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Mixed-Initiative Strategies for Real-time Scheduling of Multiple Unmanned Vehicles

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Abstract— **Advances in autonomy have made it possible to invert the typical operator-to-unmanned vehicle ratio so that a single operator can now control multiple heterogeneous Unmanned Vehicles (UVs). Real-time scheduling and task assignment for multiple UVs in uncertain environments will require the computational ability of optimization algorithms combined with the judgment and adaptability of human supervisors through mixed-initiative systems. The goal of this paper is to analyze the interactions between operators and scheduling algorithms in two human- in-the-loop multiple UV control experiments. The impact of real-time operator modifications to the objective function of an optimization algorithm for multi-UV scheduling is described. Results from outdoor multiple UV flight tests using a human-computer collaborative scheduling system are presented, which provide valuable insight into the impact of environmental uncertainty and vehicle failures on system effectiveness.**

I. Introduction

UNMANNED vehicle (UV) operations have increased dramatically over the past decade [1-3]. Typical UV operations, however, require more human operators than a comparable manned vehicle requires [1]. There is increasing pressure to reduce the training costs and manning requirements per vehicle [1] while expanding UV operations [2]. This can be achieved by leveraging advances in autonomy for both individual vehicle navigation [4] and multiple vehicle coordination [5]. The United States Department of Defense envisions a future with single operator control of multiple heterogeneous (air, sea, land) UVs [3].

A variety of computer optimization algorithms have been developed to address the problem of scheduling tasks for multiple UVs [6-8]. While varying in their method of formulating the scheduling problem and solving the optimization, most of the approaches available utilize a completely autonomous scheduler with little to no human input during the development of the schedule.

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A mixed-initiative scheduling system, where a human guides a computer algorithm in a collaborative process to solve the scheduling problem, could best handle a realistic scenario with unknown variables, possibly inaccurate information, and dynamic environments. Though fast and able to handle complex computation far better than humans, computer optimization algorithms are notoriously "brittle" in that they can only take into account those quantifiable variables identified in the design stages that were deemed to be critical [9, 10]. Human operators can aid algorithms in dealing with unforeseen problems, such as weather variations and unexpected movement of targets, which automated planners often have difficulty accounting for and responding to [11].

A number of studies have shown that humans collaborating with computer algorithms can achieve higher performance than either the human or the algorithm alone under certain conditions [12-15]. While extensive research has been conducted to develop better algorithms for planning, comparatively little research has occurred on the strategies employed by humans working with mixed-initiative systems, especially when working in dynamic, time-critical situations with high information uncertainty [16].

The goal of this paper is to analyze the interactions between operators and scheduling algorithms in two human-in-the-loop multiple UV control experiments. Both experiments used the same multiple UV control system, as described in Section II. The real-time scheduling process utilized by this system is explained in more detail in Section III. We found that the ability for operators to clearly communicate their goals to the automated planner improved performance and was essential to establishing trust. Results from simulation experiments and outdoor flight tests are presented, where we found that operators were working harder to control fewer vehicles than in simulation. These experiments provide valuable insights into the impact of operator modifications of the objective function of the automated planner as well as the impact of environmental uncertainty and vehicle failures on system effectiveness.

II. Multiple UV Control System

Both experiments utilized a collaborative, multiple UV simulation environment called Onboard Planning System for UVs Supporting Expeditionary Reconnaissance and Surveillance (OPS-USERS), which leverages decentralized algorithms for vehicle routing and task allocation. Operators controlled multiple, heterogeneous UVs for the purpose of searching the area of interest for new targets, tracking targets, and approving weapons launch. All targets were initially hidden, but once a target was found, it was designated as hostile, unknown, or friendly, and given a priority level by the user. Hostile targets were tracked by one or more of the vehicles until they were destroyed by a Weaponized Unmanned Aerial Vehicle (WUAV). Operators were presented with imagery of the target to allow them to verify the classification of the target as hostile, after which they had the final decision to approve all weapon launches. Unknown targets were revisited as often as possible, tracking target movement. A primary assumption was that operators had minimal time to interact with the displays due to other mission-related tasks.

