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Incorporating Human Factors Considerations in Unmanned Aerial Vehicle Routing

Abstract—**Unmanned aerial vehicles (UAVs) have become increasingly valuable military assets and reliance upon them will continue to increase. Despite lacking an on-board pilot, UAVs require crews of up to three human operators. These crews are already experiencing high workload levels, a problem that will likely be compounded as the military envisions a future where a single operator controls multiple UAVs. To accomplish this goal, effective scheduling of UAVs and human operators is crucial to future mission success. We present a mathematical model for simultaneously routing UAVs and scheduling human operators, subject to operator workload considerations. This model is thought to be the first of its kind. Numerical examples demonstrate the dangers of ignoring the human element in UAV routing and scheduling.**

Index Terms—**Integer programming, Aircraft control human factors, Human-machine interactions, Cooperative systems, Scheduling**

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), which were first deployed for surveillance purposes and are now capable of launching missile strikes, have become increasingly valuable assets to the U.S. Armed Forces. In 2007, up to 15 U.S. Air Force UAVs were in use somewhere in the world at any given time; by the summer of 2011 that number had increased to 60 [1]. While UAVs do not have onboard pilots, these aircraft require a significant amount of human interaction. For example, the Air Force's MQ-1 Predator UAV employs a ground crew of three, including a pilot, a sensor operator and a mission intelligence coordinator [2]. The importance of humans to UAV effectiveness is stated succinctly in the 2010–2035 U.S. Army Unmanned Aircraft Systems Roadmap [3]: "Unmanned systems are only as capable as their human operators."

These operators are already exposed to the high-demand, high-tempo of UAV operation tasks [4], [5]. According to a recent survey study on the occupational burnout of UAV operators in which 600 Predator/Reaper operators and 264 Global Hawk operators participated, 27% and 15% of the Predator/Reaper group responded that they were "stressed" and "very to extremely stressed," respectively; 31% and 19% of the Global Hawk Group did so [4]. Excessive occupational stresses degrade operators' quality of life and could hinder recruiting and retention of UAV operators.

This problem is likely to be exacerbated, as the military seeks future operators to simultaneously control multiple UAVs from a single ground station [3]. While advances in automation will facilitate the achievement of this goal, much of the technology is immature and will not be implemented in the near term. Furthermore, some activities will likely never be automated, as "It is widely accepted that weapons release will always have a human decision maker responsible for the judgment of the engagement" [3]. Therefore, it is likely that human operators will be called upon to multitask more. Unfortunately, overload due to multitasking during UAV control tasks can compromise task performance [6] and increase the likelihood of a mishap or mission failure [7], [8].

Various human factors studies have investigated different means to mitigate operator overload problems associated with unmanned vehicle control missions, including automation [9]–[11] and multi-modal interface design [12], [13]. Also, many empirical studies have investigated the effects of operator-to-vehicle ratio on performance and workload [14]–[16]. Most of these past studies were focused on addressing workload issues or enhancing performance at the single operator/workstation level. Few studies seem to have considered coordinating multiple human and machine assets through task scheduling at the global system level so as to ensure achieving overall mission objectives with limited human and machine resources. In fact, the authors are not aware of any such studies at the moment.

The objective of this paper is to develop a mathematical programming model, appropriate for generating initial mission plans, that effectively schedules both vehicles and humans to time-sensitive, geographically-dispersed tasks. We empirically demonstrate the impact of neglecting human factors considerations when developing aircraft routes, and show how overall mission effectiveness may be improved by incorporating human factors elements into the routing of unmanned aircraft. Such an approach is critical to meet the military's goal of increasing the ratio of aircraft controlled by personnel. While the proposed model was inspired by UAV operations, it has broader applications for unmanned land- or sea-based vehicles.

This paper is organized as follows. A detailed problem description is provided in Section II. Section III contains a review of relevant literature pertaining to aircraft routing and UAV operator performance. A mathematical programming formulation for UAV routing and operator scheduling is proposed in Sections IV and V. Section VI provides a numerical example to demonstrate the need for such a model. Finally, a summary and suggestions for further research are contained in Section VII.

II. PROBLEM DESCRIPTION

We consider a fleet of heterogeneous UAVs that are assigned to perform a variety of geographically-dispersed priority-based tasks. Each task must be performed within a pre-defined time window, thus reflecting the time-critical nature of this problem. UAVs may have differing capabilities, based on their configurations, operating characteristics, environmental conditions, and payload (e.g., infrared cameras or a variety of sensors). Each UAV may begin the mission at any location in the battlespace, but must end its route at a base (depot) location prior to exhausting its fuel supply.

