72
Activity Duration				
Hours slept	2, 216	109.42**	0.33	<.001
Team size	2, 216	2.68	0.01	0.07
Activity occurrence location	1,216	0.27	<.001	0.6
Hours slept x Team size	4, 216	0.85	0.01	0.5
Activity occurrence location x Hours slept	2, 216	0.44	<.01	0.65
Activity occurrence location x Team size	2, 216	0.59	<.01	0.56
Activity occurrence location x Hours slept x Team size	4, 216	0.49	<.01	0.75
Efficiency				
Hours slept	2, 216	98.12**	0.06	<.001
Team size	2, 216	1385.91**	0.81	<.001
Activity occurrence location	1,216	8.98	<.01	<.01
Hours slept x Team size	4, 216	0.99	<.01	0.42
Activity occurrence location x Hours slept	2, 216	0.92	<.001	0.4
Activity occurrence location x Team size	2, 216	3.09*	<.01	0.05
Activity occurrence location x Hours slept x Team size	4, 216	0.79	<.001	0.53

*p<.05, **p<.001

The UAV Team size and the activity occurrence location both were significant predictors of Overall Workload and also produced significant interactions, but of these three effects, only the UAV Team size produced an effect size of note ($\eta^2 = 0.98$; Figure 54). Large UAV Team sizes significantly increased Overall Workload during CLR activity. All other main effects and interactions were not statistically reliable.

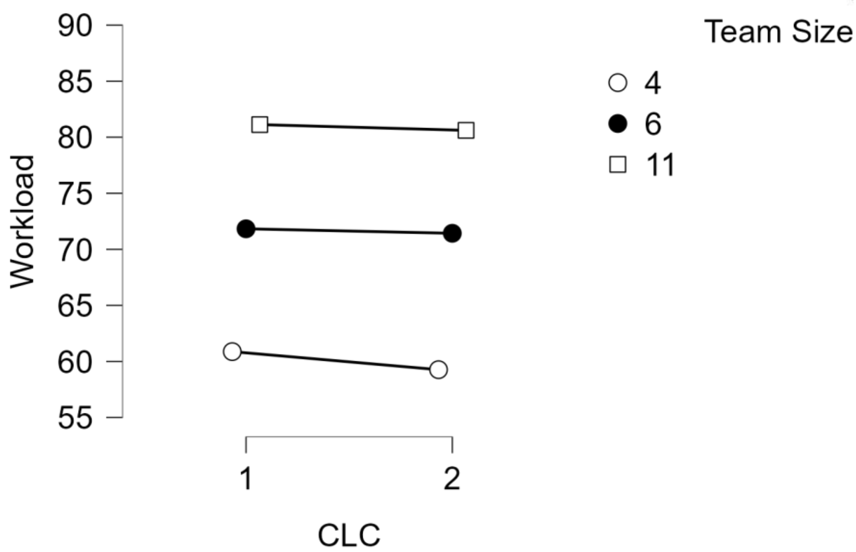


Figure 54. Overall Workload during CLR activity across the UAV Team sizes and instance timing within the mission.

The CLR's Activity duration results indicated that only Hours slept produced a significant impact, with a large effect ($\eta^2 = 0.33$, Figure 55). Few Hours slept significantly increased CLR Activity duration, but there were no other main effects or interactions.

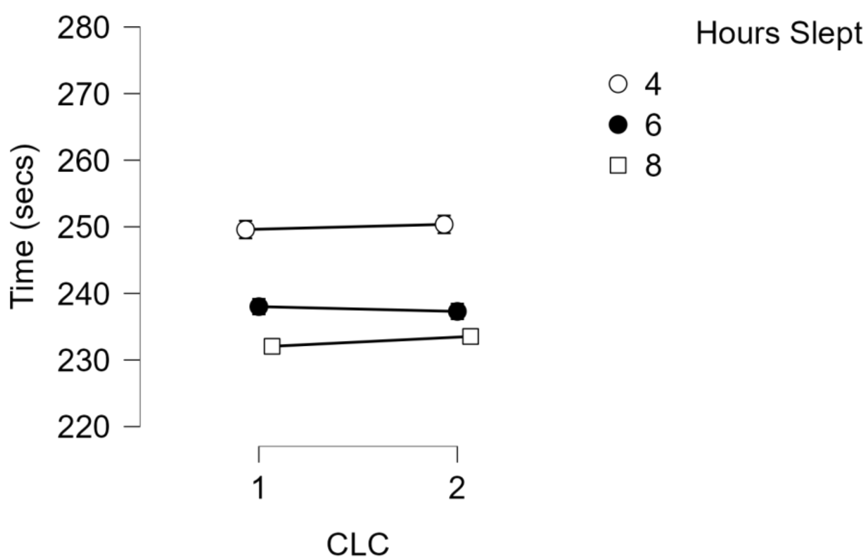


Figure 55. CLR Activity duration across UAV Team size and activity occurrence location within the mission.

A main effect of each independent variable was found for task Efficiency along with an effect of activity occurrence location. Hours slept produced a medium sized effect ($\eta^2 = 0.06$), while the UAV Team size produced a very large effect on Efficiency ($\eta^2 = 0.81$). The activity's occurrence location, while significant, produced a trivial effect size ($\eta^2 = 0.003$). The only significant interaction was between activity occurrence location and the UAV Team size, such that Efficiency dropped more over time, but especially for the larger UAV Team sizes, but this was again a trivial effect size ($\eta^2 = 0.002$; Figure 56).

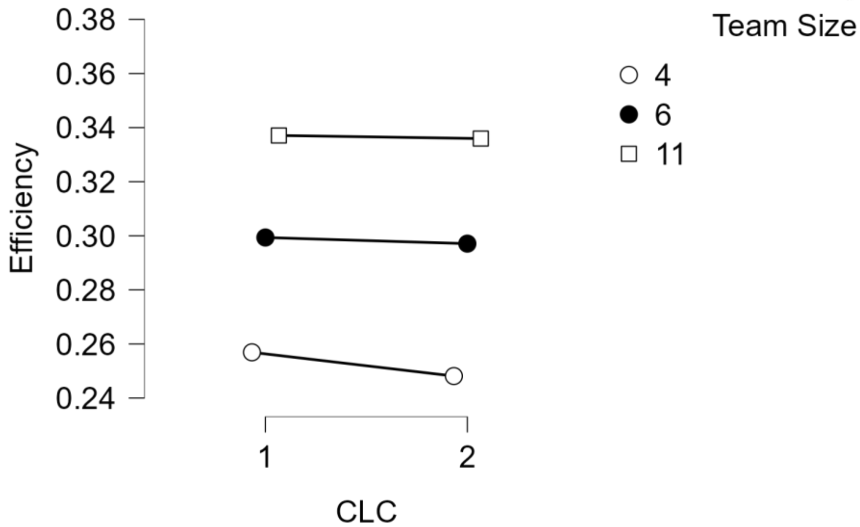


Figure 56. CLR activity Efficiency over the activity instances within a mission by UAV team size.

17.2.3.4.3. Change a Surveillance UAV(s) Monitoring Area

Twice during the modeled mission, the Supervisor adjusts the surveillance area of one of the surveillance drones, the CSA activity. Hours slept and UAV Team size were used to predict Overall Workload, activity Duration, and Efficiency over these two instances. The ANOVA results are available in Table 104.

Table 104. The ANOVA results for the CSA activity.

Factor	*df*	*F*	η^2	α
Overall Workload				
Hours slept	2, 216	0.65	<.001	0.52
Team size	2, 216	26105.22**	0.99	<.001
Activity occurrence location	1,216	8.38*	<.001	<.01
Hours slept x Team size	4, 216	0.33	<.001	0.86
Activity occurrence location x Hours slept	2, 216	0.5	<.001	0.61
Activity occurrence location x Team size	2, 216	11.63**	<.001	<.001
Activity occurrence location x Hours slept x Team size	4, 216	2.18	<.001	0.07
Activity Duration				
Hours slept	2, 216	109.21**	0.29	<.001
Team size	2, 216	0.23	<.001	0.8
Activity occurrence location	1,216	5.97*	0.01	<.05
Hours slept x Team size	4, 216	1.64	<.01	0.17
Activity occurrence location x Hours slept	2, 216	0.69	<.01	0.5
Activity occurrence location x Team size	2, 216	3.38*	0.01	<.05
Activity occurrence location x Hours slept x Team size	4, 216	0.52	<.01	0.73
Efficiency				
Hours slept	2, 216	90.55**	0.17	<.001
Team size	2, 216	168.03**	0.32	<.001
Activity occurrence location	1,216	5.79*	<.01	<.05
Hours slept x Team size	4, 216	3.01*	0.01	<.05
Activity occurrence location x Hours slept	2, 216	1.15	<.01	0.32
Activity occurrence location x Team size	2, 216	2.02	<.01	0.14
Activity occurrence location x Hours slept x Team size	4, 216	1	<.01	0.41

*p<.05, **p<.001

The UAV Team size and activity occurrence location both were significant predictors of Overall Workload, and there was also a significant interaction between these variables, but of these three effects, only the UAV Team size produced an effect size of note ($\eta^2 = 0.99$). As expected, larger UAV Team sizes increased the amount of Overall Workload. No other effects were significant.

While there was a significant effect of activity occurrence location and a significant interaction between activity occurrence location and the UAV Team size on the CSA Activity's duration, both of these effects were very small (η^2s = 0.01). However, there was also a main effect of Hours slept that produced a large impact on Activity duration ($\eta^2 = 0.29$). No other effects were significant.

Finally, for activity Efficiency, there was a significant main effect of Hours slept ($\eta^2 = 0.17$) and the UAV Team size ($\eta^2 = 0.32$), both of which were large effects. There was also an interaction between these variables, although the effect size was small ($\eta^2 = 0.01$). This result is visible in

Figure 57, as Efficiency increased with more Hours slept, this increasing effect was less pronounced with smaller UAV Team sizes.

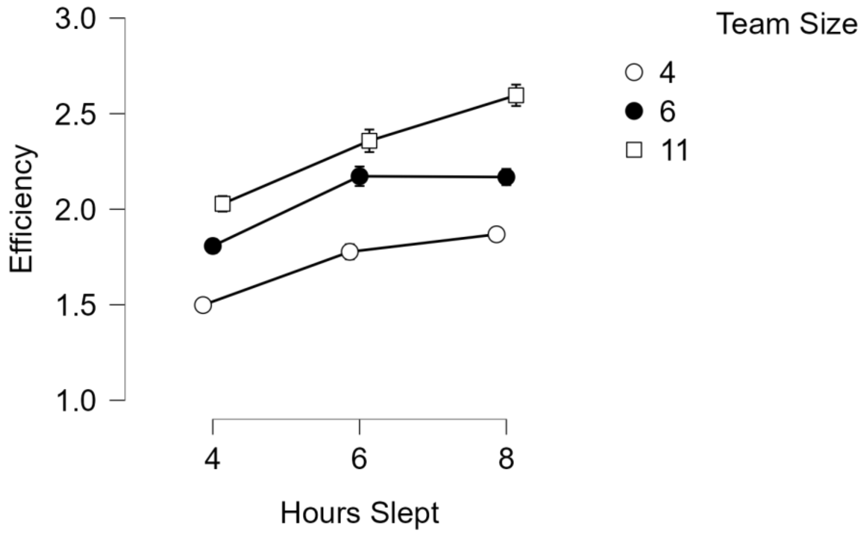


Figure 57. The impact of the UAV Team size by Hours slept on activity Efficiency for the CSA activity.

17.2.3.4.4. Switching a Navigating Surveillance UAV to Hover Surveillance Activity

The Supervisor completes the SNH activity, transitioning a Surveillance UAV from navigating to hovering, once during the modeled mission. The independent variables of Hours slept, and UAV Team size were used in a factorial ANOVA to examine Overall Workload, Activity duration, and activity Efficiency. The ANOVA results are available in Table 105.

Table 105. The single SNH activity instance's *ANOVA results.*

	Factor	*df*	*F*	η^2	*α*
Overall Workload					
	Hours slept	2, 216	0.49	<.001	0.62
	Team size	2, 216	2149.5**	0.95	<.001
	Hours slept x Team size	4, 216	0.1	<.001	0.98
Activity Duration					
	Hours slept	2, 216	0.21	<.01	0.81
	Team size	2, 216	1.01	<.01	0.37
	Hours slept x Team size	4, 216	0.75	0.01	0.56
Efficiency					
	Hours slept	2, 216	0.29	<.01	0.75
	Team size	2, 216	103.9**	0.49	<.001
	Hours slept x Team size	4, 216	0.72	<.01	0.58

*p<.05, **p<.001

Only the UAV Team size produced a significant effect (η^2=0.95) on
Overall Workload, such that more UAVs produced higher levels of Overall Workload. Hours slept did not impact Overall Workload, and there was no interaction between the independent variables. Related to Activity duration, none of the independent variables impacted the duration, and there was also no interaction. Finally, Efficiency was only impacted by the UAV Team size (η^2 = 0.49), given the increase in Overall Workload and non-adjustment of activity duration.

17.2.3.4.5. Switching a Hovering Surveillance UAV to Navigating Surveillance Activity

Once during the modeled mission, the Supervisor switches a Surveillance UAV from hovering back to navigating its path, the SHN activity. The independent variables of Hours slept and UAV Team size were used in a factorial ANOVA to examine Overall Workload, Activity duration, and activity Efficiency. ANOVA values are available in Table 106.

Table 106. The single SHN activity instance's ANOVA results.

	Factor	***df***	***F***	***η²***	***α***
Overall Workload					
	Hours slept	2, 216	0.27	<.001	0.77
	Team size	2, 216	1338.57**	0.93	<.001
	Hours slept x Team size	4, 216	0.06	<.001	0.99
Activity Duration					
	Hours slept	2, 216	54.01**	0.32	<.001
	Team size	2, 216	2.18	0.01	0.12
	Hours slept x Team size	4, 216	2.26	0.03	0.06
Efficiency					
	Hours slept	2, 216	49.68**	0.2	<.001
	Team size	2, 216	85.09**	0.34	<.001
	Hours slept x Team size	4, 216	2.51*	0.02	<.05

**p*<.05, ***p*<.001

As expected for Overall Workload, only the UAV Team size produced a significant increase (η^2 = 0.93). Hours slept did not, and there was no interaction between these factors. Only Hours slept impacted the Activity duration (η^2 = 0.32), such that less sleep increased the Activity duration. The UAV Team size did not predict Activity duration, nor was there an interaction. Finally for Efficiency, both factors produced significant main effects that were large in magnitude (η^2s > 0.20), and there was also a significant interaction, which was a small effect (η^2 = 0.02). This interaction is visible in Figure 58.

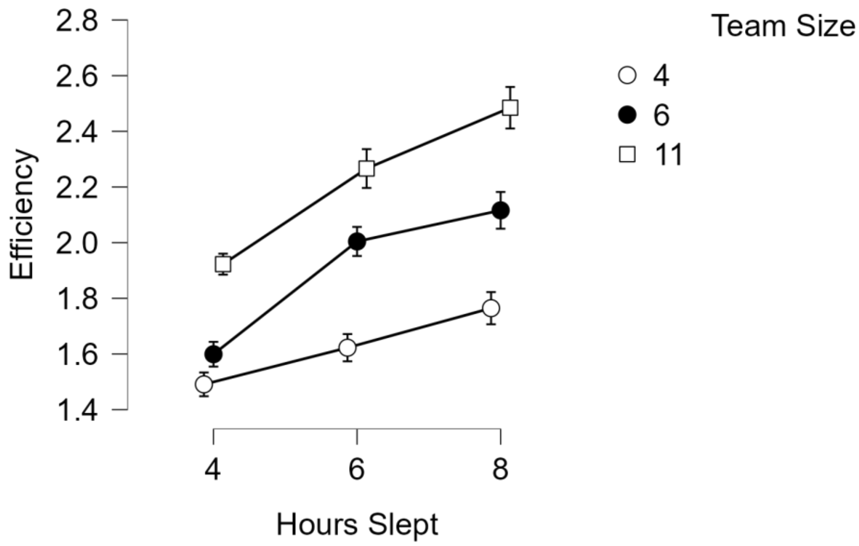


Figure 58. The interaction between UAV Team size and Hours slept on Efficiency of switching a Surveillance drone back to navigation.

17.2.3.4.6. Adjust Ignition UAV(s)' Drop Density

The ADD activity occurred once during the modeled mission. This activity requires the Supervisor to adjust the drop density of the ignition spheres to more appropriately manage fire ignition. The independent variables of Hours slept, and UAV Team size were used in a factorial ANOVA to examine Overall Workload, activity Duration, and activity Efficiency. The ANOVA values are available in Table 107.

Table 107. The single ADD activity instance's ANOVA results.

	Factor	*df*	*F*	η^2	*α*
Overall Workload					
	Hours slept	2, 216	0.06	<.001	0.94
	Team size	2, 216	3993.23**	0.97	<.001
	Hours slept x Team size	4, 216	0.33	<.001	0.33
Activity Duration					
	Hours slept	2, 216	71.25**	0.39	<.001
	Team size	2, 216	1.34	<.01	0.27
	Hours slept x Team size	4, 216	1.3	0.01	0.27
Efficiency					
	Hours slept	2, 216	53.16**	0.21	<.001
	Team size	2, 216	94.91**	0.37	<.001
	Hours slept x Team size	4, 216	1.94	0.01	0.11

*$p<.05$, **$p<.001$

Only a main effect of the UAV Team size existed for Overall Workload, which produced a large effect ($\eta^2 = 0.97$). Larger UAV Team sizes did increase Overall workload. Hours slept did not impact Overall Workload, and there was no interaction between these factors. The activity Duration was only significantly impacted by Hours slept, which was also a large effect ($\eta^2 = 0.39$). More Hours slept allowed reduced the activity Duration. The UAV Team size did not impact activity Duration, nor was there an interaction between these variables. Finally for activity Efficiency, there was both a main effect of Hours slept ($\eta^2 = 0.21$) and the UAV Team size ($\eta^2 = 0.37$), both of which were large effects (Figure 59). More Hours slept improved Efficiency, and for larger UAV Team sizes, this value was also higher, likely due to the disproportionate increase in Overall Workload over time, there was no interaction.

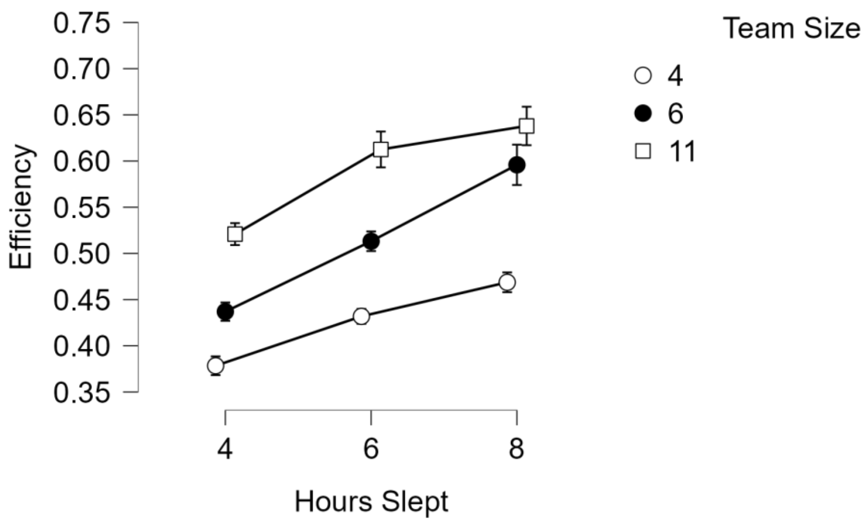


Figure 59. The impact of the UAV Team size by Hours slept on Efficiency for the ADD activity.

17.2.3.4.7. Extend Ignition UAV(s)' Mission Activity

The EIM activity, that required the Supervisor to extend an ignition UAV's mission duration, occurred only once. The independent variables of Hours slept and UAV Team size were used in a factorial ANOVA to examine Overall Workload, activity Duration, and activity Efficiency. The ANOVA values are available in Table 108.

Table 108. The single EIM activity instance's ANOVA results.

	Factor	*df*	*F*	*η²*	*α*
Overall Workload					
	Hours slept	2, 216	0.2	<.001	0.82
	Team size	2, 216	1508.55**	0.93	<.001
	Hours slept x Team size	4, 216	0.42	<.001	0.79
Activity Duration					
	Hours slept	2, 216	34.67**	0.23	<.001
	Team size	2, 216	1.19	0.01	0.31
	Hours slept x Team size	4, 216	2	0.03	0.1
Efficiency					
	Hours slept	2, 216	27.53**	0.14	<.001
	Team size	2, 216	64.58**	0.32	<.001
	Hours slept x Team size	4, 216	1.53	0.02	0.2

*p<.05, **p<.001

Once again, for Overall Workload, only the UAV Team size produced a reliable effect ($\eta^2 = 0.93$) as more UAVs during this activity increased Overall Workload. Hours slept did not impact Overall Workload, nor was there an interaction between these variables. The activity Duration had only one significant factor, Hours slept ($\eta^2 = 0.23$), such that fewer Hours slept increased how long the activity took to complete. There was also no interaction between the independent variables. Finally, for Efficiency, there were main effects of both Hours slept ($\eta^2 = 0.14$) and the UAV Team size ($\eta^2 = 0.32$), both of which were large effects. There was no significant interaction. These results are visible in Figure 60; as Hours slept increases and the UAV Team size increases, so does Efficiency.