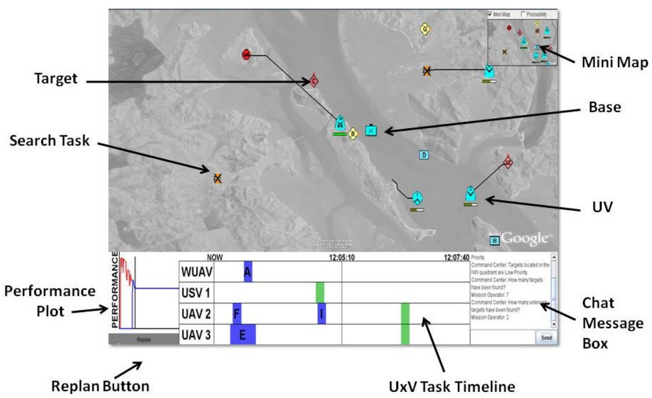

Fig. 1. The Map Display.

The primary interface used by the operator is a Map Display, shown in Fig. 1. The operator commands the UVs in collaboration with the automation by creating search tasks in the Map Display and then choosing a schedule generated by the automation that assigns vehicles to tasks. Operators had two exclusive tasks that could not be performed by automation: target identification and approval of all WUAV weapon launches. The operator compares and selects task schedules through a second display called the Schedule Comparison Tool (SCT), shown in Fig. 2.

A task-based, decentralized implementation was chosen for the automated planner to allow rapid reaction to changes in the environment [17]. The task planner used in OPS-USERS is the Consensus Based Bundle Algorithm (CBBA), a decentralized, polynomial-time, market-based protocol that can generate new schedules on the order of seconds [18]. The human operator provides high-level *task-based* control, as opposed to more low-level *vehicle-based* control, by approving which tasks should be completed by the vehicles. The vehicles then utilize CBBA to allocate tasks amongst themselves in a decentralized manner.

In such architectures, operators do not directly individually task a single vehicle. When appropriate, the decentralized task planner can modify the tactical-level plan (at the vehicle level) without human intervention, which includes changing the task assignment without affecting the overall plan quality (i.e., agents switch tasks). The CBBA algorithm is able to make these local repairs faster through inter-agent communication than it could if it had to wait for the next update from the human operator.

CBBA consists of two phases that alternate until the assignment converges. In the first phase, task selection, UVs place bids on the set of tasks for which they receive the highest reward. In the second phase, conflict resolution, plan information is exchanged between neighbors and tasks go to the highest bidder. Each individual UV only needs to know the bids of the other UVs, not the locations or trajectories of the other UVs. CBBA is guaranteed to reach a conflict-free assignment, given a strongly connected network [18].

One key advantage of CBBA is its ability to solve the multiple assignment problem where each UV is assigned a set of tasks (a plan), as opposed to solving the single assignment problem, where each UV is only assigned to their next task. Planning several tasks into the future improves effectiveness in complex missions. Also, plans can be carried out even if the communication link with the ground control station is intermittent or lost. The architecture is scalable, since adding additional agents also adds computational capability, and the decentralized framework is robust to a single point of failure, since no single agent is globally planning for the fleet [18].

Operators were shown the results of the scheduling algorithm through the SCT, a decision support interface, shown in Fig. 2. The display showed the high-level performance metrics of each schedule, as well as unassigned high, medium, and low priority tasks that could not be completed by one or more of the vehicles due to constraints on vehicle resources. If the operator was unhappy with the automation-generated schedule, he or she could create new tasks or conduct a “what-if” query process by dragging the desired unassigned task into the large center triangle. This query forces the automation to generate a new plan if possible that prioritizes a particular task, in effect forcing the decentralized algorithms to re-allocate the tasks across the UVs. Details of the interface design and usability testing are provided in previous research [19].