When a UAV is assigned to a task it must continue performing the task uninterrupted for a pre-specified duration. Human supervision may be required during the execution of each task. For example, humans may observe streaming video feeds captured by the UAV, launch/guide missiles, or manually control the aircraft. The "amount" or "cost" of human involvement required may be based on the difficulty or importance of each task.

In support of the military's future vision of individual human operators controlling multiple UAVs, we assume that operators may supervise multiple tasks simultaneously. However, at any time, human operators are limited in the amount of time or effort they may expend performing tasks, as determined by operator-specific workload thresholds. Unlike operators, UAVs are prohibited from performing multiple tasks simultaneously.

We consider three hybrid activities that may be performed by each human operator, with potentially differing levels of effectiveness (due to training or experience). First, we consider activities related to controlling a UAV as it executes a particular task. These activities may include piloting the aircraft, maintaining situational awareness, gathering target information, laser-marking targets for weapons guidance, and communicating with friendly forces. Second, we consider activities related to navigating a UAV between targets. This may include piloting the aircraft, communicating with friendly forces, and detecting potential threats. Finally, we consider activities related to sensor data analysis, including battle damage assessment, target detection and identification, and "determining hostile intentions." These activities are motivated by the 12 currently-identified duties of MQ-1 Predator and MQ-9 Reaper *pilots* [17] and the 12 duties of *sensor operators* [18] on the same platforms. The three activities proposed in our model were chosen to reflect future task automation required to increase UAV-to-operator ratios, and to improve tractability of the mathematical model.

In an effort to increase the model's usefulness, a variety of objectives are proposed, such as maximizing the overall effectiveness of assigning the most appropriately-configured aircraft to the highest priority targets, minimizing excessive operator workload, and maximizing operator effectiveness. As this is the first model of its kind, we will assume that all target locations and task durations are known *a priori*. In the event that battlespace conditions change, the proposed model may be re-executed to determine an updated mission plan.

III. Related Literature

In general, previously-published *UAV-routing models* have not addressed the human element. As a result, mission plans proposed by such models are likely to produce conflicts with human operators on the ground. This may reduce operator effectiveness, as overworked operators may be prone to errors. It may also mean that surveillance data captured by aircraft cannot be analyzed in a timely manner. Meanwhile, previously-published *human-factors studies* have investigated the effects of work overload, and have demonstrated the need to coordinate both man and machine to ensure that mission objectives are achieved. However, proposals of models capable of generating detailed task schedules for airborne and ground-based assets have been beyond the scope of these studies. For example, [19] proposed a decision support system that assists a single operator in requesting re-scheduling of tasks from multiple UAVs. When operators make the request (which may not be granted) to delay a certain UAV task, the system highlights where scheduling problems may occur in the future. While the system promises to improve an existing plan, this approach is reactive and does not generate optimal plans.

To the best of our knowledge, only [20] have addressed the problem of optimally scheduling UAVs *and* humans simultaneously. They employ a queueing model for a dynamic assignment problem, where identical UAVs and humans are servers and targets appear over time. These targets are assumed to be homogeneous, as the role of the human is to classify each target as "friend" or "foe." Time windows for targets are not considered.

In light of the scarcity of research directly related to our problem, we address the relevant literature in terms of efforts focused on the human factors considerations and optimization approaches to scheduling separately.

A. Human Factors Studies

Numerous empirical studies have been conducted to examine factors affecting operator workload and performance during the operation of UAV, unmanned ground vehicle (UGV), and other types of artificial agents mostly in the military context. An excellent review of previous literature categorizing the existing studies according to the factors examined is provided in [21].

A number of studies investigated the effects of display characteristics that affect operator perception. For example, [22] and [14] tested the effects of delays in computer image processing on operator workload during UAV or UGV tasks. The effects of camera characteristics, such as the range, perspective, or orientation of the viewpoints provided by the artificial agents are examined in [23] and [24]. Schipani [25] examined how image and environmental complexity affects workload ratings during UGV navigation. The results from these studies may provide guidelines for display design so as to reduce operator workload and improve task performance.

A group of studies were focused on the effects of task performance demands. Galster et al. [26] examined the effects of number of targets on errors, efficiency, and workload during a target processing task. Hendy et al. [27] examined the effects of time pressure in air-traffic control. Many studies investigated the effects of number of artificial agents controlled by a single operator on performance and workload, focusing on the costs and benefits of controlling multiple agents [14]–[16], [28], [29].

Finally, some studies investigated the effects of automation on human operator workload and combined performance of man-machine systems. For example, [30], [31], and [29] examined how different levels of autonomy affect task performance and operator workload. Some studies also examined the effects of automated aid reliability [10], [32]–[34].