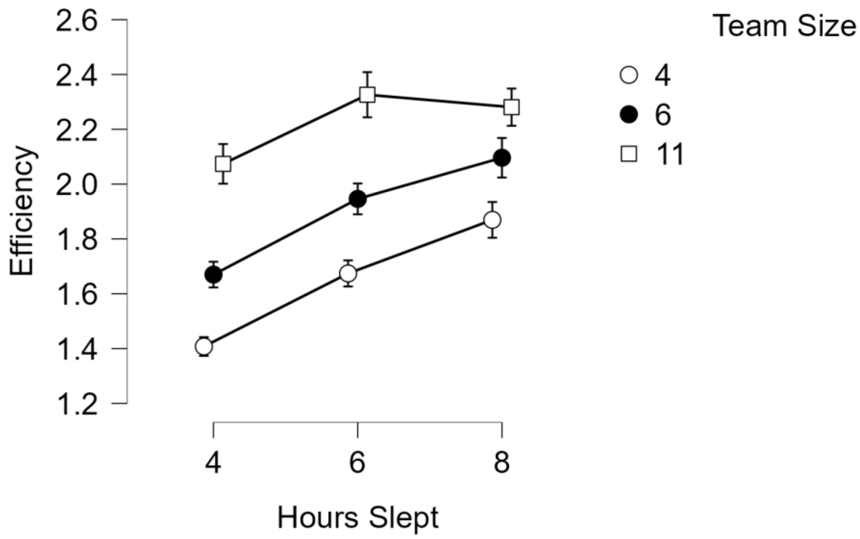


Figure 60. The UAV Team size by Hours slept on Efficiency for the EIM activity.

17.2.3.4.8. Extend Surveillance UAVs' Mission Activity

The Supervisor extends the Surveillance UAVs' missions (ESM activity) once during the modeled mission. The independent variables of Hours slept and UAV Team size were used in a factorial ANOVA to examine Overall Workload, activity Duration, and activity Efficiency. The ANOVA values are available in Table 109.

Table 109. The single ESM activity instance's ANOVA results.

	Factor	***df***	***F***	η^2	α
Overall Workload					
	Hours slept	2, 216	0.11	<.001	0.9
	Team size	2, 216	719.74**	0.87	<.001
	Hours slept x Team size	4, 216	0.11	<.001	0.98
Activity Duration					
	Hours slept	2, 216	82.23**	0.43	<.001
	Team size	2, 216	0.6	<.01	0.55
	Hours slept x Team size	4, 216	0.74	0.01	0.57
Efficiency					
	Hours slept	2, 216	60.89**	0.28	<.001
	Team size	2, 216	*p<.05, **p<.001	0.22	<.001
	Hours slept x Team size	4, 216	0.7	0.01	0.59

*p<.05, **p<.001

The only significant predictor of Overall Workload for this activity was the UAV Team size ($\eta^2 = 0.87$), as more UAVs significantly increased Overall Workload in this activity. Hours slept did not impact Overall Workload and there was also no interaction between these independent variables. Conversely, the only significant predictor of activity Duration was Hours slept ($\eta^2 = 0.43$), as less rest increased activity Duration. The UAV Team size did not impact the activity Duration, and there was also no interaction between these variables. Both independent variables significantly impacted Efficiency, but there was no interaction. Hours slept increased Efficiency ($\eta^2 = 0.28$) as did the UAV Team size ($\eta^2 = 0.22$) due to the heightened Overall Workload in similar amounts of time. These effects are visible in Figure 61.

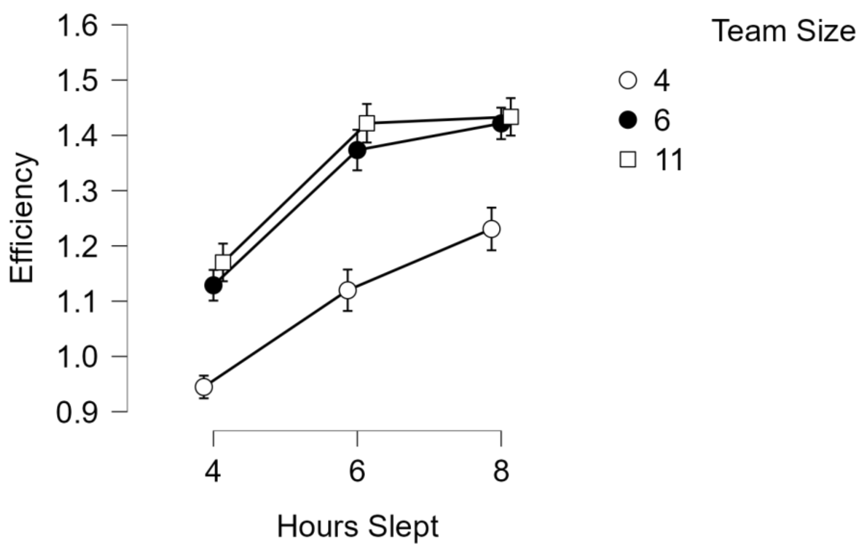


Figure 61. The UAV Team size by Hours slept and their effect on Efficiency for the ESM Supervisor activity.

17.3. Discussion

The overall analyses of the first 83 minutes of the mission seem to suggest that the main driver of Overall Workload is UAV Team size. While the Hours slept did impact Overall Workload, this was a very small effect. Further, an analysis of the # of swapped UAVs across the mission also appears to be highly influenced by UAV Team size, and not at all by Hours slept. This finding makes sense conceptually, as the more UAVs that are flying in a given shift, naturally the more swaps must occur, due to battery drain and mission duration. Interestingly, the patterns of Overall Workload and the # of swapped UAVs do look very similar, perhaps suggesting that a main driver of Overall Workload may be related to the UAVs swapping in and out of the mission.

Overall, it appears the Supervisor's experienced Overall Workload is largely driven by the UAV Team size for any given situation. The overall analyses across the first 83 minutes of the mission, irrespective of activity type, but over time, demonstrated that UAV Team size was the main predictor of Overall Workload increases, such that larger UAV Team sizes significantly increased Overall Workload. Taken together with the analysis of Overall Workload by activity type, there is a compelling picture that across activity and time, Overall Workload is increased with larger UAV Team sizes. The number of Hours slept did not impact Overall Workload (either across the entire mission, or by activity), but exerted its main influence in the time to complete a given

activity. This result is consistent with the SAFTE plugin influences
human performance based on the number of hours slept each of the last four nights, as it reduces activity effectiveness, thereby prolonging the activity Duration. An Efficiency metric was calculated in an effort to connect these notions of Overall Workload and the activity Duration. The UAV Team size often impacted Efficiency, such that it increases the amount of work disproportionately to the simultaneous increase in activity Duration. Hours slept often impacted Efficiency as well, as fewer Hours slept produces an inflation in activity Duration. Importantly, an interaction between independent variables was observed several times, such that while Efficiency increased with more Hours slept, this effect was less pronounced if there were more UAVs flying.

Ultimately, it appears that the UAV Team size is the critical factor influencing the Supervisor's Overall Workload; however, the Hours slept can also impact the activity Duration on duration, and the ratio of Overall Workload to time (i.e., Efficiency).

18. CONCLUSION

Task 4 leveraged the results from the Task 1 literature review, and Task 3's understanding pilot proficiency requirements, in order to develop extensive models of two types of tasks, the Loosely Coupled task (i.e., delivery drones) and the Tightly Coupled task (i.e., ridgeline aerial ignition). The models for both tasks were developed using IMPRINT Pro and focused on human workload. All models assumed autonomous UAVs and a single human Supervisor.

The Loosely Coupled task assumed a single Supervisor was responsible for up to 100 delivery UAVs. It is important to note that in this task, each UAV has an independent goal and is not required to coordinate with other UAVs in order to achieve that goal. The modeled UAVs are homogeneous. The Supervisor is located in a climate-controlled control room and no specific assumptions about the C^2 interface were made. A nominal use case, as well as three unexpected event use cases and two distraction use cases were modeled and analyzed. The UE use cases were modeled for the best case, in which the handling of the event was handed off to a special Supervisor who only handles UEs, and the worst case in which the primary Supervisor handled the situation. The fatigue distraction use case leveraged the SAFTE model's IMPRINT Pro plug-in to represent Supervisor effectiveness based on the number of hours slept each of the last four nights.

The Tightly Coupled task assumes a small team travels to a remote mountain ridge to conduct a ridgeline ignition task to clear the underbrush ahead of a wildland fire. The team is composed of the UAV Supervisor, the Communications lead (who also severs to monitor UAV sensor data), and the Logistics coordinator. The Supervisor uses a handheld C^2 station (e.g., tablet), and the Communication lead uses a similar handheld device to monitor the sensor feeds. The team deploys two types of UAVs, which means the team is responsible for a heterogeneous team of UAVs. Each Ignition UAVs is equipped with a device that drops ignition spheres to ignite the underbrush for the controlled burn. The Surveillance UAVs are equipped with sensors (e.g., cameras) that allow the team to monitor the burn, other response teams in the area, and the general environmental conditions. The developed model simulates UAV Team sizes of 4, 6, and 11 UAVs; however, only a subset of the UAVs are deployed for the mission, with the remaining UAVs held in reserve to replace deployed UAVs that have a depleted battery, and for Ignition UAVs, those that are out of ignition spheres. The nominal use case and the Fatigue distraction were modeled and analyzed.

The nominal use cases for both the loosely and Tightly Coupled tasks
assumes that the Supervisor is simply monitoring the progress of the deployed UAVs. No unexpected events or distractions occur.

The models do not assume a specific C^2 user interface for either the loosely or Tightly Coupled tasks. Rather, the models assume information components, either as outputs to the Supervisor or inputs by the Supervisor, without specifying the exact means of providing the outputs or inputs. However, a reasonable expectation is that the C^2 interface will incorporate a map, some visual representation of each UAV being monitored, and possibly its path and important way points (e.g., delivery destination, ignition sphere drop points), the launch/landing zones, and potentially the Loosely Coupled task's secondary landing zones. It is assumed that different manufacturers or corporations may choose the most relevant implementation of the expected information components.

Most available human factors related modeling tools do not account for the type of use cases and the Supervisor being responsible for multiple UAVs. Further, validated models of Supervisor workload for these use cases that are based on real-world systems and objective results do not exist. As a result, the team had to research, develop, and implement a representative workload model for the modeling tool.

The key results and gaps were identified. The key results are provided in Table 110, with the identified gaps being presented in

Table 3.

Table 110. The A26 Task 4 key findings, overall and by task type.

Overall Key Findings
Assuming highly autonomous UAVs, that are capable of responding appropriately to unexpected events, does permit a single human Supervisor to manage a larger number at lower Overall Workload levels.
A primary driver of a Supervisor's Overall Workload is the number of UAVs being supervised, irrespective of the specific modeled Loosely or Tightly Coupled task types.
The statistical results, across both the Loosely and Tightly Coupled tasks, resulted significant differences but with small to non-existent effect sizes, which means the results are not always interesting in a practical sense.
Loosely Coupled Task Key Findings
Industrial subject matter experts expect that the Supervisor will likely have some training, but may only have a high school level education or equivalent.
The industrial subject matter experts predict that an individual UAV will experience a UE about once per week, and that for the majority of the UEs, the UAV will autonomously respond to the UE, taking any necessary actions.
The manipulation of the shift characteristics (e.g., shift, work period, and break length) did not have a significant impact on the Supervisor's Overall Workload.
Two task characteristics had the most reliable impacts on the Supervisor's Overall Workload Max # of UAVs and the Max # of UAVs to launch simultaneously. Larger numbers of UAVs being monitored and larger numbers of UAVs launching simultaneously increased Overall Workload.
If one considers the prior industrial expectation regarding a UE for a single UAV and also assumes that a major corporation with thousands of UAVs conducting deliveries on a daily basis, then there will be a very large number of UEs occurring daily. A means of ensuring that UEs requiring human responses or monitoring is to assign them to a UE Supervisor. The UE Supervisor handles all UEs in a much larger region than the Supervisors. This approach allows the Supervisors to remain focused on the monitoring task, which is considered the best-case scenario in this report. Modeling of the UE Supervisor is beyond the scope of the A26 effort.
While the goal is a clean work environment (e.g., no external distractions such as personal devices), this may be unachievable in this domain. Further, distractions can occur for reasons other than personal devices (e.g., fatigue due to a poor night's sleep). The Supervisor may be unaware that a distraction is hindering their performance. A Watch Supervisor is a necessary role to monitor the Supervisors and to take corrective actions to ensure Supervisor attention. Modeling of the Watch Supervisor is beyond the scope of the A26 effort.
Thirty-four UE use cases were developed, as provided in the Task 3 final report. Each UE represents who/what is aware and responsible for responding to the UE (e.g., UAV autonomy, unmanned traffic management, Supervisor, UE Supervisor). The UE use cases cover a very large breadth of events. Depending on the response to the UE, there may be limited if any impact on the Supervisor's performance. However, UEs that are involved (e.g., Emergency in a portion of the Supervisor's airspace region) and require the Supervisor to handle the event will lead to additional workload.
The protocol used to respond to the modeled UEs, either handing off the UE in the best-case scenario to the UE Supervisor or in the worst case the Supervisor handing the UE, impacted Overall Workload. The Supervisor's Overall Workload was least impacted, or was reduced by handing a UE off to the UE Supervisor.

Loosely Coupled Task Key Findings: Continued
Ten distraction use cases were developed (provided in the Task 3 final report) that include the actions to be taken by the Watch Supervisor and the Supervisor in order to ensure optimal performance. Distractions generally reduce the Supervisor's Overall Workload since the individual is not paying attention to their tasks.
Tightly Coupled Task Key Findings
The modeled Overall Workload was very high, often overloaded, even with four UAVs.
Spikes in Overall Workload corresponded to the Supervisor's activities.
UAV Team size impacted the Supervisor's Efficiency, such that it increases the amount of work disproportionately to the simultaneous increase in activity Duration.
Hours slept often impacted the Supervisor's Efficiency, as fewer Hours slept via the SAFTE model inflated the activity Duration.
While the Supervisor's Efficiency increased with more Hours slept, this effect was less pronounced were more UAVs deployed simultaneously, either due to larger team size or UAV swaps.

Table 111. The A26 Task 4 identified key gaps by overall and task type.

Overall Key Gaps
The common human factors modeling tools do not incorporate human performance models that account for the Supervisor's performance when monitoring more than one or a few UAVs. The Task 1 literature review also found that no reasonable models existed. The team conducted an additional investigation into the human-robot interaction research, human visual perception literature, and the human visual scanning literature, but was unable to identify any applicable models for human performance, specifically workload that are based on real systems (i.e., not simulated systems) and objective human factors results. Based on the additional literature review and Dr. Adams' field work results, the team developed a logarithmic workload model that has been applied in this effort.
A primary gap is the existence of representative models for the focus domains.
Many human factors modeling tools do not adequately model task switching for multiple UAV deployments. IMPRINT Pro has a task switching capability, but it was unable to be used to support this effort.
IMPRINT Pro does not adequately represent fatigue in the standard modeling tools. IMPRINT Pro does provide a plugin for the SAFTE model; however, that model has some limitations. For example, the SAFTE model primarily impacts human user efficiency by considering the number of hours an individual has slept the last four nights. The SAFTE model does not account for other aspects of fatigue, such as long shifts or extreme working conditions. Additional different fatigue models need to be investigated or developed.
The developed models do not fully consider all of the on-board UAV engineering and monitoring requirements for a UAV to autonomously detect internal faults (e.g., difficulty managing stability).
The developed models do not incorporate cascading demands on the Supervisor, be it from normal activities, unexpected events or distractions. Such cascading demands need to be modeled.
Generally, there are no similar human factors models representative of the complexity of the Loosely Coupled or Tightly Coupled domains' tasks, particularly that model the nominal use case, as well as the unexpected event and distraction use cases.
The developed models are quite complex, but are unable to model the true complexity of the representative systems. Achieving a 100% match to the deployed systems is impractical; however, increasing the model complexity can provide additional insights.

Overall Gaps: Continued
The provided results focus on the Supervisor's overall workload; however, workload is really a multi-factor variable that is composed of the cognitive, visual, speech, auditory, fine grained, and tactile components. The developed models' focus on the interaction components, rather than specific user interface designs, does incorporate estimates for each workload component, but a more detailed analysis of the component workload results was not completed. Further, future work must focus on how the workload components impact overall workload. For example, the Tightly Coupled task assumes that the Supervisor can hear the UAVs when taking off and returning to the launch/landing area. While this auditory component can increase overall workload, it can also decrease workload on another channel, such as a visual check of vehicles in the launch/landing area. These more nuanced interactions need to be modeled and understood.
The developed models provide key insights into human performance for these single human Supervisor-multiple UAV tasks, they are simply models and cannot provide a complete picture of actual human performance. Representative systems must be built and evaluated using actual UAVs and human Supervisors with the requisite domain training and knowledge in ecologically valid experiments.
All results based on the developed models must be verified with human subjects evaluations.
Loosely Coupled Task Key Gaps
The developed Loosely Coupled task model focuses only on the en-route portion of the delivery task, and does not include the take-off, ascend to altitude (either for initial flight or post-package delivery), descent from altitude (either on return to launch or for actual package delivery), or the transition from horizontal to vertical flight and vice versa.
The Loosely Coupled task modeled en-route flights assume that the outbound and return flight phases are equivalent; however, a number of factors can influence this flight time.
The developed Loosely Coupled task model does not represent the breadth of intermittent communication problems that can occur in delivery environments. Built environments will result in communication drops that occur on a frequent basis.
The developed model assumes a single Supervisor; however, modeling a control room with multiple Supervisors may change some of the results.
Neither the UE Supervisor or the Watch Supervisor were modeled.
Handoffs of responsibility between Supervisors or between a Supervisor and the UE Supervisor need to be more extensively modeled.
The UEs were modeled to occur completely within a Supervisor's work period; thus, UEs during Ramp down that continue past the current Supervisor's work period (i.e., cross between shifts or work periods) were not modeled. Such UEs need to be modeled.
Distractions naturally create a backlog of task duties. The developed model does not incorporate the Supervisor being required to catch up on that backlog. Further, a model that does require catching up must also incorporate the Supervisor's error rate while attempting to catch up.
The models need to be extended to incorporate additional types of UEs and distractions.
The modeling of the UEs and distractions need to consider additional durations and timing occurrences.
The modeled UEs and distractions (within each use case) have fairly homogeneous magnitudes, but each use case requires modeling with varying magnitudes of impact on the Supervisor.
The models do not incorporate multiple simultaneous UEs, distractions, or a combination thereof.
The Loosely Coupled task model does not model Supervisor multitasking, rather, it is assumed that the Supervisor completes all UE related tasks before returning to the visual scanning on the unaffected UAVS. This limitation is due to IMPRINT Pro limitations. More realistic modeling of multitasking is required.

Tightly Coupled Task Key Gaps
The modeled use case did not consider extreme weather conditions or other serious impacts on the Supervisor's performance, other than hours slept the last four nights. More realistic extreme deployment conditions need to be modeled.
No UEs were modeled for the Tightly Coupled task.
Only the fatigue distraction, using the SAFTE model plugin, was modeled for the Tightly Coupled task.
UAVs are not currently used for monitoring ridgeline aerial ignition missions; human wildland responders serve in those roles. The developed scenarios were based on discussions with SMEs and Dr. Adams' field experience. Surveillance UAVs, as modeled, need to be evaluated in actual deployments.
The modeled Ignition UAV assumes that the UAV can carry sufficient ignition spheres such that the UAV runs out of ignition spheres at the same time the battery is depleted, resulting in a single type of swap behavior. While Ignition UAVs are being developed to hold 1000 spheres (e.g., dragon eggs), such UAVs will require a sphere refill before battery depletion. The result will be heterogeneous types of swap behaviors, one for ignition sphere refill and another for battery replacement. A more realistic representation of heterogeneous swaps is needed, and will impact the Supervisor's Overall Workload.
The Tightly Coupled task model incorporates very limited Supervisor multitasking. The Supervisor is modeled as completing the visual scan task, and the modeled Supervisor activities simultaneously. However, much more realistic and extensive multitasking needs to be modeled.
The developed model does not extensively model task switching, which must be modeled.
The developed model does not represent the complexity of the environmental working conditions for the Tightly Coupled scenario. It is questionable if IMPRINT Pro, or any human performance modeling tool can represent such complex working environments.