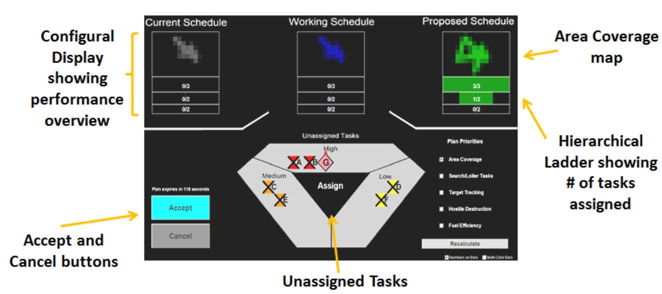

Fig. 2. The Schedule Comparison Tool (SCT).

III. Real-time Mixed-Initiative Scheduling Process

To evaluate the potential benefits of the real-time mixed-initiative scheduling process utilized by this testbed, the Human-Automation Collaboration Taxonomy (HACT) was employed. HACT was developed to provide system designers with a model that can be used to analyze collaborative human-computer decision making systems [20, 21]. HACT extends the Parasuraman [22] information processing model by adding an iterative data analysis stage combined with an evaluation step where operators can request more information or analysis, as shown in Fig. 3.

The authors of HACT included three distinct roles in the decision-making process: the moderator, generator, and decider. The moderator is responsible for ensuring that each phase in the decision-making process is executed and that the process moves forward. The generator develops feasible solutions and begins to evaluate the solutions. Finally, the decider makes the final selection of the plan and has veto power over this selection. Each of these roles could have different Levels of Collaboration (LOC) between human and computer, qualitatively rated with integer categories from -2 where the role is entirely assumed by the automation, to 2 where the human is responsible for the role. A LOC of 0 is a balanced collaboration between the human and automation.

HACT's ability to delineate degrees of collaboration between the human and computer at different points in the decision-making process makes it well suited to model the collaborative scheduling process used by the testbed in this effort. The moderator role in this process was assigned to level 2 because the human operator fully controls the replanning process by deciding when to replan, modify the plan, and accept a final plan. The operator cannot change the criteria to evaluate plans and can only modify the plans by attempting to assign tasks through the "what-if" process. Therefore, the generator role was assigned to level -1, which indicated a mixed role, but with a larger automation presence. Finally, the decider role was assigned to level 1, since the automation presented a final solution to the operator, but the selection of the final solution was completely up to the human operator and the automation did not have veto power.

The HACT framework was extended and slightly modified to illustrate two specific human-automation collaborative scheduling techniques in OPS-USERS, as shown by the red lines in Fig. 3. The first was the "what-if" sensitivity analysis tool that already exists in the testbed. The second was a proposed method to allow the human operator to modify the weightings of optimization variables in the objective function of the automated planner during a mission.

As previously discussed, the operator can query the automated planner in a "what-if" manner to determine the feasibility and performance consequences of adding a task to the schedule of the UVs. As shown in Fig. 3, this process occurs when the human operator is in the decider role, looking at a proposed plan that has been selected by the automated planner. The human operator essentially modifies the constraints placed on the schedule, by specifying that a specific task be assigned in the schedule. These changes send the automated planner back into the generator mode, to recalculate potential solutions to the optimization problem. Many iterations of this "what-if" loop would be required to achieve a solution that the human operator desires, especially if the automated planner is choosing solutions based on an objective function that does not place an emphasis on the quantities of interest to the human operator at that point in the mission.

As illustrated in Fig. 3, providing the operator with the capability to modify the objective function of the automated planner could result in a shorter loop within the collaborative decision-making process than the "what-if" loop. This changes the method by which the automated planner would select the best solution, which occurs in the decider role. In terms of the HACT framework, it would change the LOC designation for the decider role from -1 to a more balanced collaborative level of 0. The human operator would have the ability to modify the way that the automation evaluates plans