Research findings and empirical human workload and performance data from studies such as the above would serve as a basis for developing task scheduling models that coordinate multiple human and machine assets.

The empirical approach described above cannot be utilized to evaluate a system if the system is only a concept and a physical mockup is not available. A number of workload prediction tools have been developed to estimate operator workloads associated with conceptual designs. An example of such workload prediction tools is the Army Research Laboratory's improved performance research integration tool (IMPRINT) [35]. IMPRINT predicts operators' workload-time profiles during a mission given an input scenario describing:

human activities during the mission, their time windows and workload levels, crewmember assignments and available automation aids. Based on the input scenario, a discrete event simulation is performed and each crewmember's workload-time profile during the mission is estimated. This process is referred to as workload task analysis (WLTA) [36]. The simulation results identify the peaks of mental workload for each crewmember and can guide redesigning the system so as to alleviate severe overloads. Also, the simulation results can facilitate designing effective and efficient training strategies by helping training system designers address the questions of what to train and how best to train [36].

B. Optimization Approaches

Extensive research has been conducted on the development of mathematical models for UAV routing and scheduling, including models suitable for determining initial mission plans (c.f., [37], [38]) and those designed for dynamic re-routing (c.f., [39]). These models consider only UAV assignments, ignoring the human elements. Similarly, several approaches to scheduling tasks to humans, without determining optimal UAV routes, have been proposed. For example, [40] consider the problem of assigning a single operator to multiple UAV tasks, where UAV routes are pre-specified and operators are prohibited from multitasking. Savla and Frazzoli [41] apply a queueing theoretic approach to scheduling operators, where the service time of an operator depends on the operator's prior workload. Again, the determination of UAV routes is not considered.

We should also mention that while air traffic control (ATC) problems involve the assignment of human controllers to aircraft, these problems do not require the controllers to actually pilot the planes or analyze sensor data captured from them. For example, [42] developed a mixed integer math programming model for use by air traffic controllers in which humans may perform six task types. However, multi-tasking is not allowed and plane flight paths are predetermined.

Another related area is in the field of human-robot interaction. Crandall et al. [43] consider the problem of assigning a human operator to oversee multiple semi-autonomous, homogeneous, robots. Mau and Dolan [44] presents a modified shortest processing time heuristic for scheduling a single human to supervise multiple robots, where the human may only supervise one robot at a time.

Finally, in the broader context of scheduling and operations research, we note that several studies have looked at optimization with human factors considerations in industrial settings. For example, [45] proposed a mathematical model for assigning workers in cellular manufacturing, where worker skill levels may be increased by training. Tharmmaphornphilas et al. [46] and Tharmmaphornphilas and Norman [47] provided mathematical models to determine job rotation schedules for humans, with an objective of minimizing ergonomic risk. Wirojanagud et al. [48] optimized the number of workers, the assignment of workers to machine centers (groups of machines), and the production rate in a problem where humans have differeng skill levels. A math programming model for ergonomic considerations in assembly line balancing is provided by [49]. Lodree et al. [50] proposed a framework for sequencing order-picking tasks in a warehouse, and provide an extensive review of literature related to human factors in scheduling theory. These studies demonstrate the growing interest in, and importance of, considering both man and machine. However, these approaches are not applicable to our problem of interest, as models designed for manufacturing or industrial settings involve tools in fixed locations, where machine routing is not a consideration.

IV. Vehicle Assignment and Routing Constraints

In this section we describe the mathematical formulation of the constraints governing UAV routes. This formulation is based on the dynamic aircraft re-assignment model presented by [39], and therefore does not incorporate human factors considerations. However, such considerations are addressed by the constraints in Section V, which also contains mathematical formulations of several potential objective functions.

A. Notation

We define M to be the set of required (mission-critical) tasks that may be assigned to UAVs. Each task $j \in M$ must be performed by as few as $u_j^{\min}$, and by as many as $u_j^{\max}$, aircraft. Task j has a priority value of p_j, such that larger values of p_j represent greater importance of the task. A fleet of heterogeneous UAVs, represented by the set V, are available to perform tasks, such that the set $V_j \subseteq V$ represents the set of vehicles that are capable of performing task j. Because each vehicle may be uniquely equipped, the parameter $e_{v,j}$ represents the effectiveness level of vehicle v when performing task j.

We utilize a time-discretization approach, such that the time horizon of the mission is partitioned into a discrete set of time intervals, given by the set $T = \{t_0, t_0 + 1, \ldots\}$, where t_0 represents the initial time interval of the mission. Vehicles assigned to task $j \in M$ must begin performance of the task during a time interval $t \in T_j \subseteq T$. This captures the fact that tasks may be time-sensitive. If $u_j^{\min} \geq 2$, then multiple UAVs are required to perform task j. However, these UAVs do *not* need to be assigned to the task at the same starting time (provided that all assigned vehicles begin the task at some $t \in T_j$). The duration of task j is given by $d_j^T \geq 0$, and is measured in units of discrete time intervals.