19. REFERENCES

Alion Science and Technology (S & T), MA&D Operation, The SAFTE Plugin for IMPRINT Pro v. 4.0: Incorporation of a Model of Fatigue, 2012.

Archer, S., M. Gosakan, P. Shorter, and J. Lockett (2005) New capabilities of the Army's maintenance manpower modeling tool. *Journal of the International Test and Evaluation Association*, 26(1): 19 – 26.

Atherton, K.D. (2022) An inside look at how one person can control a swarm of 130 robots. *Popular Science*, Published on-line, January 20, 2022.

Bakeman, R. (2005). Recommended effect size statistics for repeated measures designs. *Behavior Research* Methods, 37(3), 379-384.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.).* Hillsdale, NJ: Erlbaum.

Cummings, M. L., and S. Guerlain (2007) Developing operator capacity estimates for Supervisory control of autonomous vehicles. *Human Factors*, 49(1): 1-15.

Goodrich, M. A. (2010) On Maximizing Fan-Out: Towards Controlling Multiple Unmanned Vehicles. In *Human-Robot Interactions in Future Military Operations* edited by M. Barnes and F. Jentsch. Ashgate Publishing, Surrey, England.

Gouraud, J., Delorme, A., and Berberian, B. (2018) Influence of automation on mind wandering frequency in sustained attention. *Consciousness and Cognition*, 66: 54-64.

Hancock, P. A., ad Verwey, W. B. (1997). Fatigue, workload and adaptive driver systems. *Accident Analysis & Prevention*, *29*(4): 495-506.

Harriott, C. E., G. L. Buford, T. Zhang, and J. A. Adams, (2015) Mental Workload and Task Performance in Peer-Based Human-Robot Teams, *Journal of Human-Robot Interaction*, 4(2).

Heard, J. and J. A. Adams (2019) Multi-Dimensional Human Workload Assessment for Supervisory Human-Machine Teams. *Journal of Cognitive Engineering and Decision Making*, 13(3): 146-170.

Heard, J., R. Heald, C. E. Harriott, and J. A. Adams (2019) A Diagnostic Human-Workload Assessment Algorithm for Collaborative and Supervisory Human-Robot Teams. *ACM Transactions on Human-Robot Interaction*, 8(2): 7.

Kang, Z. and Landry, S. J. (2015) An eye movement analysis algorithm for a multi-element target tracking task: Maximum transition-based agglomerative hierarchical clustering. *IEEE Transactions on Human-Machine Systems*, 45(1), 13-24.

Lewis, M. (2013) Human interaction with multiple remote robots (Chapter 4). *Reviews of Human Factors and Ergonomics,* edited by David B. Kaber, Sage Publications, 9(1): 131-174.

McClung, S. N. and Kang, Z. (2016) Characterization of visual scanning patterns in air traffic control. *Computational Intelligence and Neuroscience*, 2016, 19-35.

Olejnik, S., & Algina, J. (2003). Generalized eta and omega squared statistics: Measures of effect size for some common research designs. *Psychological Methods*, *8*, 434-447.

Plott, B. (2019) Improved Performance Research Integration Tool (IMPRINT) Pro User Guide: Version 4.6. Alion Science and Technology, Louisville, CO. USA.

Wang, Z., Lleras, A., & Buetti, S. (2018) Parallel, exhaustive processing underlies logarithmic search functions: Visual search with cortical magnification. *Psychonomic Bulletin & Review*, 25(4), 1343-1350.

Williams, K. W., T. C. Mofle, and I. Choi (2021) Evaluating the preventive alert function for UAV detect and avoid systems. Report Number: DOT/FAA/AM-21/17.

Wolfe, J. M. (2020) Visual Search: How do we find what we are looking for? *The Annual Review of Vision Science*, 6:2.1-2.24.

Wolfe, J. M. (2021) Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, 28: 1060-1092.

Wu, C-C., A. Alaoui-Soce, J. M. Wolfe (2018) Event monitoring: Can we detect more than one event at a time? *Vision Research*, 145: 49-55.

Wu, C-C., and J. M. Wolfe (2016) Multiple event monitoring, *Cognitive Research: Principles and Implications*, 1:21.

Yanko, M. R., and Spalek, T. M. (2014) Driving with the wandering mind: The effect that mind-wandering has on driving performance. *Human Factors*, *56*(2): 260-269.

A. LOOSELY COUPLED TASK

A.1 UNEXPECTED EVENTS

This appendix provides the decision trees for all implemented and considered example unexpected events. This Appendix also provides example output from the developed UE models, including best case and worst-case scenarios by shift period.

A.1.1 Decision Trees

This appendix provides the decision trees for the following example UE use cases:

- Emergency in the airspace (Figure 62)
- Mid-air collision (UAV can fly, but damaged. Cannot complete the mission) (Figure 63)
- C^2 Link Loss (Figure 64)
- UAV physically damaged midflight (not modeled as part of A26 - Figure 65)
- UAV fly away (not modeled as part of A26 - Figure 66).

The decision trees represent the actions and decisions made by the autonomy and the human Supervisor. The decision trees generally represent the elements that must be modeled or are modeled using common elements (circles in the figures). The human Supervisor's items (the primary Supervisor) are represented as blue items, while the autonomy related items are red. The green items represent items associated with software other than the UAV and the C^2 station that are part of the broader ecosystem.

The Emergency in the airspace decision tree demonstrates the complexity of the potential responses to this particular event, which presents too many alternatives for proper and complete modeling within the context of the A26 project. The decision was to model two situations. The first hands-off the unexpected event immediately to the UE Supervisor, who takes responsibility for all UAVs impacted by the Emergency in the airspace and relieves the primary Supervisor of responsibility for the UE. This path is shorter and is a less complicated sequence of responsibilities, as represented by the purple highlighted path. The UE Supervisor hand-off path is expected to allow the primary Supervisor to maintain their workload or reduce it.

The second modeled case represents the worst case, from the perspective of the amount of work the primary Supervisor must do in order to respond to the event. This worst-case scenario requires that the UAVs in the air at the time of the emergency must be split into two groups, both addressed in a different manner. One group represents the UAVs actually in, headed into or nearby the area of the emergency. The other represents UAVs that are outside of that area and are not heading into it. The black bold nodes and graph edges indicate the path for handling the UAVs in, heading into or nearby the emergency area, while the brown bold edges represent the path for handling the second set of vehicles that are outside and not headed into the area in question.

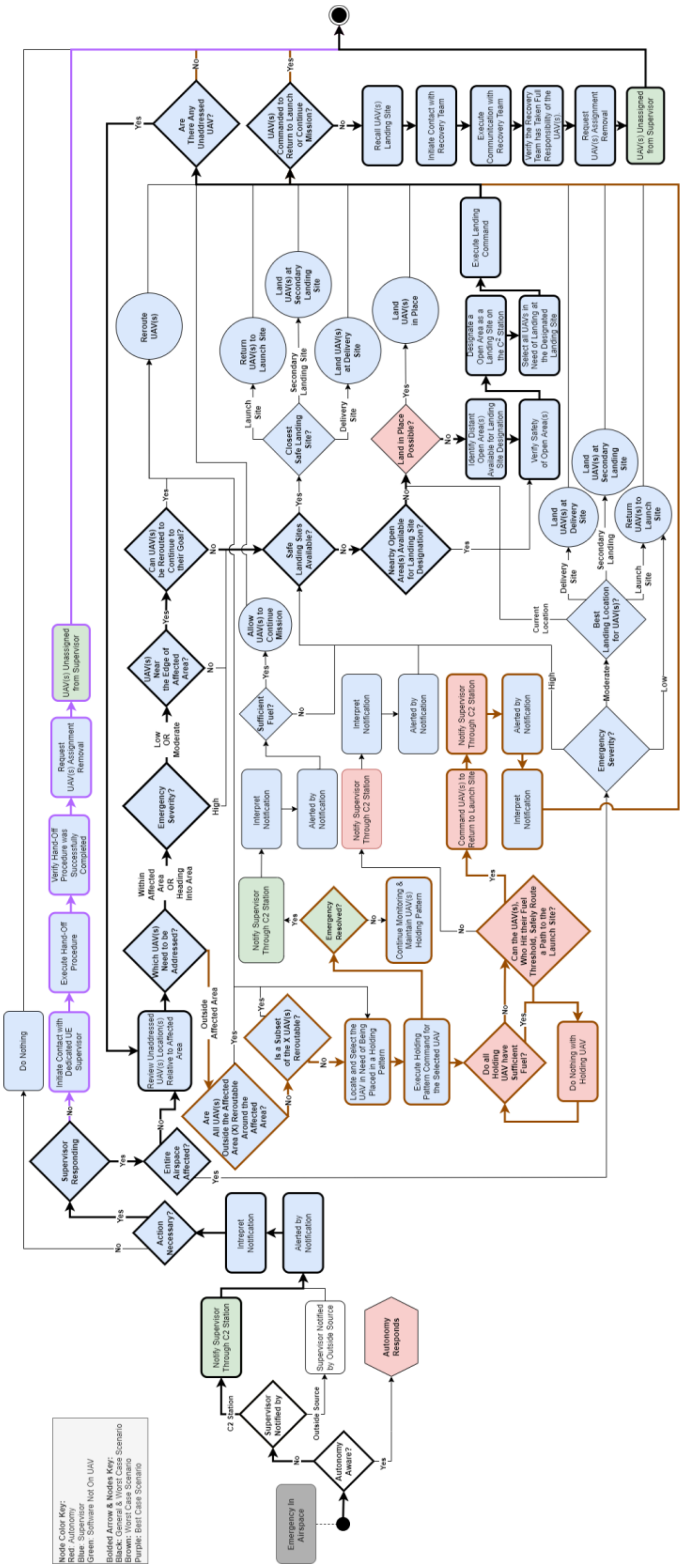


Figure 62. The Emergency in the airspace (Autonomy Unaware) UE, showing the path for the UE being handed-off to the UE Supervisor (purple) and the primary Supervisor handling the UE (black/brown).

The example Mid-air collision (UAV can fly, but damaged and unable to complete mission) best case requires the UAV autonomy to notify the Supervisor via the C^2 station (black path) and any necessary human-based response is handed-off to the UE Supervisor (purple path).

The worst-case scenario begins using a similar path as the best-case scenario that notifies the Supervisor, while simultaneously, the UAV takes actions to attempt to land the UAV (black paths). If the UAV cannot return to the launch zone, there are no nearby safe landing sites, and the UAV cannot identify a nearby open area in which to land, then the Supervisor is notified and begins identifying potential nearby areas for the UAV to land before issuing the command to land the UAV, which notifies the UAV recovery team automatically. While the UAV is reasoning over the potential landing options, prior to the Supervisor beginning the process of identifying nearby open areas, the Supervisor has received notification of the event (downward black path) and begins working the tasks to determine the level of damage and the need to file an incident report to the Airspace Officials. This path is interrupted if the UAV Autonomy requires assistance selecting an open area in which to land. The Supervisor returns to the reporting task, if it was interrupted, once the landing command has been executed. Note that once the UAV lands, the responsibility for the UAV transfers to the UAV recovery team, who goes out to physically recover the landed vehicle.

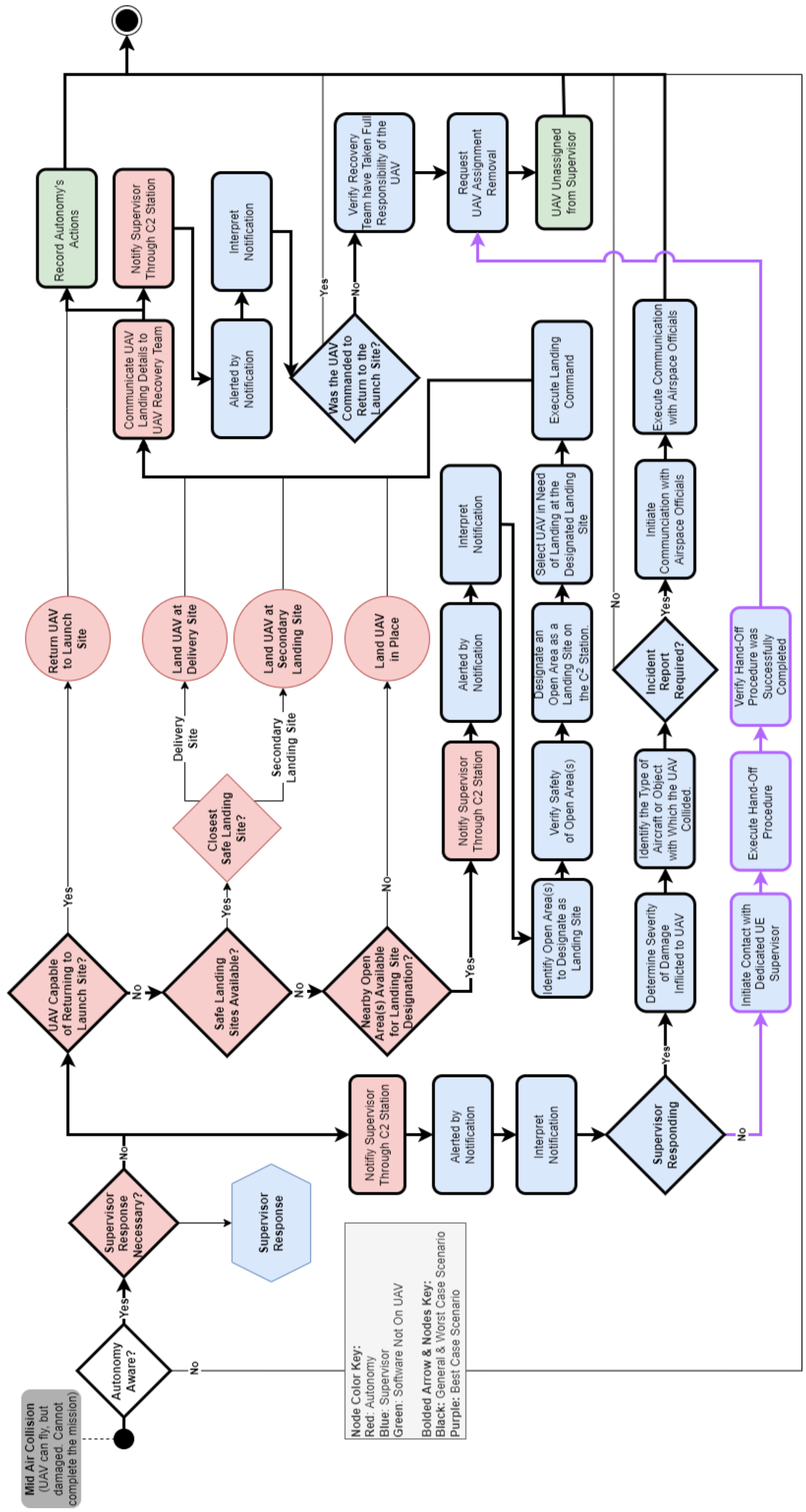


Figure 63. The Mid-air collision (UAV can fly, but damaged. Cannot complete the mission) UE, showing the path for the UE being handed-off to the UE Supervisor (purple) and the primary Supervisor handing the UE (black/purple).

The example C^2 link loss UE incorporates two UEs, the UAV Experiences C^2 Temporary Link Loss (first gray node in Figure 64) and the UAV Experiences C^2 Extended Link Loss (second gray node). The Temporary Link Loss is expected to be more frequent, and only requires the Supervisor to monitor the activities. The primary focus of the current modeling effort is the Extended Link Loss UE for a single UAV. The case of multiple UAVs simultaneously experiencing C^2 link loss was not modeled, but the use case and decision tree remain the same and, in all likelihood, the UE Supervisor will assume responsibility for such a simultaneous link loss UE. Once at the Supervisor Responding node in the decision tree, if the answer is "No", the UE is handed-off to the UE Supervisor (purple), which represents the best-case situation. The "Yes" path represents the worst-case scenario in which the primary Supervisor must respond to the UE.

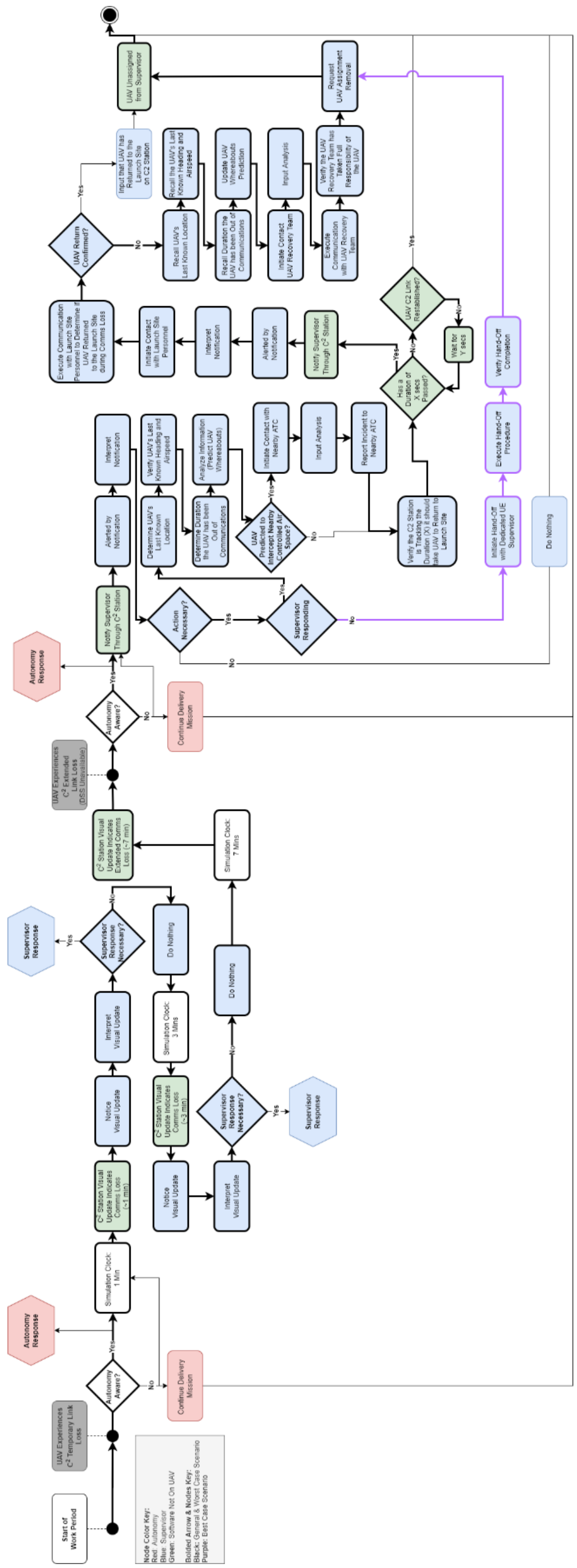

Start of Work Period
Autonomy Aware?
Autonomy Response
Continue Delivery Mission
Simulation Clock: 1 Min
Notice Visual Update
Interpret Visual Update
Supervisor Response Necessary?
Supervisor Response
Do Nothing
Simulation Clock: 3 Mins
Simulation Clock: 7 Mins
Notify Supervisor Through C² Station
Alerted by Notification
Interpret Notification
Action Necessary?
Supervisor Responding
Input Analysis
Report Incident to Nearby ATC
Initiate Contact with Nearby ATC
Wait for X secs
UAV C2 Link Reestablished?
Execute Hand-Off Procedure
Verify Hand-Off Completion
UAV Return Confirmed?
Request UAV Assignment Removal
UAV Unassigned from Supervisor
Yes
No

Figure 64. The C^2 link loss (decision support system is unavailable) UE,
showing the path for the UE being handed-off to the UE Supervisor (purple) and the primary Supervisor handing the UE (black/purple).