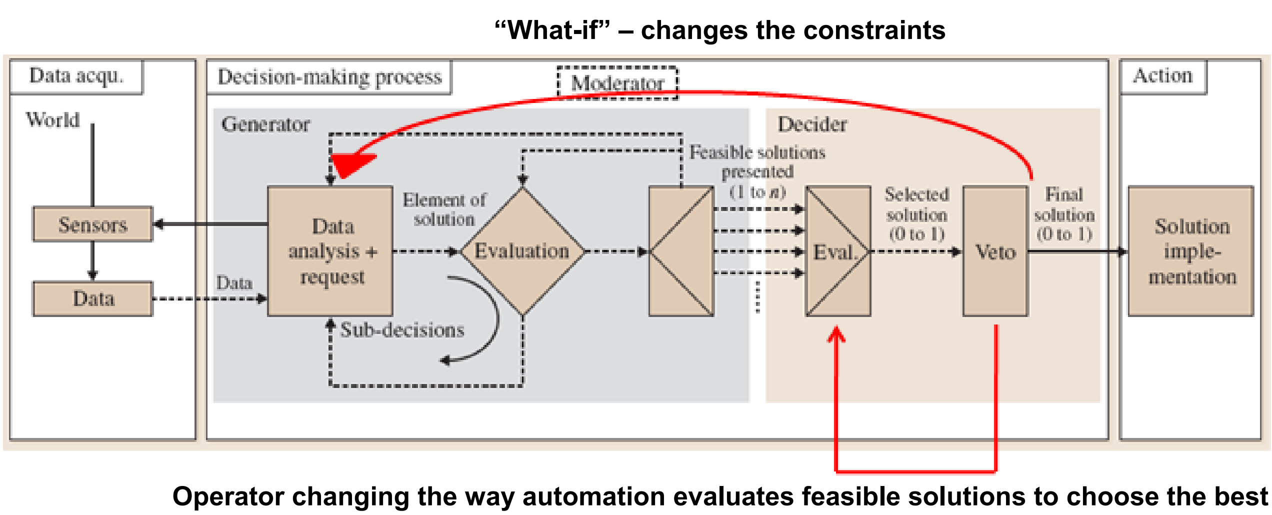

Fig. 3. Modified HACT Model with Dynamic Objective Function.

by changing the weightings in the objective function. Positive performance results have been shown in previous research where the human operator could change the search space of the automation [15] or modify the way that the automation evaluates plans [23], even under time-pressure [24].

In a highly dynamic environment and scenario, aligning the objectives of the operator and automated planner is crucial. Providing the operator with a dynamic objective function could reduce the number of cognitive steps and amount of time necessary for the combined human-automation team to evaluate and select a new schedule. The impact of a dynamic objective function is evaluated in the next section along with the results of outdoor flight tests.

IV. Case Studies in Real-time Mixed-Initiative Scheduling: From Laboratory Experiments to Outdoor Flight Tests

Two human-in-the-loop multiple UV control experiments using the OPS-USERS testbed were conducted. First, the OPS-USERS interface was modified slightly to allow the operator to either choose one quantity or choose any combination of equally weighted quantities for the automated planner to use in evaluating mission plans. To compare the performance and workload of operators using these dynamic objective functions against operators using a static objective function, an experiment was conducted where 30 participants performed two 20-minute long simulated UV missions [25]. Each scenario had 10 targets initially hidden to the operator. Some of the operators could adjust the objective function of the algorithm in the SCT, as shown in Fig. 2, while others had a static objective function. It was assumed that all UVs and sensors operated normally throughout the mission.

OPS-USERS was also adapted to operate with real UVs in an uncontrolled, outdoor environment [26]. The purpose of the effort was to demonstrate the technology in the context of a real-world operational scenario and to incorporate design elements into the system to make it robust to unpredictable hardware failures. Eight outdoor flight tests were conducted at Fort Devens, Massachusetts, with three quadrotor helicopters carrying video cameras that could broadcast images to the command center and one fixed wing Unmanned Aerial Vehicle (UAV). One operator, who was very familiar with the entire system, conducted all of the missions. Each scenario had three targets initially hidden to the operator and target detection was automated based on the GPS position of the target. The average mission length was 22 minutes.

Additions to the system included a high-level health monitoring system that was implemented to alert the operator of potential health degradations in the UVs (e.g. failures in communications or GPS tracking). In addition, the operator could a) command an individual vehicle to hold its current position and temporarily allow other UVs to accomplish its tasks or b) remove a UV entirely, with the capability to repair or replace it without needing to stop and restart the mission.