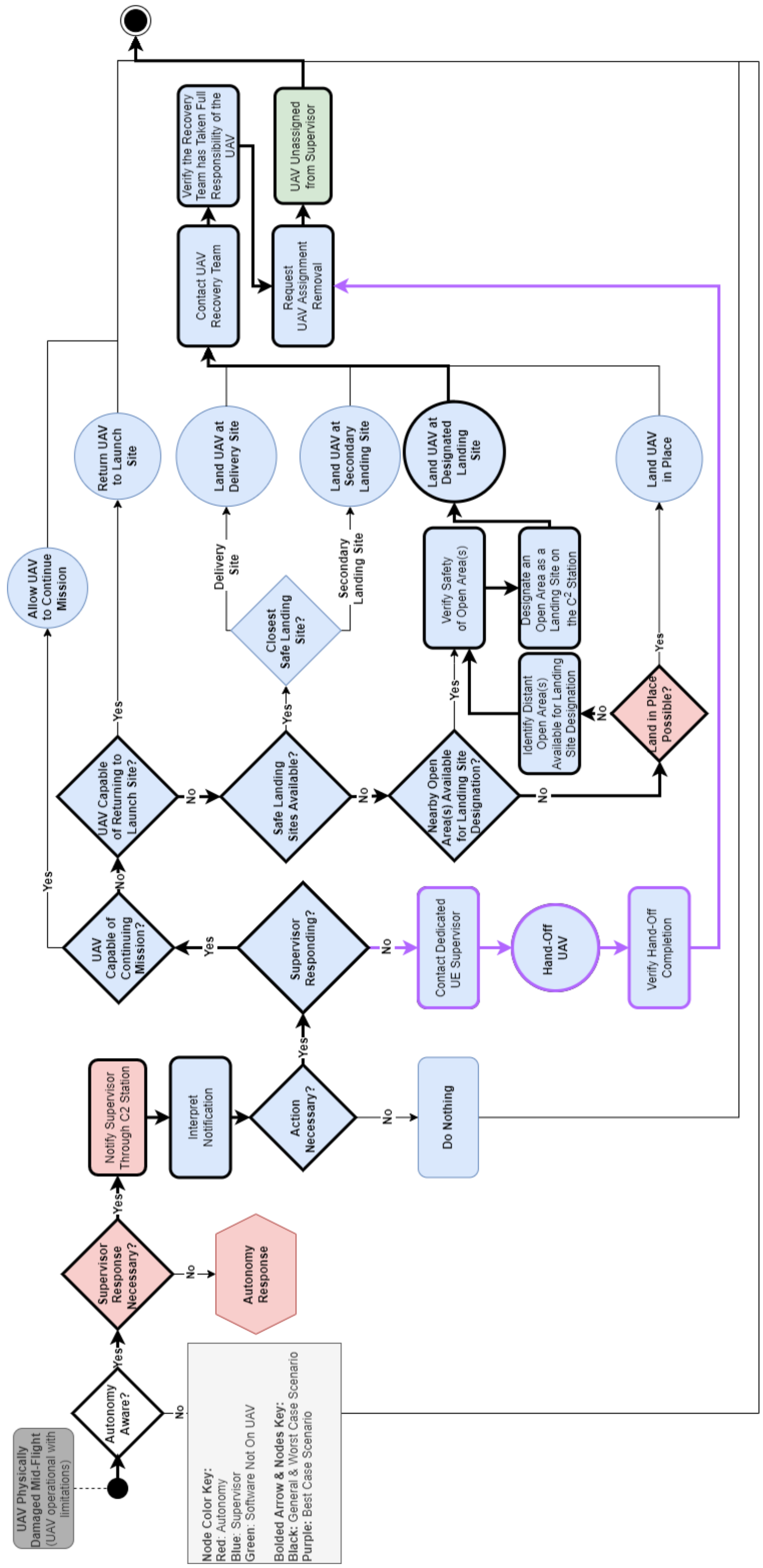


Figure 65. UAV Physically Damaged Midflight UE decision tree.

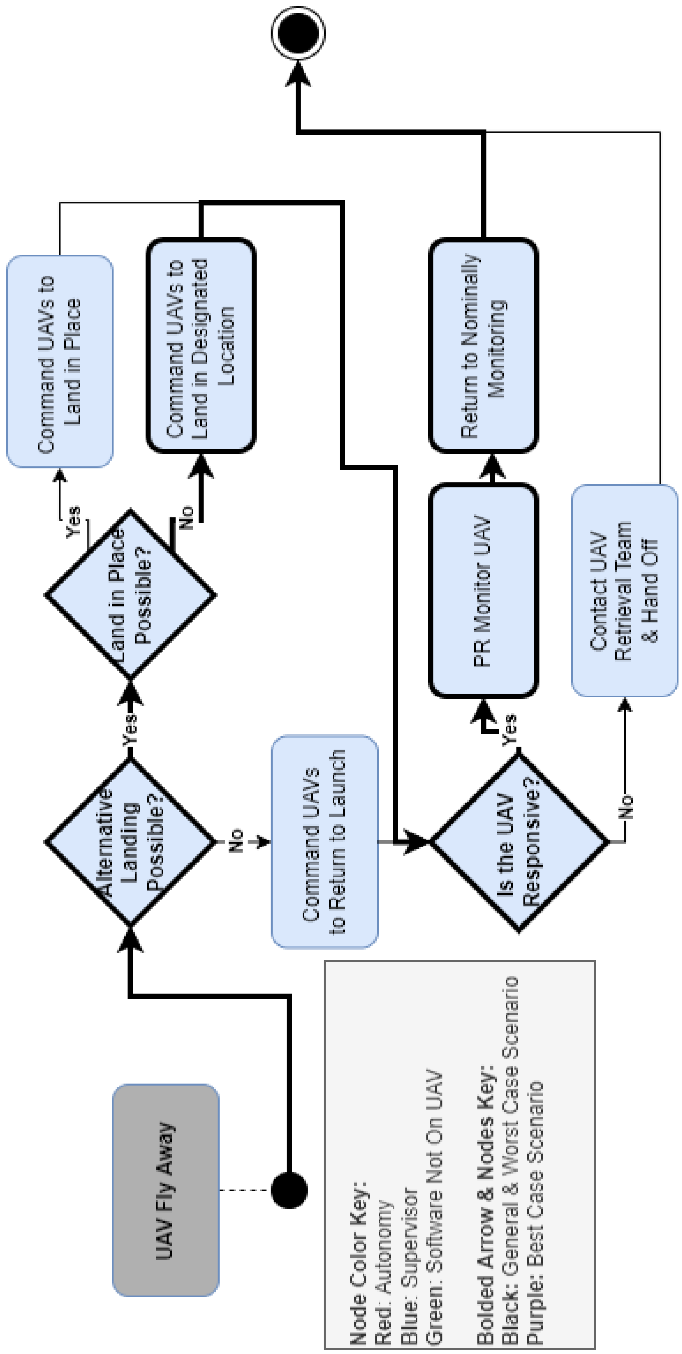
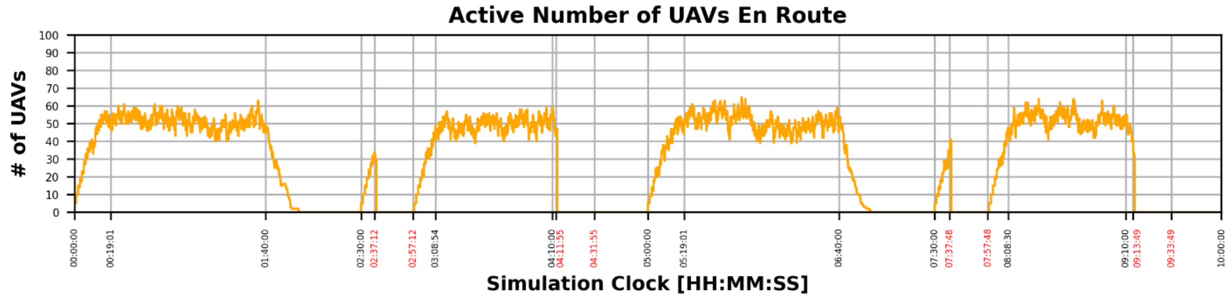


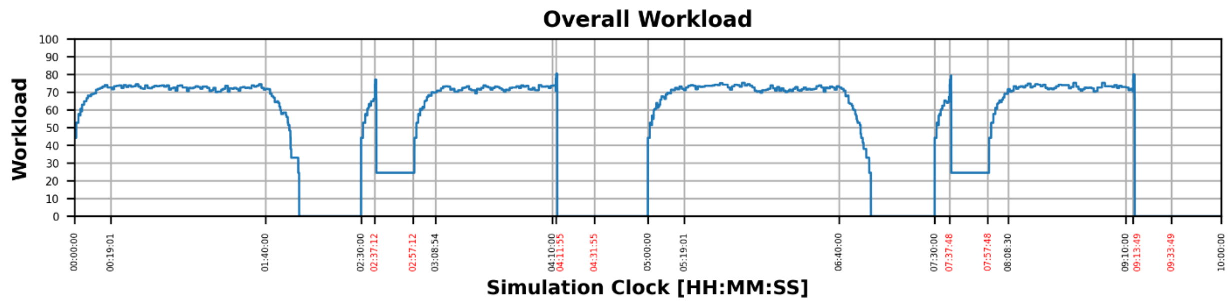
Figure 66. UAV Fly Away UE decision tree.

A.1.2 UE Model Output Examples

A.1.2.1 Emergency in the Airspace UE

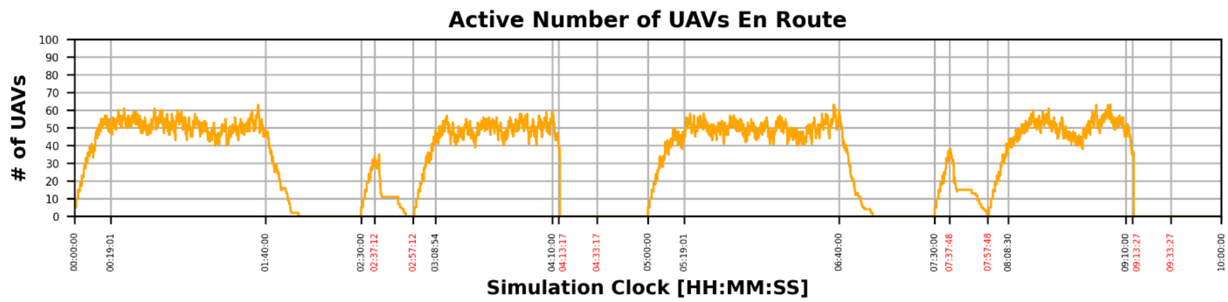


(a) Number of UAVs.

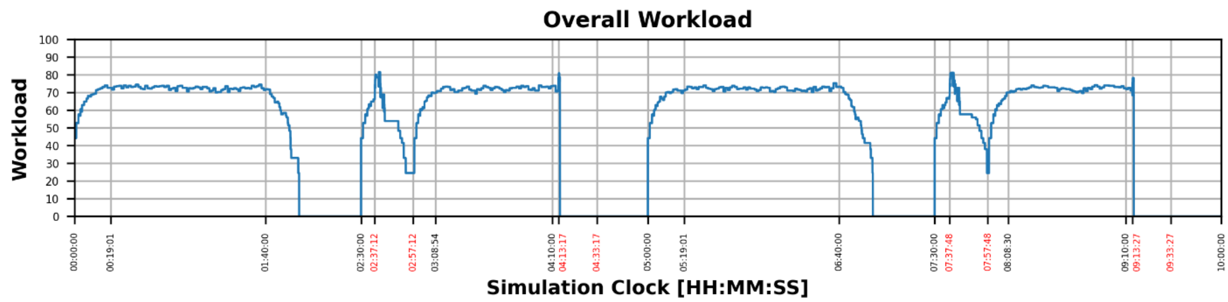


(b) Overall Workload

Figure 67. An example of the Emergency in the airspace's UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

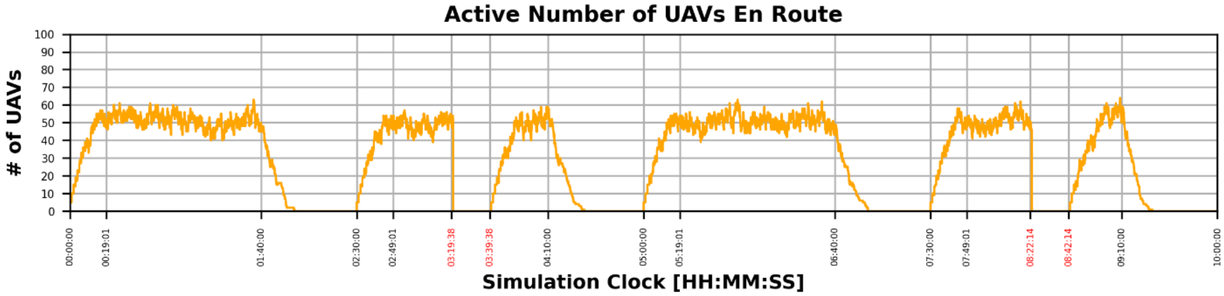


(a) Number of UAVs.

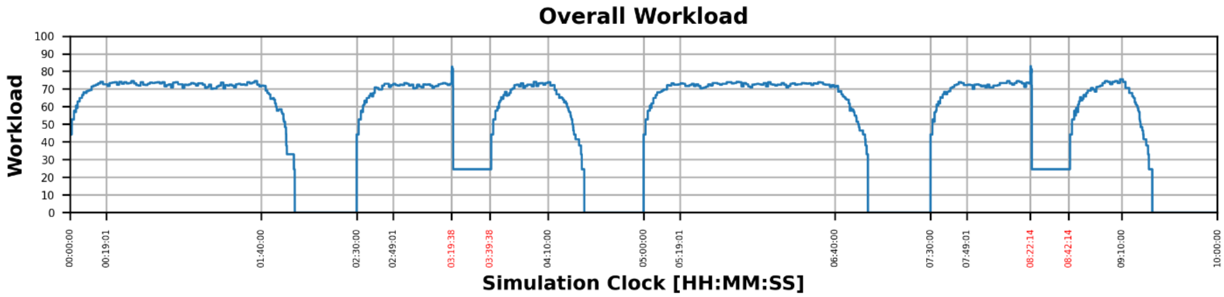


(b) Overall Workload

Figure 68. An example of the Emergency in the airspace's UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

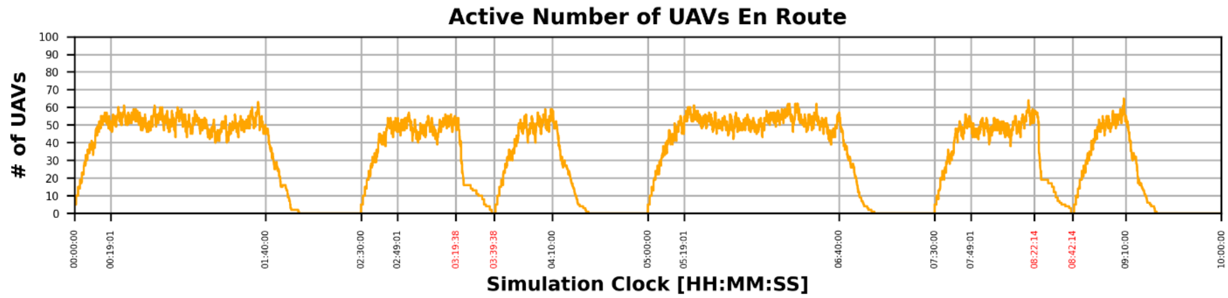


(a) Number of UAVs.

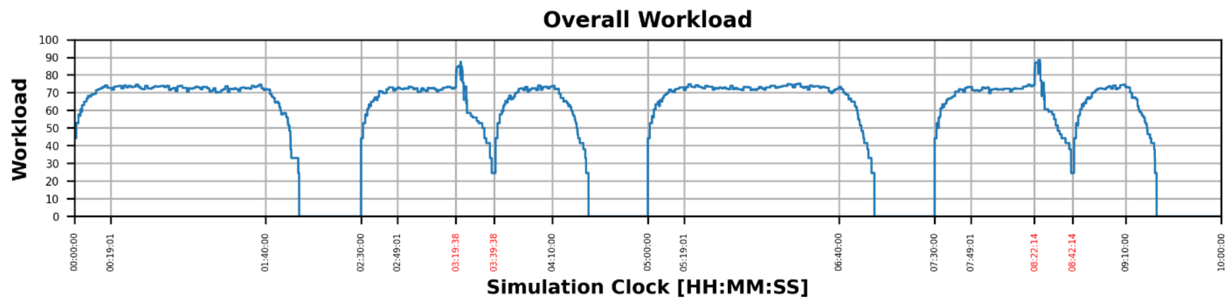


(b) Overall Workload

Figure 69. An example of the Emergency in the airspace's UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Steady state shift state of the 2nd and 4th work period.



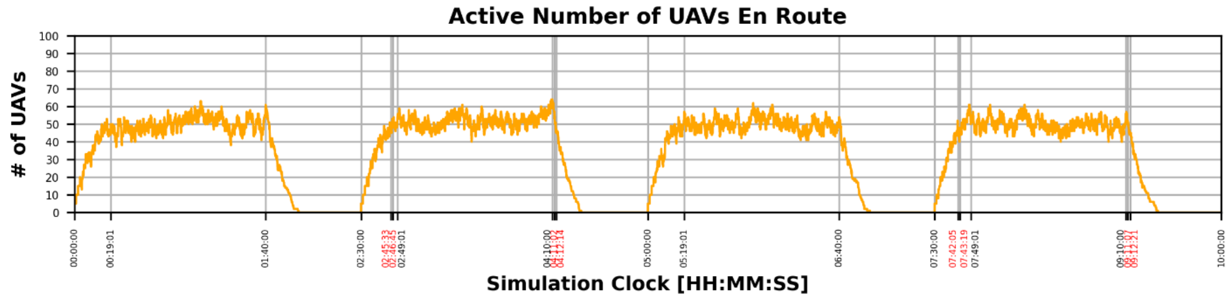
(a) Number of UAVs.



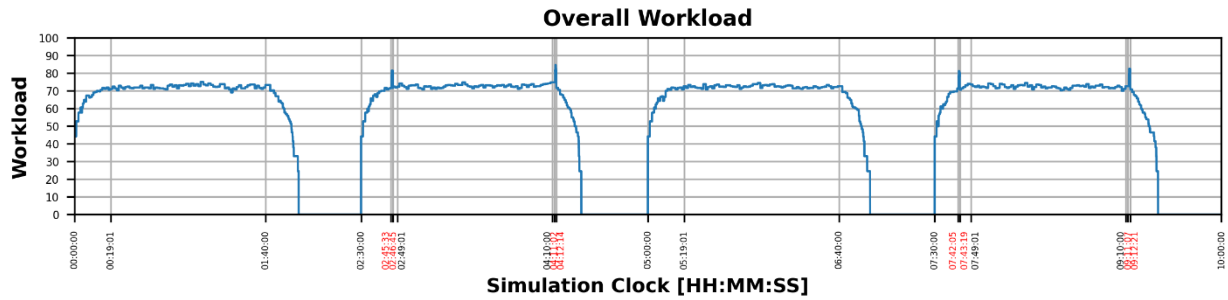
(b) Overall Workload

Figure 70. An example of the Emergency in the airspace's UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Steady state shift state of the 2nd and 4th work period.

A.1.2.2Mid-Air Collision UE

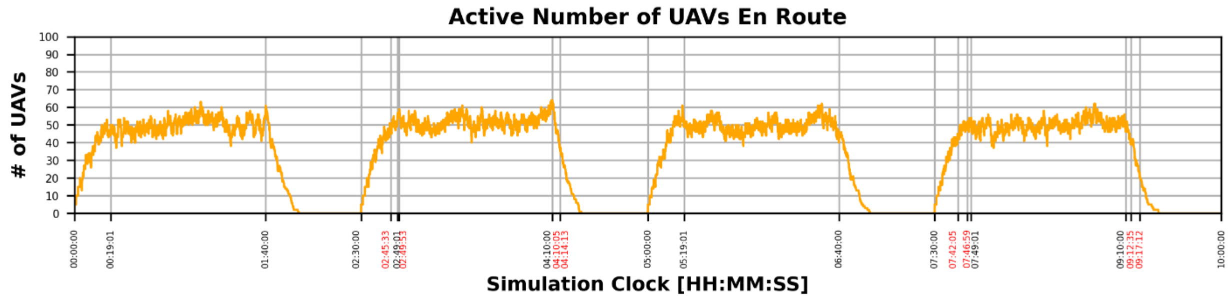


(a) Number of UAVs.

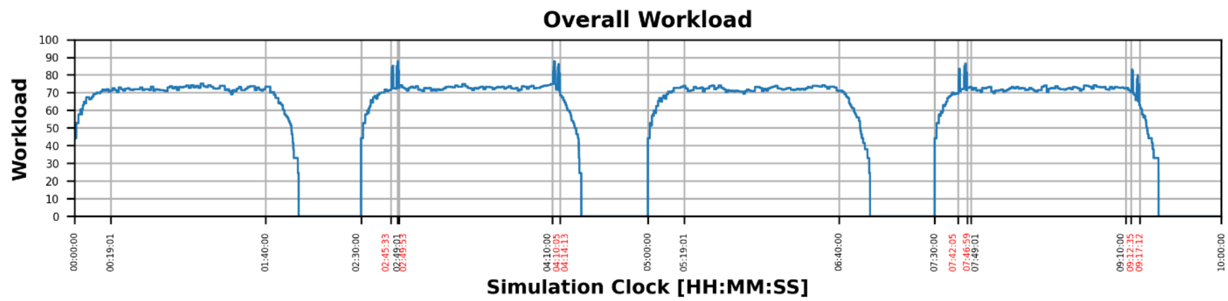


(b) Overall Workload

Figure 71. An example of the Mid-air collision UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

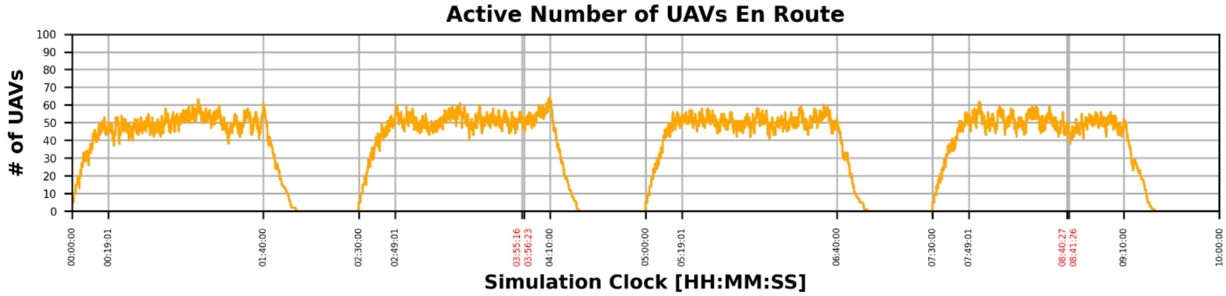


(a) Number of UAVs.

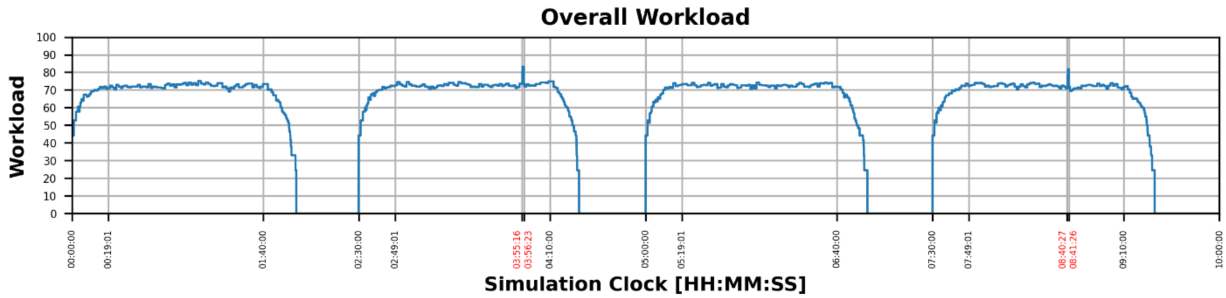


(b) Overall Workload

Figure 72. An example of the Mid-air collision UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

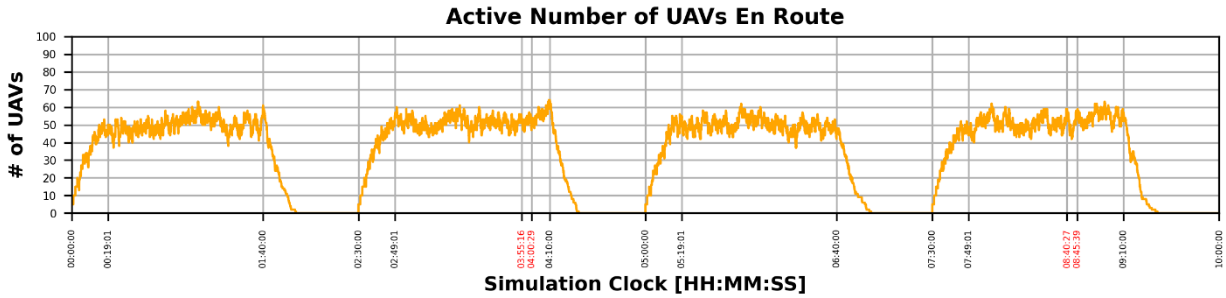


(a) Number of UAVs.

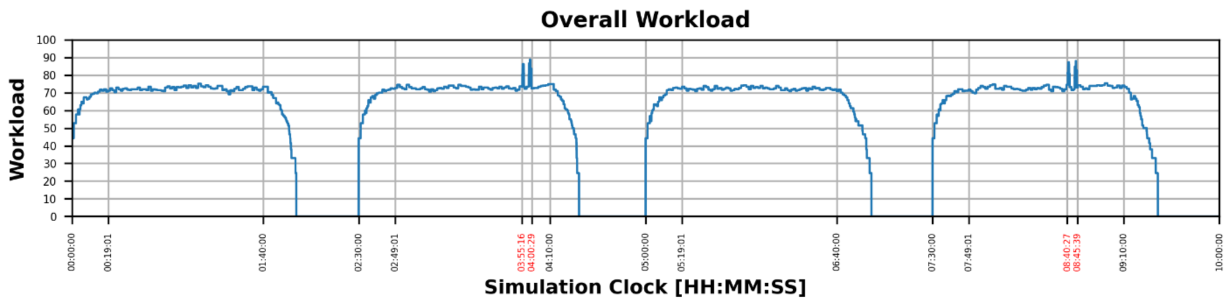


(b) Overall Workload

Figure 73. An example of the Mid-air collision UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during Steady state of the 2nd and 4th work period.



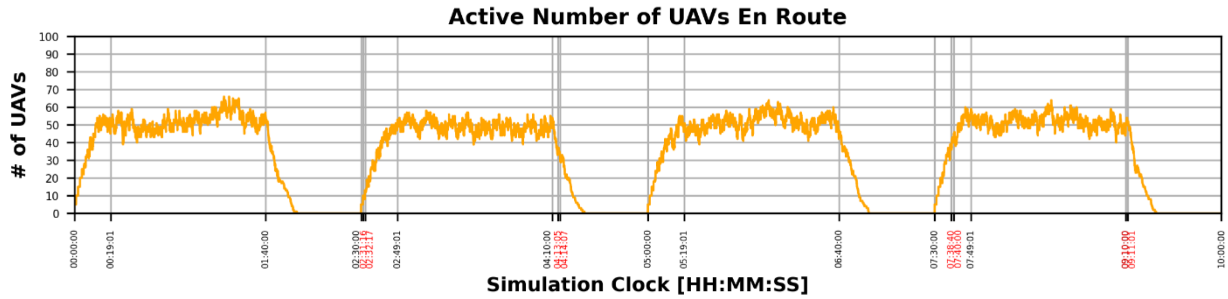
(a) Number of UAVs.



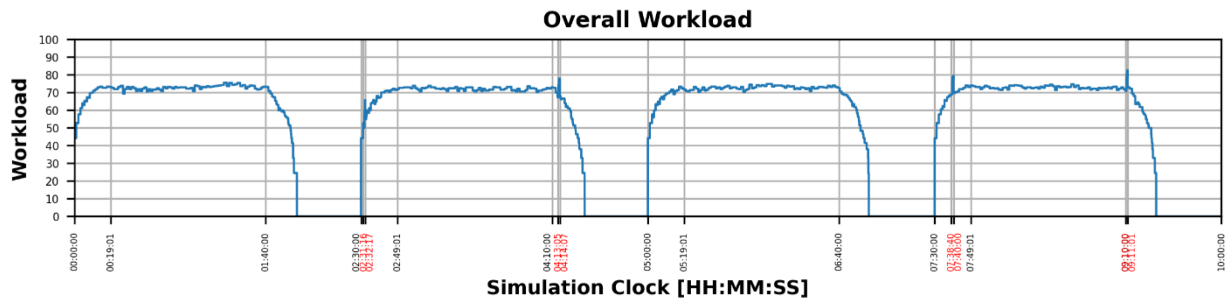
(b) Overall Workload

Figure 74. An example of the Mid-air collision UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during Steady state of the 2nd and 4th work period.

A.1.2.3 C² Link Loss UE

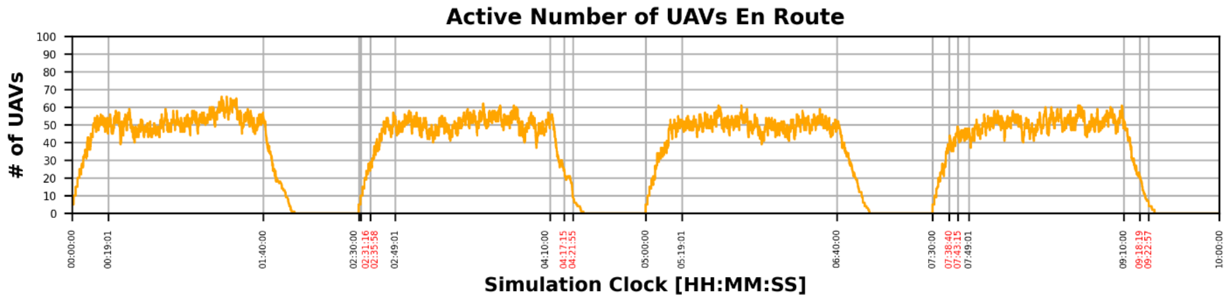


(a) Number of UAVs.

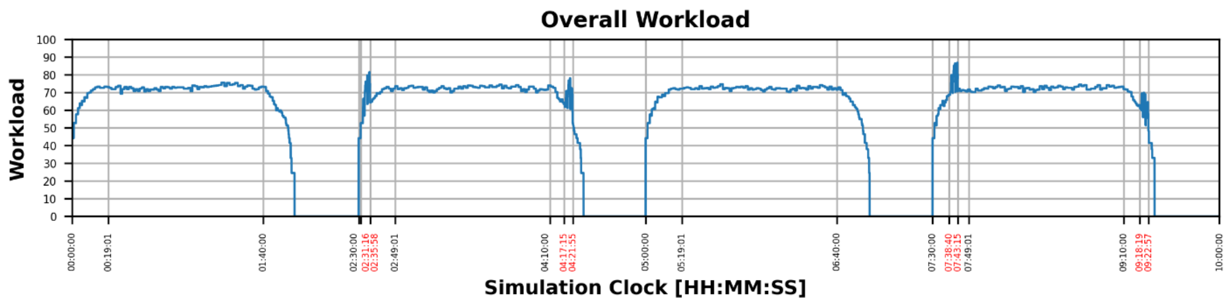


(b) Overall Workload

Figure 75. An example of the C² link loss UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

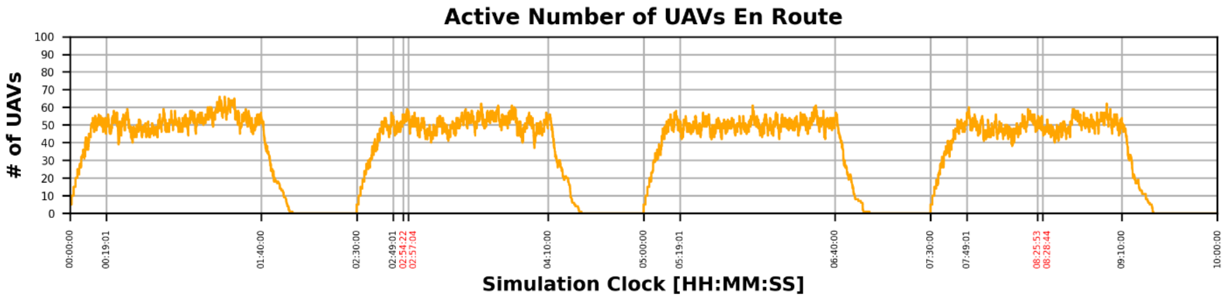


(a) Number of UAVs.

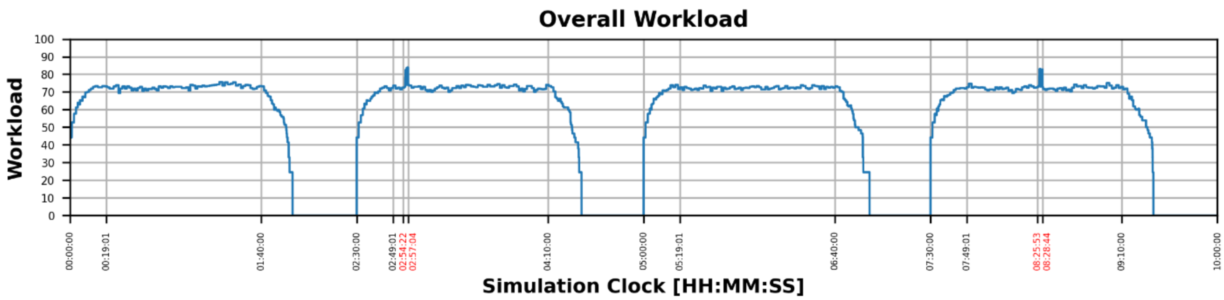


(b) Overall Workload

Figure 76. An example of the C^2 link loss UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

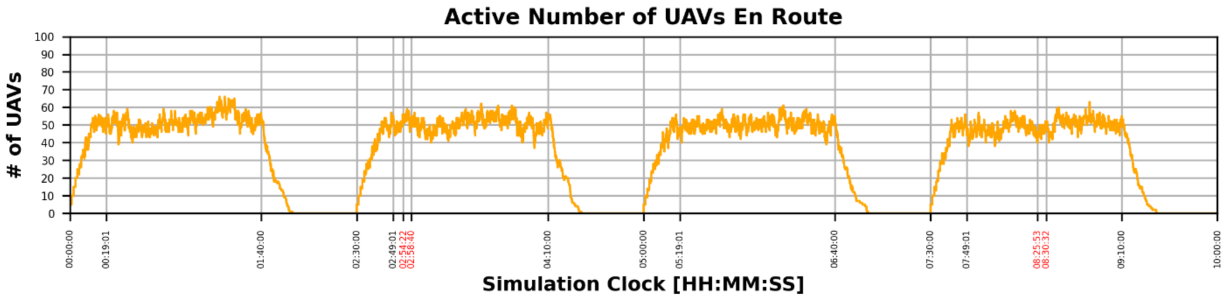


(a) Number of UAVs.

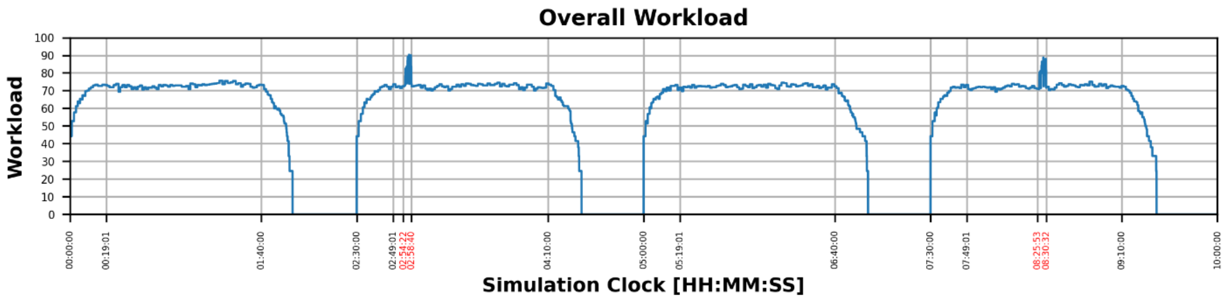


(b) Overall Workload

Figure 77. An example of the C^2 link loss UE's best-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during Steady state shift states of the 2nd and 4th work period.



(a) Number of UAVs.



(b) Overall Workload

Figure 78. An example of the C^2 link loss UE's worst-case path's number of UAVs (a) and Overall Workload (b) when the UE occurs during Steady state shift states of the 2nd and 4th work period.

A.2 DISTRACTION EVENTS

This appendix provides the decision trees for the implemented example distraction events. This Appendix also provides example output from the developed distraction models

A.2.1 Decision Trees

This appendix provides the decision trees for the example distraction use cases:

- Mindwandering (Figure 79)
- Fatigue (Supervisor unaware) (Figure 80)
- Phone call distraction (not modeled as part of A26 - Figure 81)
- Biological need distraction (not modeled as part of A26- Figure 82).

The example Mindwandering distraction demonstrates a Supervisor who is Mindwandering, but is unaware of their Mindwandering or its effects on their task performance. The bold path through the decision tree represents the path modeled for A26. The Supervisor is Mindwandering significantly, but is unaware they are doing so, while they continue to attempt to perform their job duties as normal. Although the Watch Supervisor is responsible for acknowledging the effects of distraction on the Supervisor, this example assumes the Watch Supervisor remains unaware of the distraction's effects. The effects of the Mindwandering distraction on the Supervisor are active for a period of time. Once the distraction ends, so do its effects and the Supervisor continues working as normal.

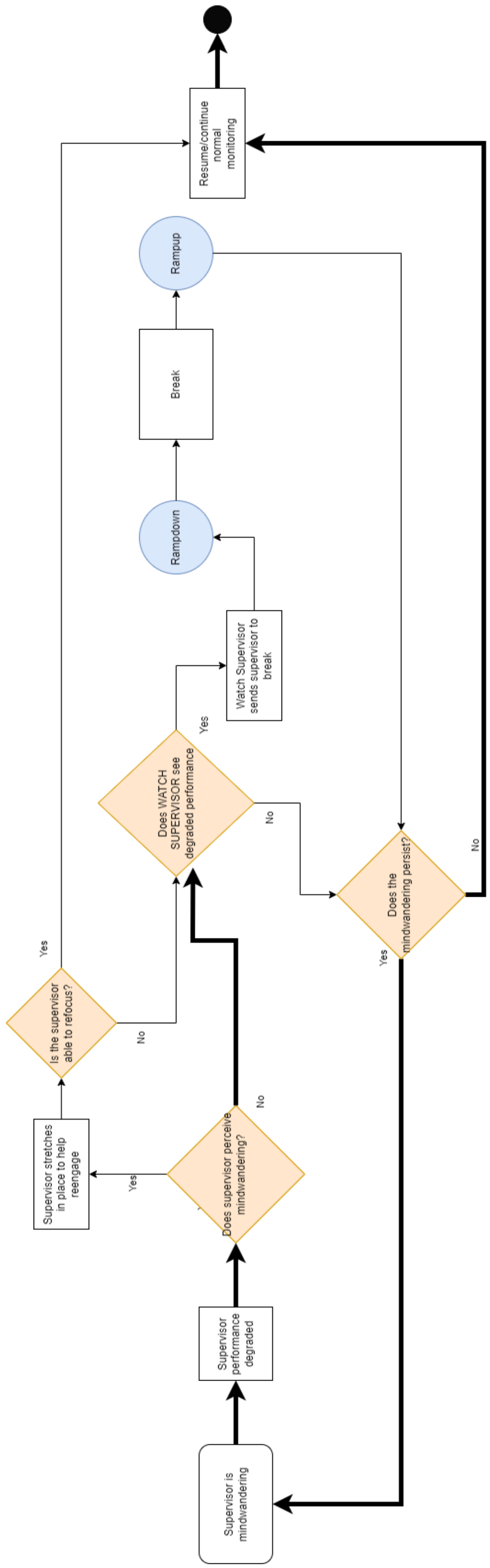


Figure 79. Mindwandering distraction.

The example Fatigue (Supervisor unaware) distraction demonstrates a Supervisor under cognitive fatigue, who is unaware of their fatigue level and its effect on their task performance. The path through the decision tree is highlighted via the bold arrows. The Supervisor is experiencing excessive fatigue, but given that they are unaware of their fatigue level and its associated impact on performance; thus, the Supervisor continues to attempt to perform their job duties as normal. Although the Watch Supervisor is responsible for acknowledging the effects of fatigue on the Supervisor, this example assumes the Watch Supervisor remains unaware of the fatigue's effects. The effects of the Fatigue distraction on the Supervisor are active from the beginning until the end of the shift. The effects of fatigue gradually change over the course of the shift.

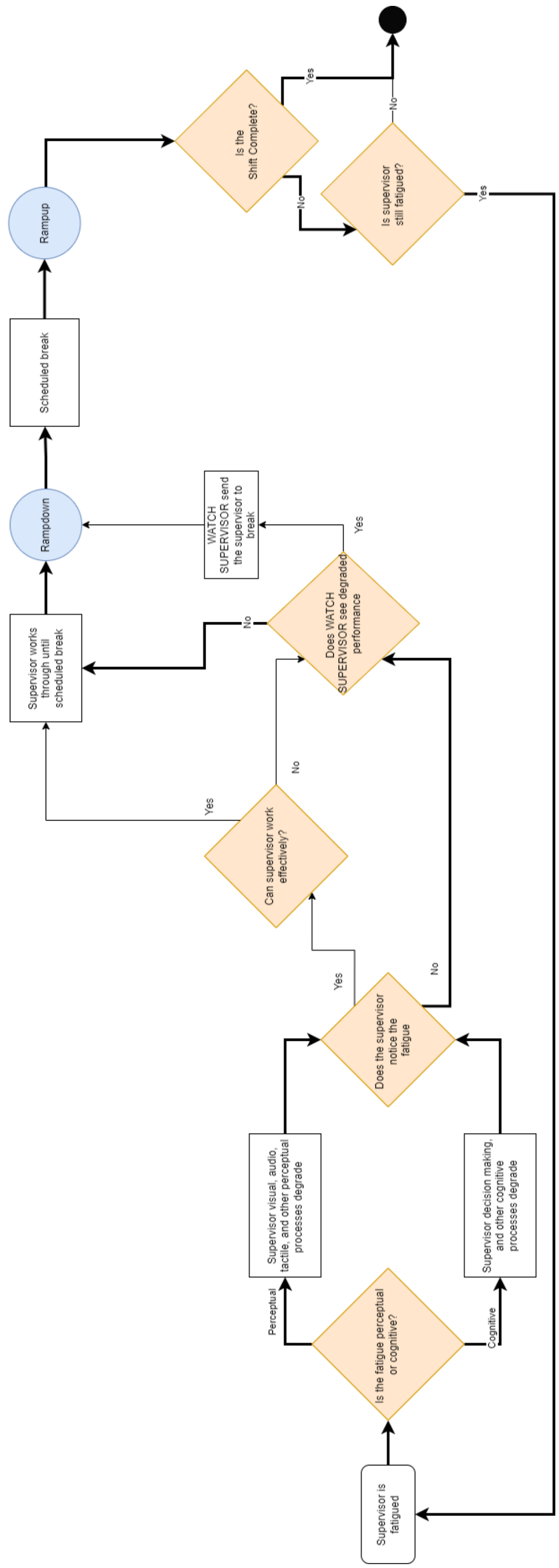


Figure 80. Fatigue (Supervisor unaware) distraction.