A number of insights can be gained from these two experiments. First, general lessons learned from both tests are shared. Second, the impact of a highly uncertain outdoor environment with vehicle failures on operator and system performance is analyzed.

A. *OPS-USERS in Simulation and in Flight*

Requirements for future real-time mixed-initiative scheduling systems can be derived from the results of both experiments:

1) Allow operators to communicate their goals to the automated planner as clearly as possible. In the simulation experiment, one group of operators could only choose one of the five objective function variables at a time to be their highest priority for evaluating plans. Another group of operators had a “multi-objective” option, which enabled them to choose any combination of these quantities as high priority. By providing operators with multiple options and the capability to communicate their goals more clearly to the automated planner, it halved the number of times that the operator had to modify the objective function of the automated planner [25]. This supports the findings from the previous HACT analysis and it appears that the multi-objective function increased automation transparency and decreased “brittleness.” It is likely why operators using the multi-objective function generally rated their confidence and performance higher [25].

In the outdoor flight tests, the operator merged potentially conflicting information coming in from a variety of intelligence sources available during the mission. He then made decisions about the priorities of various tasks and how those priorities changed throughout the mission. By allowing the operator to communicate his or her priorities to automation, the algorithm could quickly decide how to allocate vehicles to handle the highest priority tasks, freeing up the operator to focus on how the mission was progressing.

2) Enhancing operator Situational Awareness (SA) and managing operator workload are crucial to preventing errors. Operators who were limited to single-objective optimization, and thus were limited in their ability to collaborate with the automation, were the only operators who violated any Rules of Engagement [25]. These errors could have been caused by the lower measured SA of this group and because it appears that they were working harder by making double the amount of changes to the objective function throughout a mission [25].

The use of multi-objective optimization, which encouraged greater operator engagement, may have caused this enhanced SA. Operators who could interact with the system were more actively involved with goal management, which also led to improved performance of secondary tasks, such as answering queries measuring SA. Additionally, at certain points during the mission, operators with access to a dynamic objective function were able to respond more quickly to queries than operators using a static objective function. This suggests that these operators had higher spare mental capacity, however, overall utilization (% busy time) and subjective workload measures show that there were no differences in overall workload across the three objective function types.

In comparing workload levels between the simulation experiment and outdoor flight tests, the primary workload measure was a utilization metric calculating the ratio of the total operator "busy time" to the total mission time. For utilization, operators were considered "busy" when performing one or more of the following tasks: creating search tasks, identifying and designating targets, approving weapons launches, interacting via the chat box, replanning in the SCT, or using the health monitoring panel (which was unique to the outdoor flight trials).

Differences between the two tests needed to be taken into account for this comparison. As the number of targets in the mission is a large driver of workload, the utilization metric across the two studies was normalized by the number of targets in each test, ten for the simulation experiments and three for the outdoor flight tests. In addition, there was a difference in speed between the vehicles, with the simulated UVs moving faster than the real UVs outdoors. The larger number of targets and faster UVs were utilized in the simulated environment to create a more challenging mission that might lead to differences in performance based on different operator strategies.

The results of the workload comparison showed that when normalized by the number of targets in the mission, the operator was working harder in the outdoor mission ($p<0.001$). The average normalized utilization was 4.2% (SD=0.82%) for the simulation experiments and 7.9% (SD=2.1%) for the outdoor flight tests. Despite the need for normalization, it is clear that operators were working harder in the outdoor missions considering that there were more than three times as many targets in simulation, with faster vehicles, but the average non-normalized utilization was only 78% greater (42.1% for simulation versus 23.6% for the outdoor flight tests). This increased workload in the outdoor missions can likely be attributed to the need to monitor the health and status of the vehicles, as discussed later in Section B.