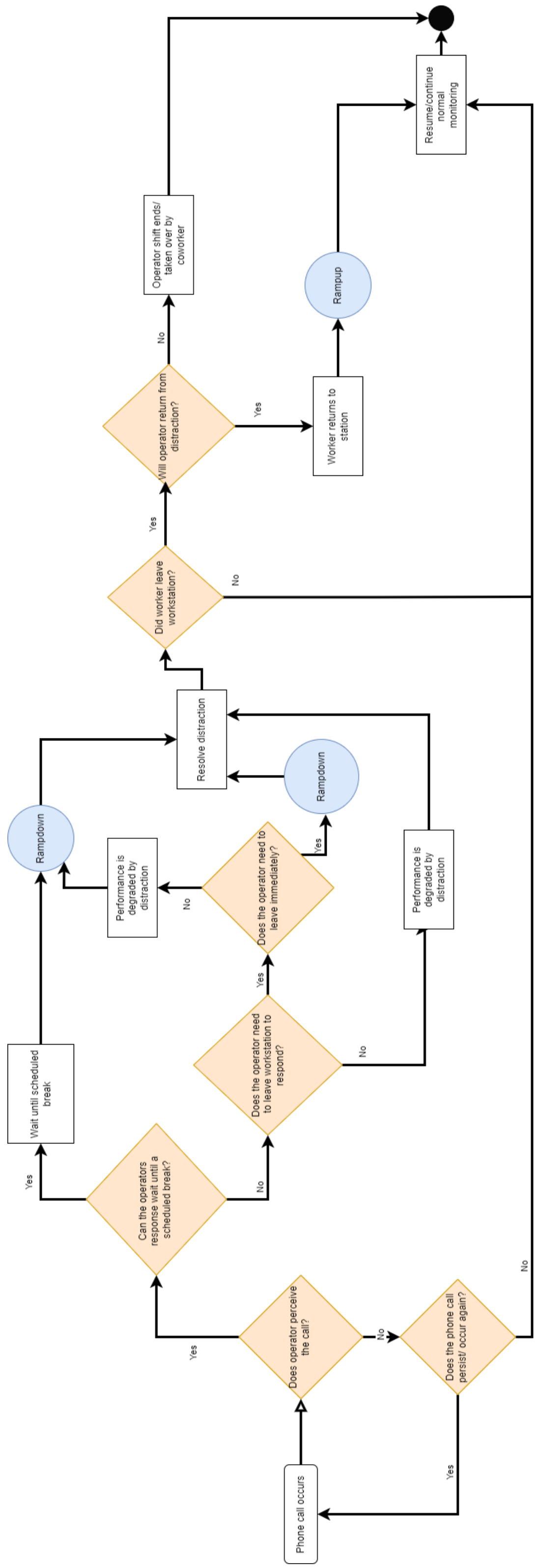


Figure 81. The Phone Call distraction decision tree.

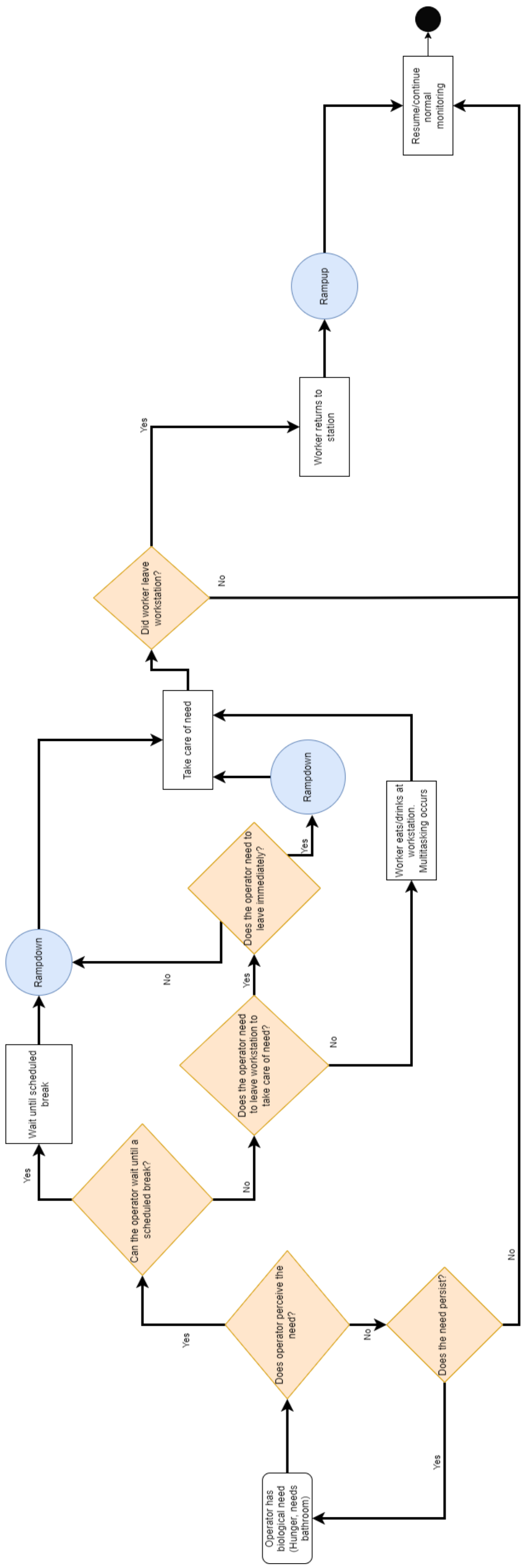
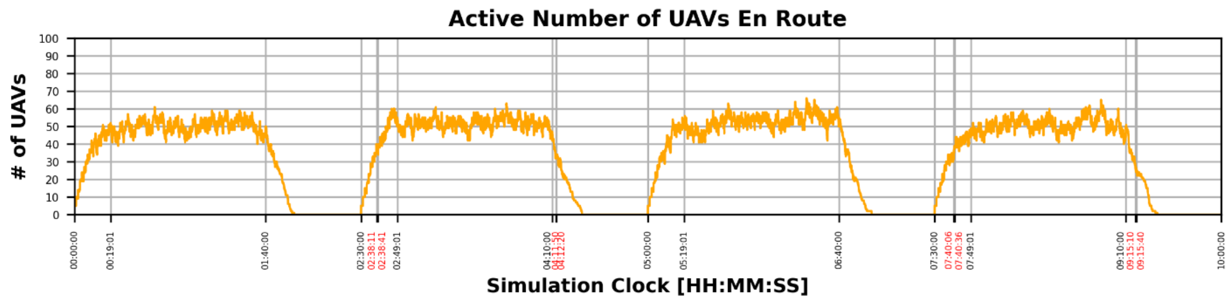


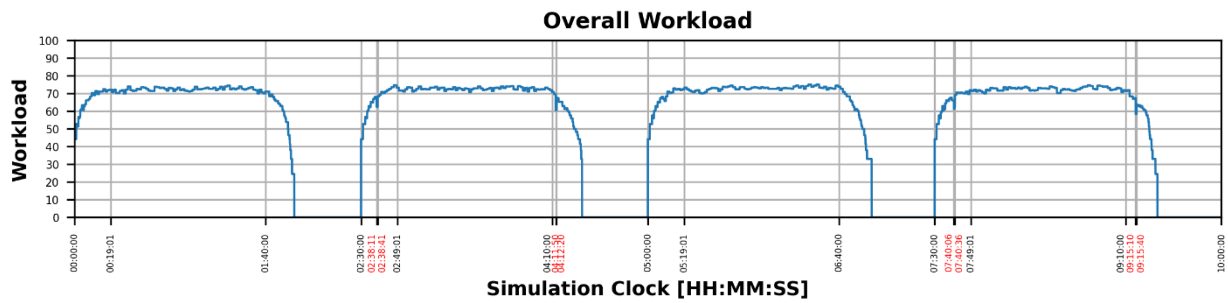
Figure 82. The Biological Need distraction decision tree.

A.2.2 Model Output Examples

A.2.2.1Mindwandering Distraction

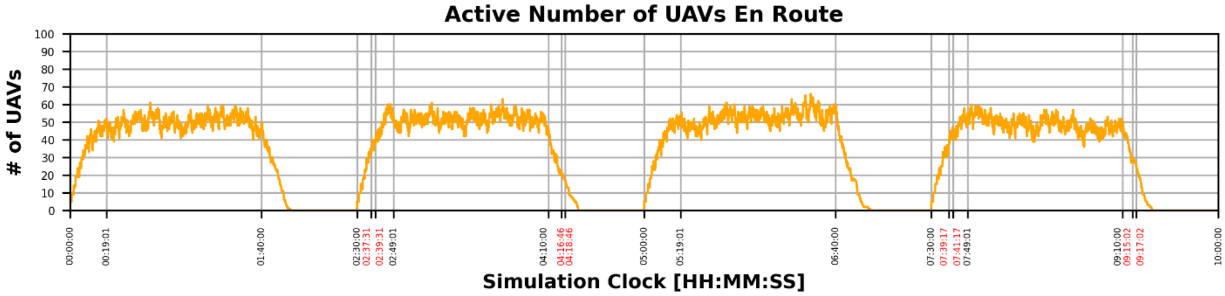


(a) Number of UAVs.

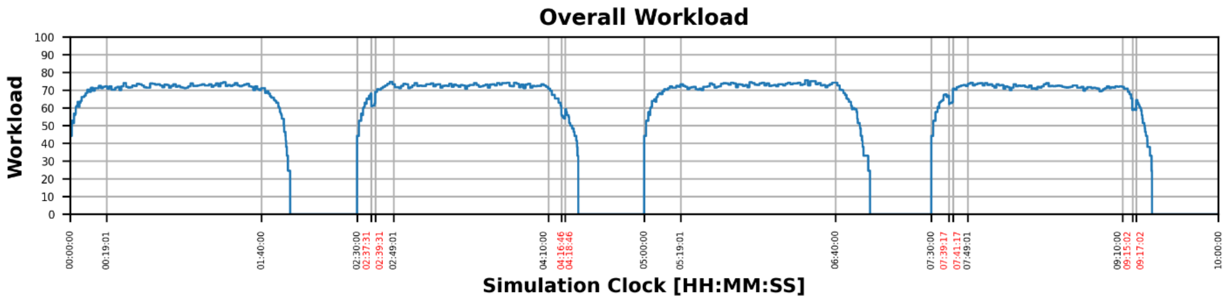


(b) Overall Workload

Figure 83. An example of the short (2nd and 4th work periods) Mindwandering distraction event's number of UAVs (a) and Overall Workload (b) when the distraction occurs during the Ramp up and the Ramp down periods.

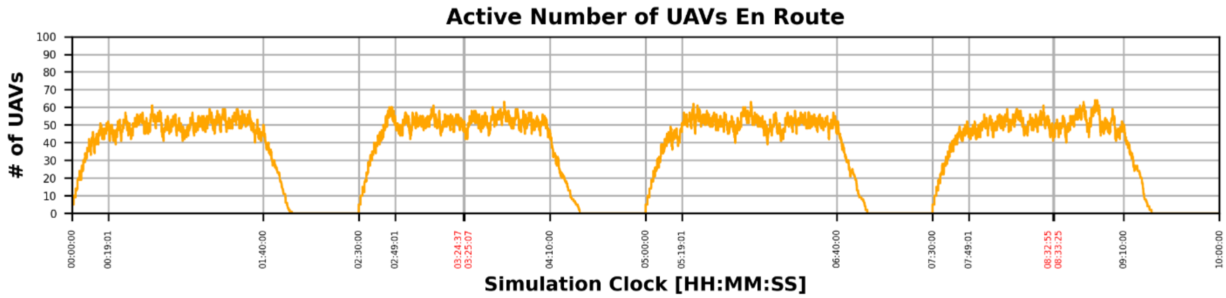


(a) Number of UAVs.

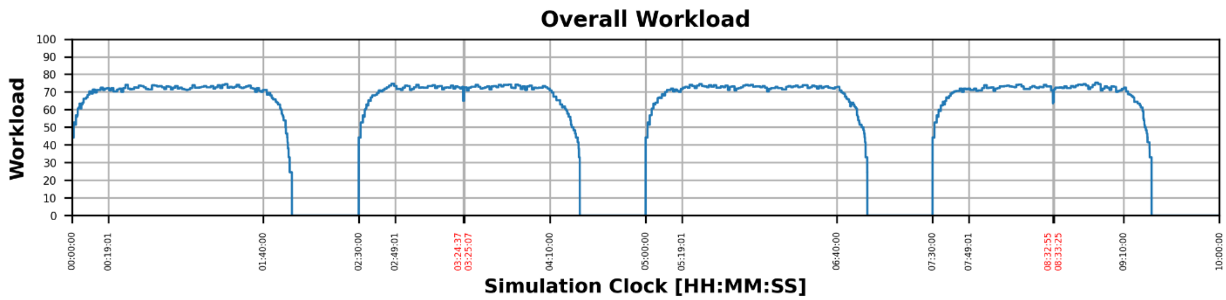


(b) Overall Workload

Figure 84. The number of UAVs (a) and Overall Workload (b) during an example trial with a long Mindwandering distraction event during the Ramp up and Ramp down shift states of the 2nd and 4th work period.

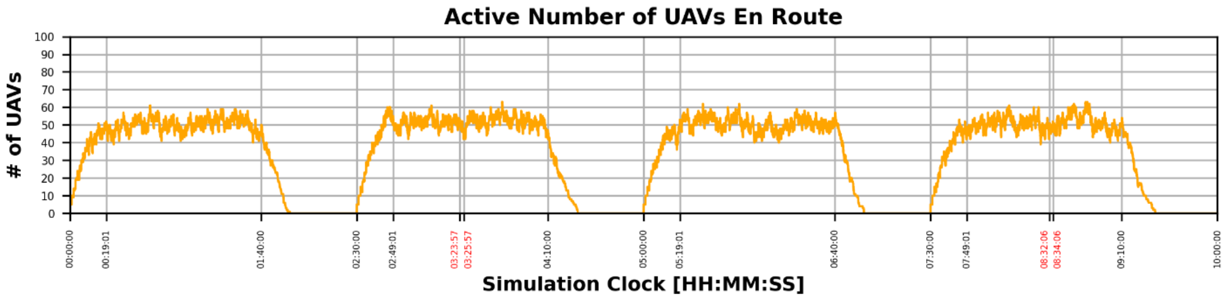


(a) Number of UAVs.

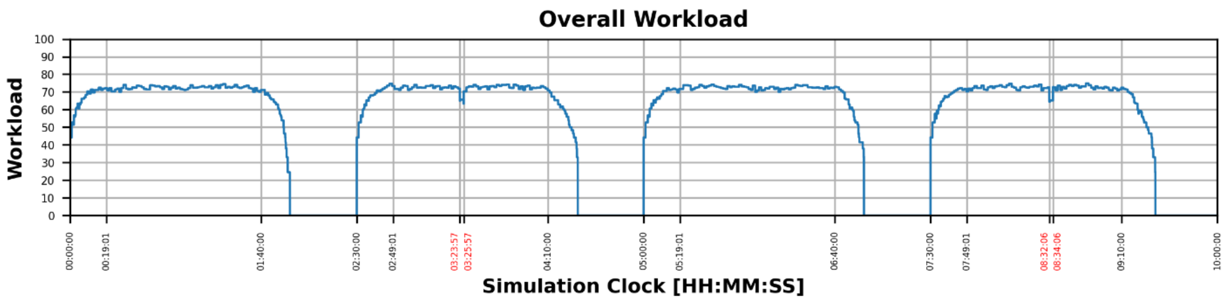


(b) Overall Workload

Figure 85. The number of UAVs (a) and Overall Workload (b) during an example trial with a short Mindwandering distraction event during the Steady state shift states of the 2nd and 4th work period.



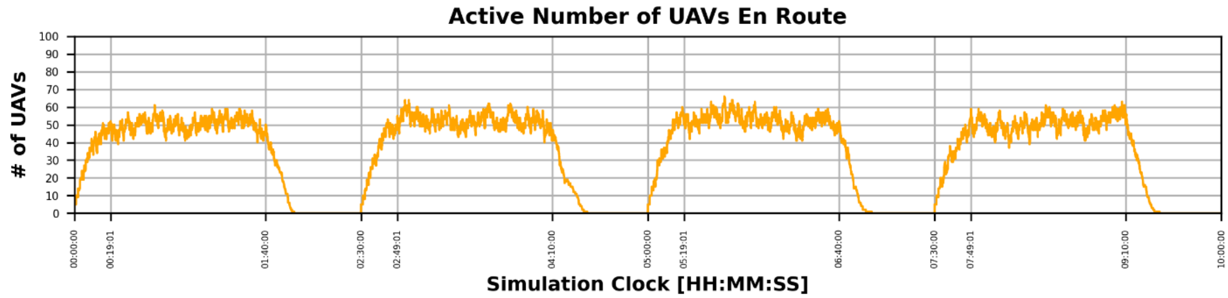
(a) Number of UAVs.



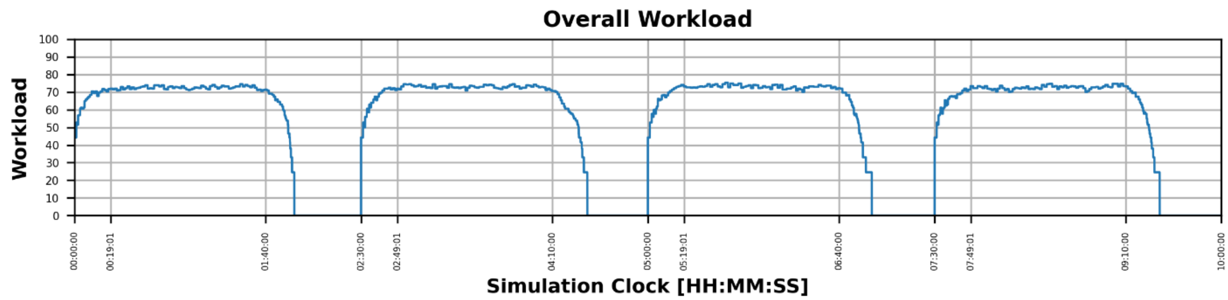
(b) Overall Workload

Figure 86. The number of UAVs (a) and Overall Workload (b) during an example trial with a long Mindwandering distraction event during the Steady state shift states of the 2nd and 4th work period.

A.2.2.2Fatigue Distraction

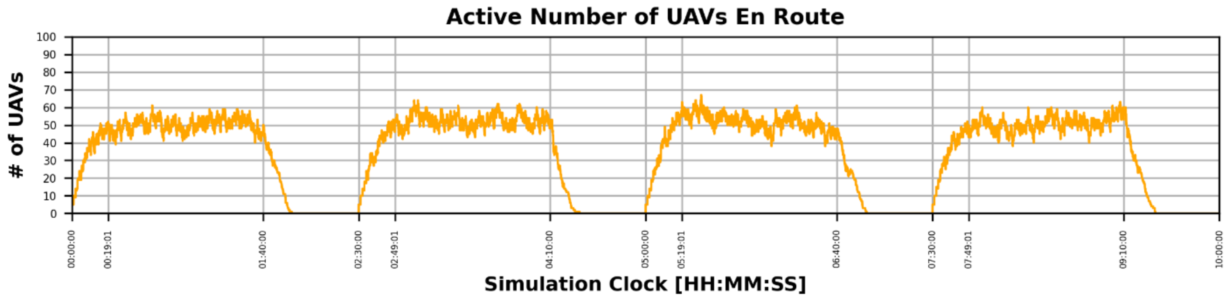


(a) Number of UAVs.