3) Automation "brittleness" can be avoided through careful design choices. Two design decisions in the OPS-USERS system a) illustrate automation "brittleness" and b) show a method for dealing with brittleness. First, in the outdoor tests, a hierarchical system was used to determine which vehicle had priority in path planning for collision avoidance. By utilizing this system, however, a lower priority vehicle was temporarily forced to move away from a target that it was tracking, causing the target to be lost. As shown in Fig. 4, UAV 2 was the lower priority vehicle that was forced to move away from tracking Target J as the WUAV flew by. While this problem could be resolved through dynamically ordering the priority of vehicles throughout the mission, it is a representative example of automation brittleness, where the automation worked exactly as designed, but in a way that may not have been appropriate at the time due to the complex nature of a command and control mission.

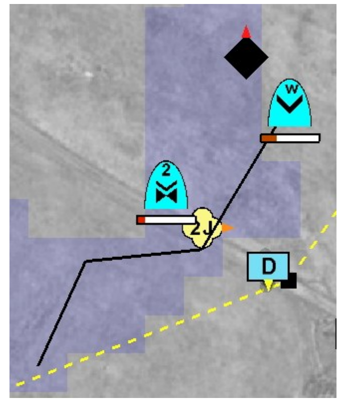

Fig. 4. Automation "brittleness" caused UAV 2 to lose Target J

In the simulation experiment, by limiting some operators to only single-objective optimization capabilities, we experimentally induced automation brittleness. Despite this, there were no significant differences in system performance between operators using either the dynamic or static objective functions [25]. How did this occur?

Further analysis of the simulation experiment data showed that operators who were limited to only single-objective optimization capabilities chose to perform more "what-if's" via the SCT than multi-objective operators in order to obtain acceptable plans from the automated planner. There was a marginally significant difference ($p=0.085$) in the number of "what-if's" between single-objective (Mean=9.95, SD=5.90) and multi-objective operators (Mean=7.00, SD=4.30). When faced with a more brittle system, that did not allow them to communicate as clearly to the automation, "what-if" sensitivity analysis may have contributed to these operators' ability to maintain the same performance level as the other operators. Operators attempted at least one "what-if" approximately 30% of the time that they entered the SCT. When a "what-if" query was conducted, only one "what-if" query was necessary 94% of time.

It should be noted that in the outdoor experiment, the number of "what-if's" was much lower, on average 1.5 per mission. The operator attempted at least one "what-if" only 12% of the time that they entered the SCT to replan. The lower number of "what-if's" can likely be attributed to two facts. First, the operator for the outdoor experiments was highly experienced with the system and understood the inner workings of the algorithm. Thus, he felt less of a need to question the automation-generated schedules. Second, with fewer targets, the system resources (i.e. the vehicles themselves) were rarely at full capacity. If the system was not operating at full capacity, then trade-offs were not needed, as all tasks could be scheduled. "What-if" queries are only valuable if the system is constrained by the available resources.

4) The system must aid operators in understanding how the algorithm is performing. Subjective operator assessments of the algorithm collected after both simulated and real outdoor missions showed that operators were often confused about why the algorithm produced certain schedules. A few participants reported that they were frustrated because of *perceived* sub-optimal automation performance [25]. As was shown in previous experiments [27], a common complaint from participants was a desire for increased vehicle-level control, as opposed to only task-level control. Fifty-three percent of all simulation experiment subjects wrote about wanting to manually assign vehicles to certain tasks because they disagreed with an assignment made by the automation.

These participants had little knowledge of the inner workings of the task allocation and path planning algorithm and thus it is likely that they were not aware of all of the variables and constraints that the algorithm took into account when creating plans. This is likely representative of future real-world operations, where human controllers will have limited knowledge of exactly how the "black box" automation works. When the final plans did not seem "logical" to the operator (regardless of the actual plan quality), trust in the automated planner decreased. Informing operators about algorithm performance in real-time and understanding how and why operators perceive algorithms to be suboptimal are crucial to future system designs.

B. The Impact of Uncertain Environments and Vehicle Failures on Operator and System Performance

The adaptation of OPS-USERS for outdoor flight tests was generally successful, as the system worked well in executing the mission, planning paths for the UVs, allocating tasks to the UVs, and conducting the given tasks. Based on the results, a number of valuable insights were gained from outdoor flight testing with regards to real-time human-computer collaborative scheduling in a highly uncertain environment with vehicle failures:

1) Health monitoring greatly increased operator workload. The workload for monitoring both the health and altitude of the UVs was so high that it needed to taken on by a second human operator to allow the primary operator to run the mission. The altitude monitoring could be remedied by more reliable sensors on board the vehicles. Health monitoring, however, is a very significant problem for single operator control of multiple UVs and even with highly automated vehicles may drive workload to unacceptably high levels. More highly automated health monitoring, error detection, and self-repair are necessary before single operator control of multiple UVs becomes feasible.

2) In real-world operations, the operator must be allowed to override the automation in case of failures. It was discovered during operations that the automated planner had a poor model of battery discharge rate, due both to environmental uncertainty, such as wind, and the hardware that was chosen for use. This caused the automation to be indecisive about scheduling refuel times. More advanced vehicles have already been developed with better models of fuel usage and better prediction of flight time remaining. However, had this been an operational system, allowing the human operator to be able to override the automation when it entered this indecisive mode would have been crucial to mission success and vehicle safety.

3) Robustness to real-world hardware failures and environmental uncertainty is challenging. Overall, from a planning and scheduling perspective, the system was fairly robust to hardware failures. The ability to remove and then re-engage a vehicle from the system was crucial for dealing with hardware issues. The decentralized implementation was also robust to poor communications between the vehicles.

Two specific examples of environmental uncertainty created challenges for the scheduling system. First, imperfect waypoint tracking (due to wind, GPS noise, etc.) caused the automation to occasionally "churn" or alternate rapidly between two plans for how a vehicle would travel around an obstacle or avoid a collision. This sometimes resulted in travel delays or erratic paths. While the automation eventually made a decision without major impact to the mission, churning behavior can reduce operator confidence and trust in the automation, factors which have been shown to influence system performance [28].

Second, scheduling multiple vehicles to perform tasks that have highly uncertain time lengths is a very challenging scheduling problem. Due to this uncertainty in task time lengths, a design decision was made for these outdoor flight tests to create conservative schedules with short planning horizons. Each vehicle typically was assigned only a single task at a time and assumed that it would be performing that task infinitely, until the vehicle was notified either by the operator or another source that the task was complete. It is debatable as to whether this was the right choice for a highly dynamic mission with new tasks being created throughout the mission or whether it caused vehicles to avoid taking on multiple tasks that they were capable of accomplishing. Future work could include attempts to estimate the time length of certain tasks to allow for a longer planning horizon.

4) There are a number of subjective factors that are difficult for algorithms to take into account in missions with high uncertainty. Human judgment, of both operators and safety pilots, played a crucial role in a number of areas. The operator had to subjectively determine when enough intelligence had been collected about the area of interest to proceed to the next portion of the mission. Sometimes the camera imagery of targets was unclear or blurry and classification of a target as friendly, unknown, or hostile required a subjective assessment. Safety pilots had to use their own judgment to determine how "well" a vehicle was behaving and whether it needed to be taken out of the mission. Safety pilots had to understand that vehicle behavior changed as battery levels reached critical levels, causing landing to become difficult.

V. Conclusion

Utilizing advances in autonomy, a system has been designed and utilized for single-operator decentralized control of multiple heterogeneous UVs. This system leverages mixed-initiative scheduling, where a human operator collaborates with an optimization algorithm to assign tasks to the UVs in real-time. Insights from two experiments using this system were presented. Both a simulation experiment and outdoor flight tests showed that operators must be able to communicate their goals to the automated planner as clearly as possible. A key insight for system designers is that operators benefit from the ability to modify the objective function of the automated planner in real-time. Managing operator SA, workload, and trust in the automation are crucial to system performance, along with implementing design interventions to avoid automation brittleness. Finally, environmental uncertainty and hardware failures make for a much more challenging operational environment, but a mixed-initiative scheduling system can overcome these challenges by combining the computational ability of optimization algorithms with the judgment and adaptability of human supervisors.

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