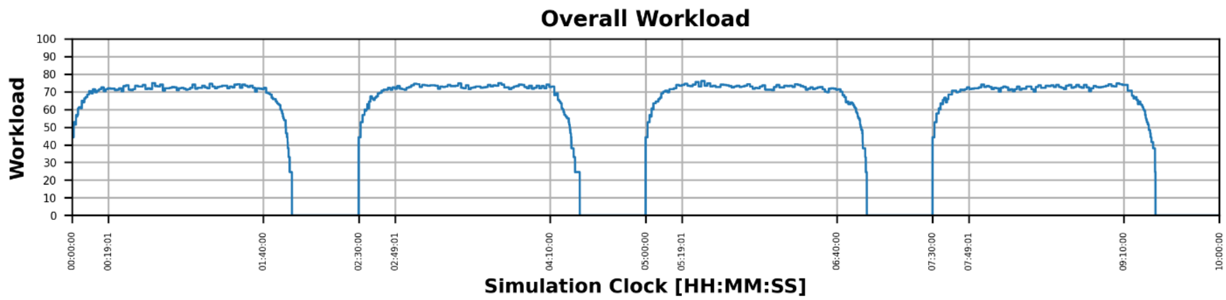


(b) Overall Workload

Figure 87. The number of UAVs (a) and Overall Workload (b) for a trial where the Supervisor has slept for eight hours each night for the last four nights.

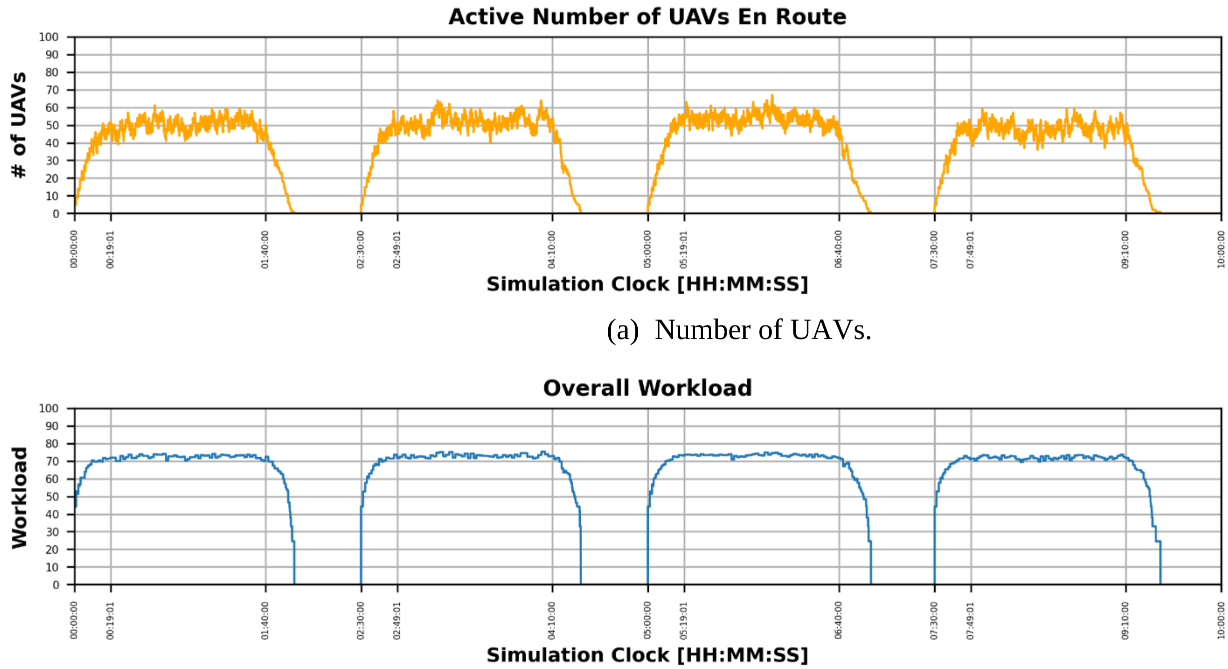


(a) Number of UAVs.



(b) Overall Workload

Figure 88. The number of UAVs (a) and Overall Workload (b) for a trial where the Supervisor has slept for six hours each night for the last four nights.



(a) Number of UAVs.

(b) Overall Workload

Figure 89. The number of UAVs (a) and Overall Workload (b) for a trial where the Supervisor has slept for four hours each night for the last four nights.

B. TIGHTLY COUPLED USE CASE

B.1 NOMINAL USE CASE DECISION TREE

This appendix provides the nominal use case decision tree in Figure 90.

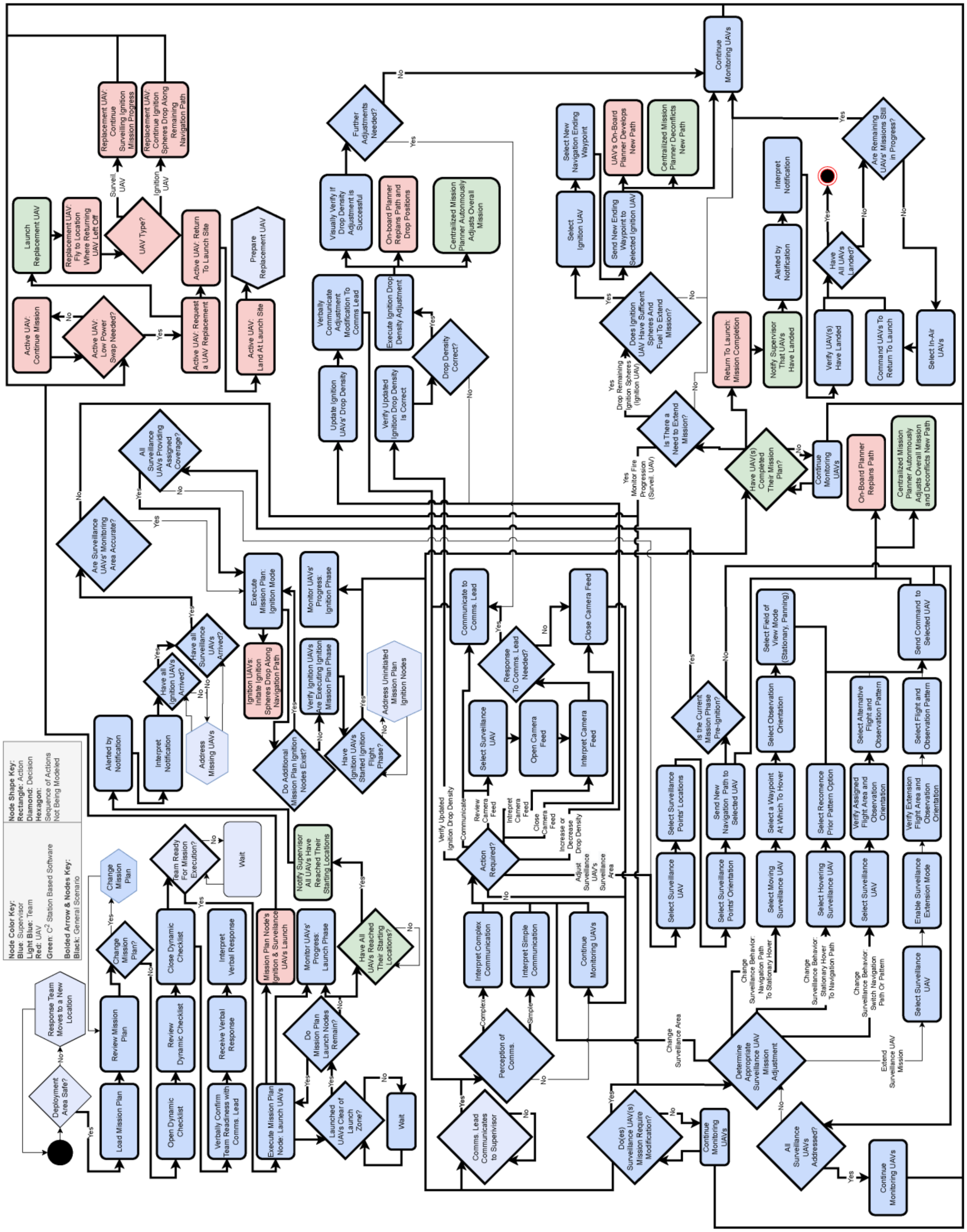
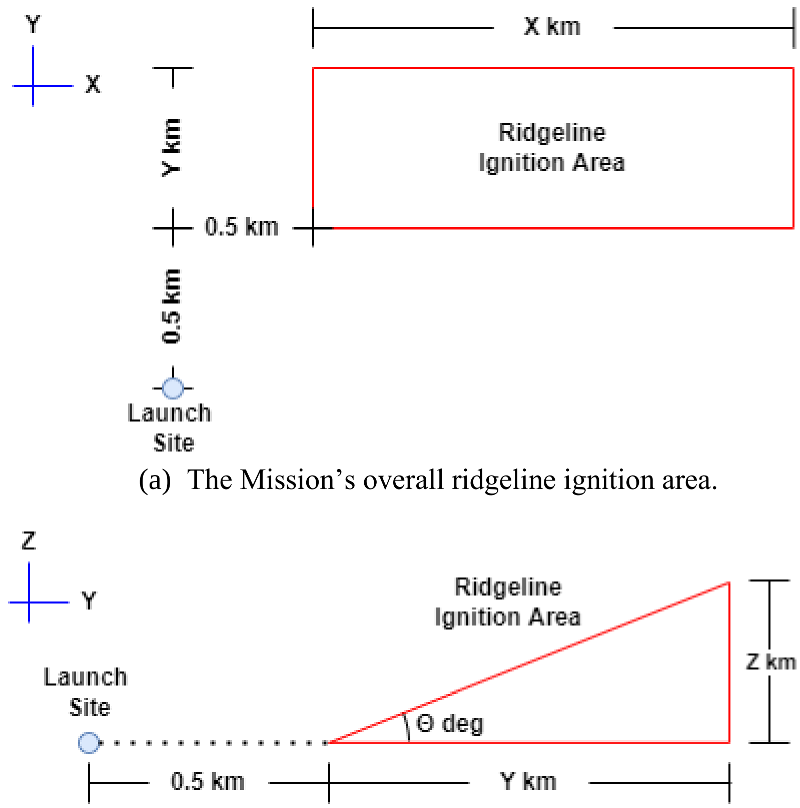


Figure 90. Aerial ignition Tightly Coupled use case decision tree.

B.2 ADDITIONAL MODEL ASSUMPTION DETAILS

The overall ignition area that can be covered during a mission is dependent on a number of factors, but most importantly, the number of Ignition UAVs. As such, steps were taken to generate a base line for the example calculations. Since the intended domain is a ridgeline, it is not a flat surface and the slope of the ridge line must be considered in this calculation. The assumptions for these calculations are provided in Figure 91.



(a) The Mission's overall ridgeline ignition area.

(b) The calculation of the ridgeline ignition area's height.

Figure 91. General measurement aspects of the launch/landing area relative to the mission's overall ridgeline ignition area in the *X* (length) and *Y* (width) dimensions (a) and the calculation of *Z* (height) (b).

All experimental trials with more than one Ignition UAV require the mission's overall ignition area be divided into multiple subregions based on the number of Ignition UAVs to be deployed simultaneously (i.e., two or four). Two subregions are delineated in Figure 92.

It is assumed that the Ignition UAVs always begin the ignition mission in the upper left corner of their assigned subregion. The example in the figure indicates a 10 meter distance between the lawn mower pattern paths. There is a buffer of 5 meters from the top of the ridge and from the left side of the subregion to the initial waypoint.

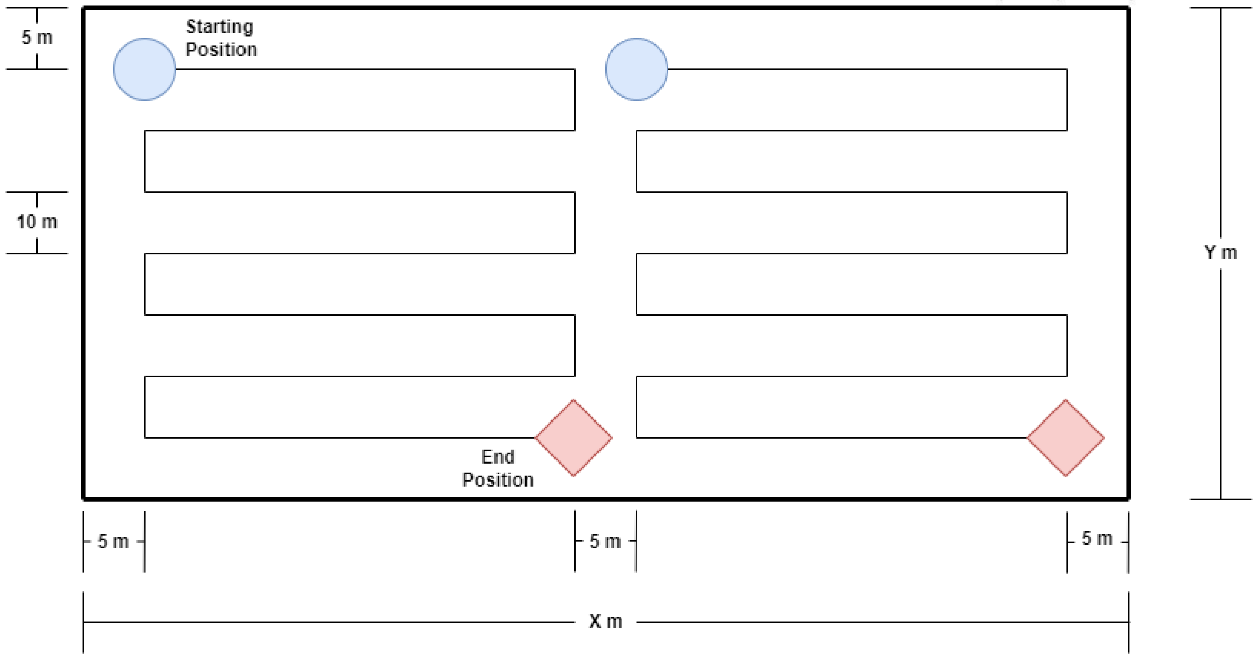
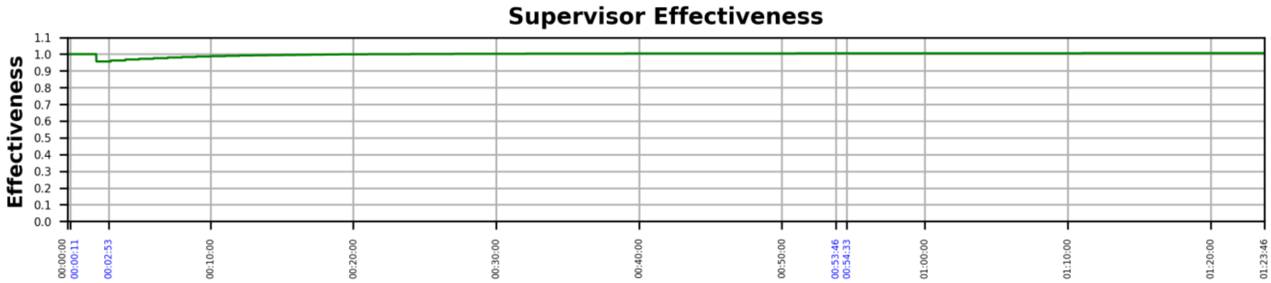


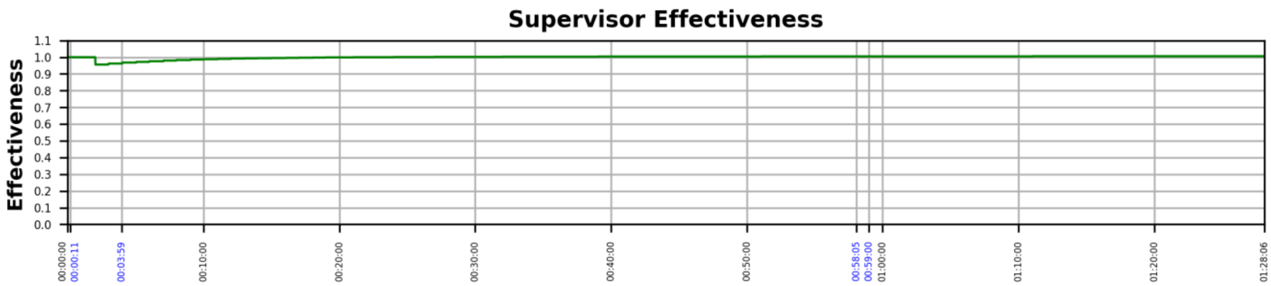
Figure 92. An example of the overall ignition area divided into two subregions, with measurement details.

B.3 NOMINAL USE CASE RESULTS FIGURES

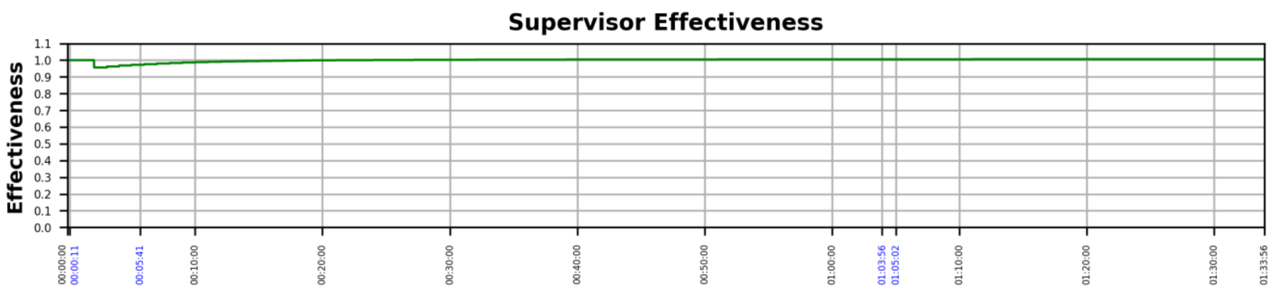
This appendix provides the effectiveness graphs for the nominal use case by team size in Figure 93.



(a) The 4 UAV team size.



(b) The 6 UAV team size.



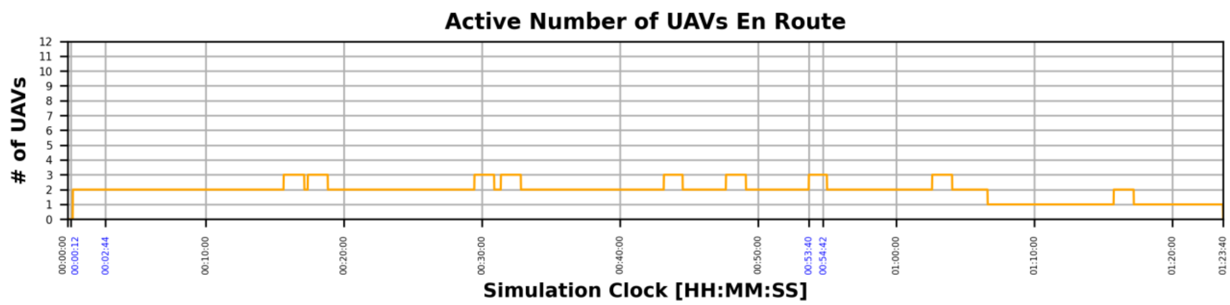
(c) The 11 UAV team size.

Figure 93. The SAFTE model's Effectiveness results for a single nominal use case (the Supervisor has slept 8 hours each of the last four nights) trial by UAV team size: (a) 4 UAVs, (b) 6 UAVs, and (c) 11 UAVs. The blue time points represent only four distinct moments during the mission, in order: mission plan execution, the start of the Ignition phase of the mission plan, the end of the Ignition phase, and the extension of the Surveillance UAVs.

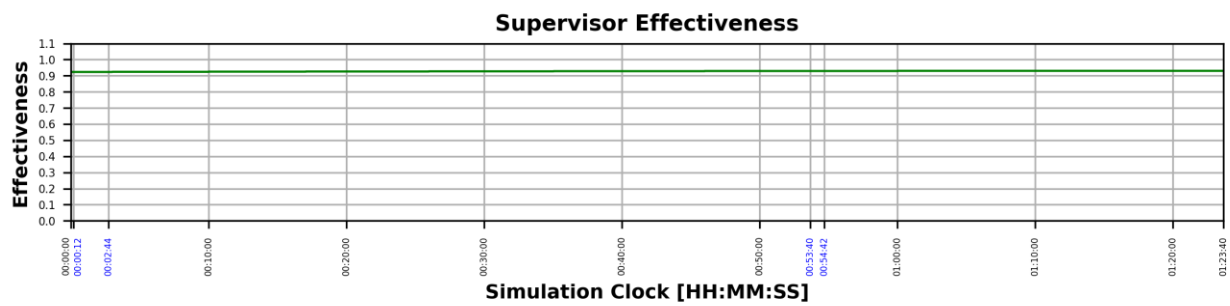
B.4 FATIGUE DISTRACTION USE CASE RESULTS FIGURES

This appendix provides figures for the Number of Deployed UAVs, the SAFTE model's effectiveness values, and Overall Workload for the example Fatigue distraction events by Number of UAVs in the team. The same random seed number was used for the trials featured in the provided results.

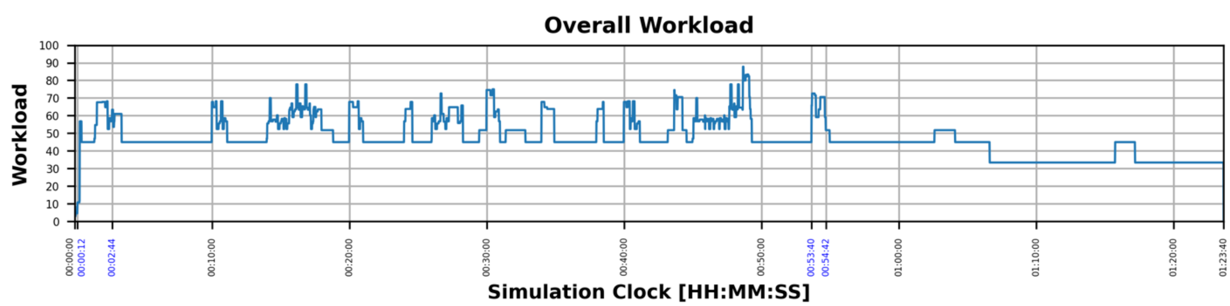
Teams with 4 UAVs



(a) The number of active UAVs.

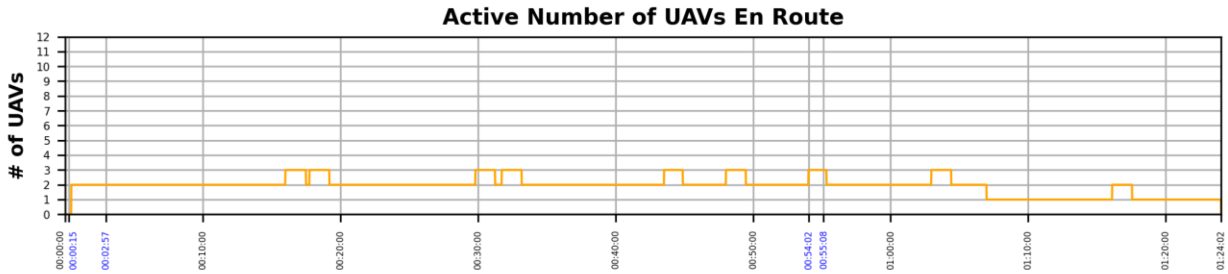


(b) The Supervisor's efficiency.

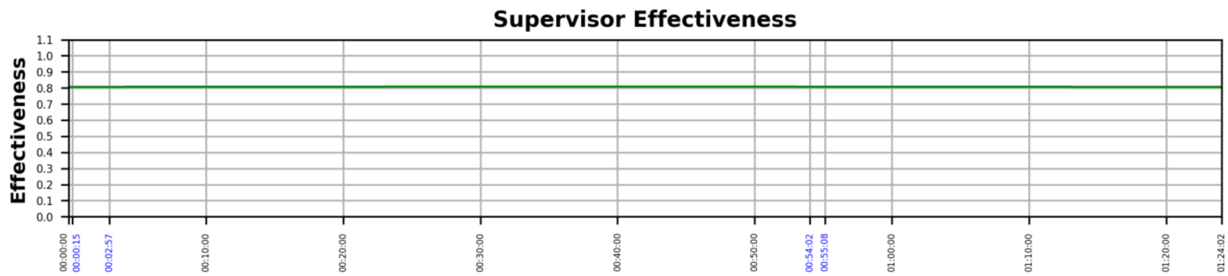


(c) The Overall Workload.

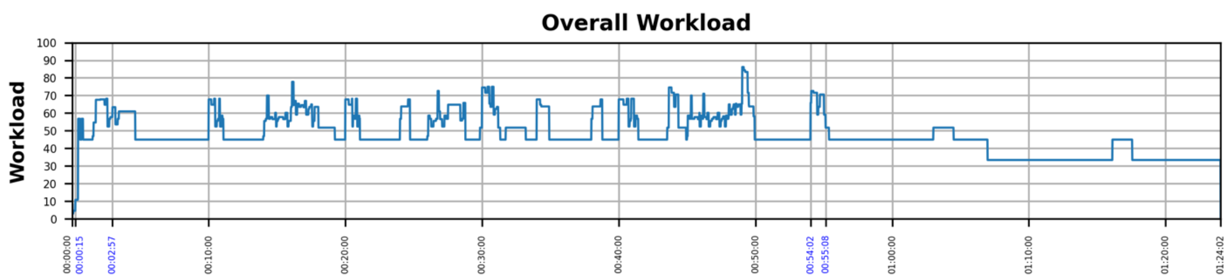
Figure 94. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 4 UAVs, where the Supervisor has slept 6 hours each of the last four nights.



(a) The number of active UAVs.



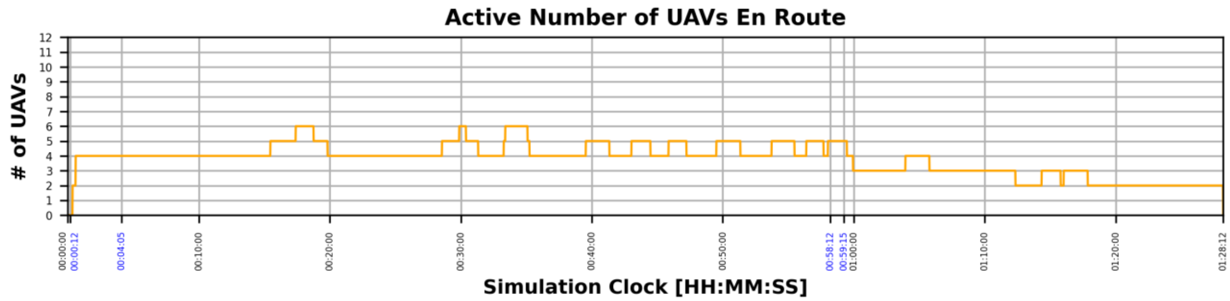
(b) The Supervisor's efficiency.



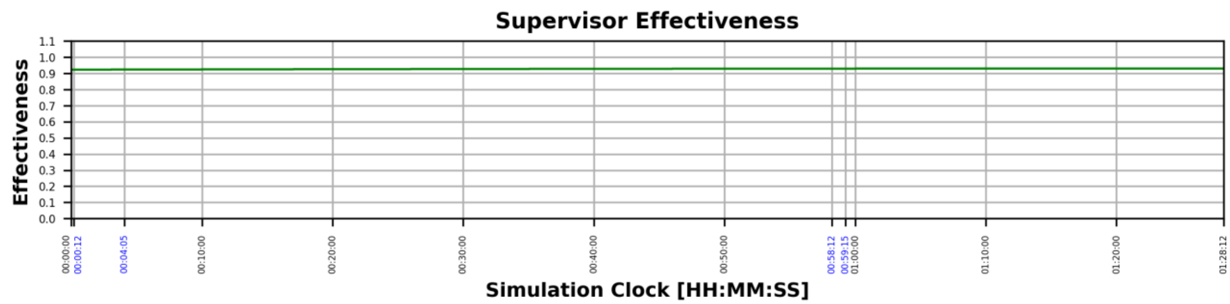
(c) The Overall Workload.

Figure 95. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 4 UAVs, where the Supervisor has slept 4 hours each of the last four nights.

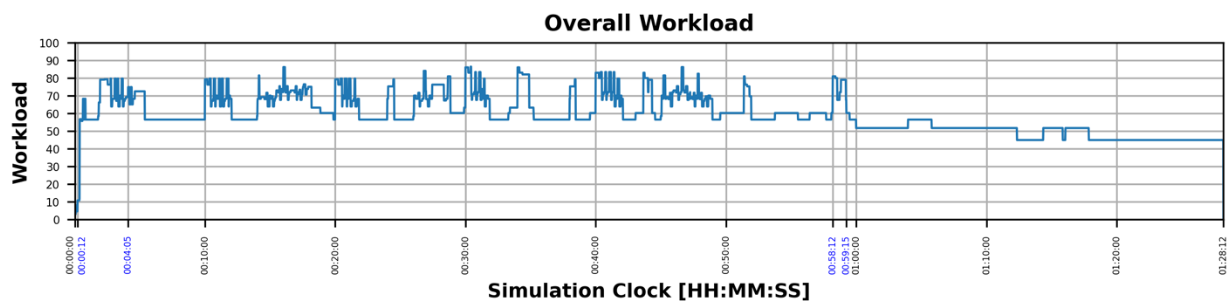
Teams with 6 UAVs



(a) The number of active UAVs.

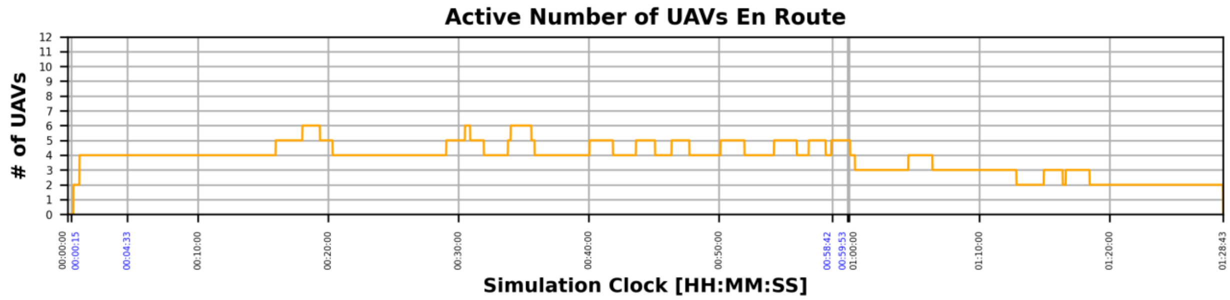


(b) The Supervisor's efficiency.

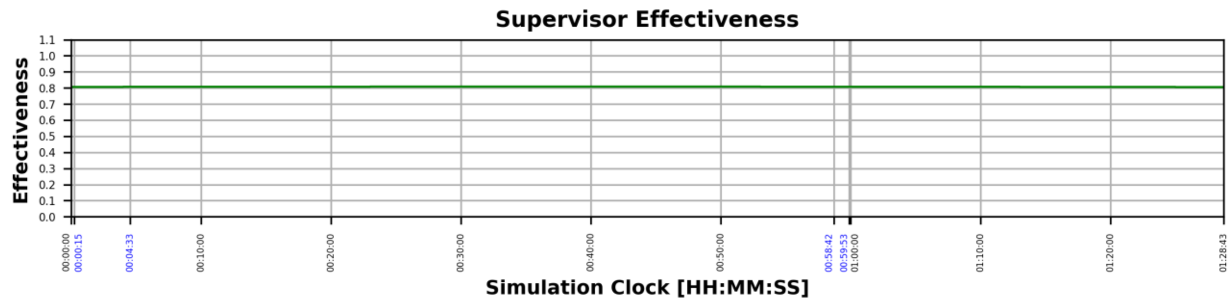


(c) The Overall Workload.

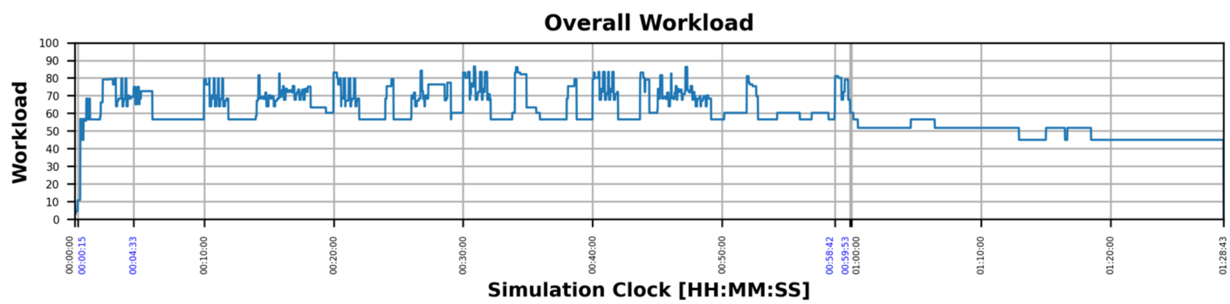
Figure 96. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 6 UAVs, where the Supervisor has slept 6 hours each of the last four nights.



(a) The number of active UAVs.



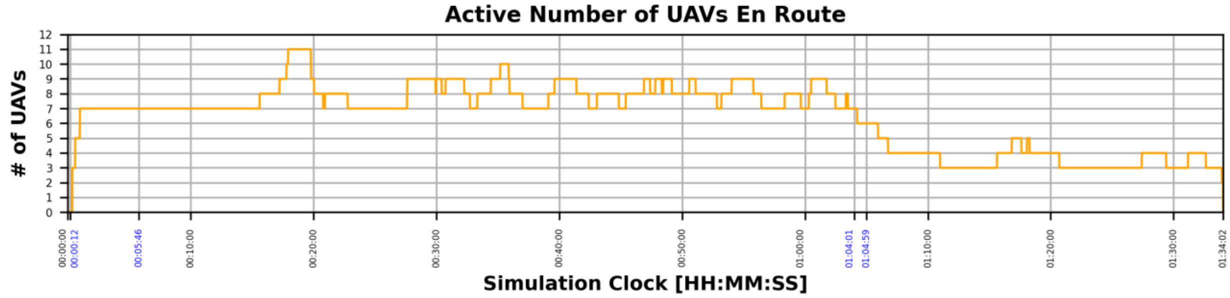
(b) The Supervisor’s efficiency.



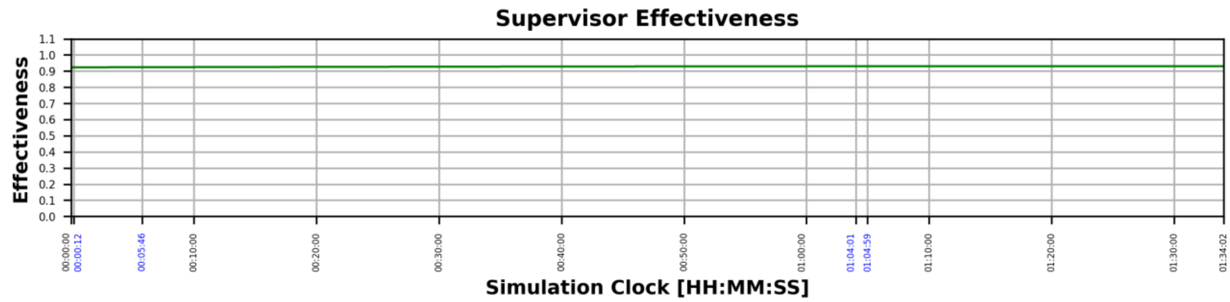
(c) The Overall Workload.

Figure 97. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 6 UAVs, where the Supervisor has slept 4 hours each of the last four nights.

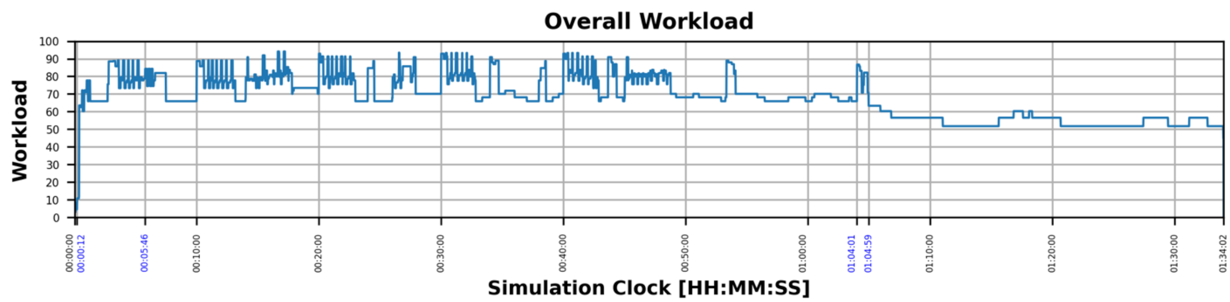
Teams with 11 UAVs



(d) The number of active UAVs.

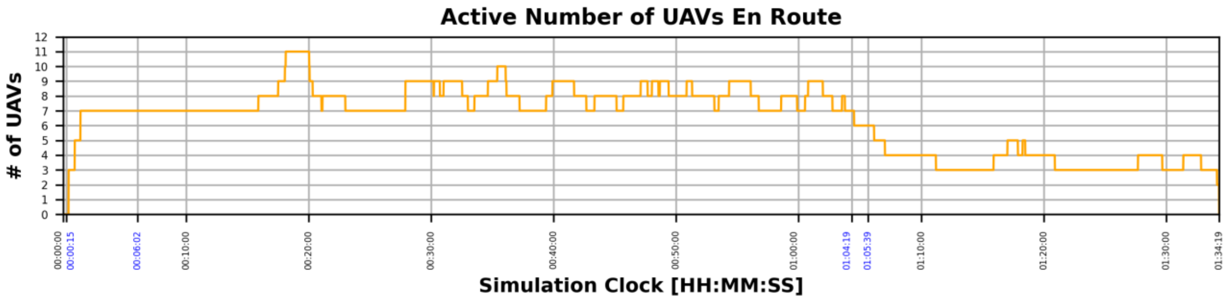


(e) The Supervisor's efficiency.

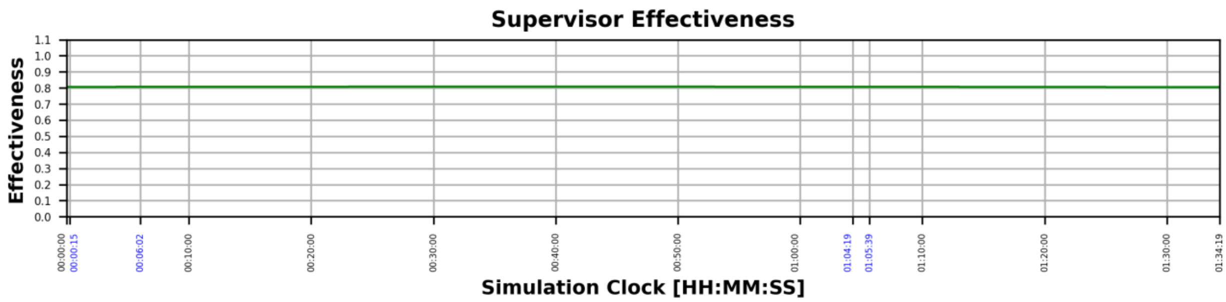


(f) The Overall Workload.

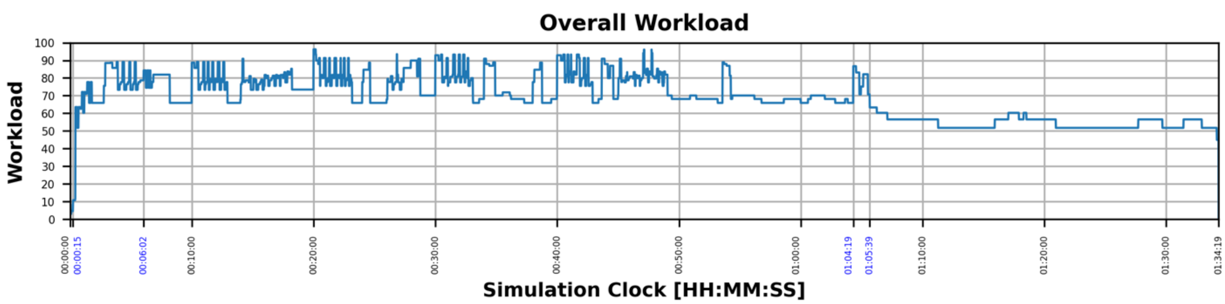
Figure 98. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 11 UAVs, where the Supervisor has slept 6 hours each of the last four nights.



(d) The number of active UAVs.



(e) The Supervisor's efficiency.



(f) The Overall Workload.

Figure 99. Example Number of active UAVs, Supervisor Effectiveness, and Overall Workload results for a team of 11 UAVs, where the Supervisor has slept 4 hours each of the last four nights.

C. GRAPHICS SOURCES

This appendix lists the graphics sources for Figure 38.

The Rocky Mountain Ridgeline Photo, by Hal Bergman Photography, Flickr: https://www.flickr.com/photos/pyrokinetic/4855350054/.

The humans holding "tablet devices" (i.e., Supervisor and Communications lead) and the Logistics coordinator: CanStockPhoto: https://www.canstockphoto.com/man-controlling-drone-quadcopter-28774472.html .

The UAV image: iStock by Getty Images https://www.istockphoto.com/illustrations/uav-silhouette.

The Fire image: Vecteezy, https://www.vecteezy.com/vector-art/3240818-fire-icon-vector-illustration-in-flat-design.