Vehicle routes (schedules) are defined to be a sequence of visits to nodes (or waypoints), where a node in the network may represent the initial location of vehicle v (denoted as Δ_v^0), a task location ($j \in M$), or a base location that may be visited by v ($b \in B_v$). Each vehicle v begins its route at node Δ_v^0 and ends its route at a base node. If the vehicle's initial location corresponds to a base, we let B'_v represent the node number of the base. Otherwise, if v begins its route at a non-base location (perhaps already in-flight), we let $B'_v = \varnothing$. This distinction is important, as the initial location of each vehicle is necessary to determine its remaining flight endurance. The flight endurance, as limited by the vehicle's fuel capacity, is given by g_v, which is expressed as the integer number of time intervals for which the vehicle may remain in service.

To facilitate construction of the necessary constraints, we define Δ_v^+ to be the set of all nodes that may be visited by vehicle v. This includes tasks and bases. Similarly, $\Delta_{v,j}^-$ is defined to be the set of all nodes from which vehicle v may travel to node j. This may include the initial node (Δ_v^0) or other task nodes. Because vehicles are assumed to be prohibited from re-entering service after returning to a base, base nodes are not contained in $\Delta_{v,j}^-$. To capture vehicle-dependent travel time between tasks, the parameter $f_{v,i,j}$ represents the integer number of time intervals required for vehicle v to travel from node i to node j in the network. If node i is a task, $f_{v,i,j}$ also includes the duration of task i, d_i^T.

B. Integer Programming Constraints

From the perspective of scheduling UAVs to tasks, two types of decision variables are required. The first of which, $x_{t,v,i,j}$, is binary, such that $x_{t,v,i,j} = 1$ if vehicle v is assigned to begin performing task $j \in M$ at time interval $t \in T_j$, given that v travels arc (i, j). The second decision variable, $z_j \in \{0, 1, \ldots, u_j^{\min}\}$, represents an "infinite" resource (IR). This is a fictitious asset that is employed by the model solely to guarantee mathematical feasibility in cases where insufficient vehicles are available to perform tasks. The use of an IR is highly penalized in the objective function. The inclusion of IRs ensure that decision-makers are provided feedback as to where asset capacity shortfalls or timing conflicts exist, rather than simply being instructed that the problem is infeasible. Thus, a non-zero value of z_j indicates the gap between the minimum required number of resources and the actual number of resources assigned to task j.

Given these two decision variables, the mathematical representation of UAV-assigned tasks is given by the following constraints.

$$u_j^{\min} \le \sum_{v \in V_j} \sum_{t \in T_j} \sum_{i \in \Delta_{v,j}^-} x_{t,v,i,j} + z_j \le u_j^{\max} \quad \forall\ j \in M, \tag{1}$$

$$\sum_{t \in T_j} \sum_{i \in \Delta_{v,j}^-} x_{t,v,i,j} \le 1 \quad \forall\ j \in \{M : u_j^{\max} \ge 2\}, v \in V_j, \tag{2}$$

$$\sum_{j \in \{\Delta_v^+ : t \in T_j\}} \sum_{i \in \Delta_{v,j}^-} x_{t,v,i,j} \le 1 \quad \forall\ v \in V, t \in T, \tag{3}$$

$$\sum_{j \in \{\Delta_v^+ : \Delta_v^0 \in \Delta_{v,j}^-\}} \sum_{t \in \{T_j : t \ge t_0 + f_{v,\Delta_v^0,j}\}} x_{t,v,\Delta_v^0,j} = 1 \quad \forall\ v \in V, \tag{4}$$

$$\sum_{j \in B_v} \sum_{i \in \Delta_{v,j}^-} \sum_{t \in \{T_j : t \le t_0 + g_v\}} x_{t,v,i,j} = 1 \qquad \forall\ v \in \{V : B_v' = \varnothing\}, \tag{5}$$

$$t_0 + 1 \le \sum_{j \in B_v} \sum_{i \in \Delta_{v,j}^-} \sum_{t \in T_j} t x_{t,v,i,j} \le \sum_{j \in \Delta_v^+} \sum_{t \in T_j} (t - f_{v,\Delta_v^0,j} + g_v) x_{t,v,\Delta_v^0,j} \qquad \forall\ v \in \{V : B_v' \ne \varnothing\}, \tag{6}$$

$$\sum_{i \in \Delta_{v,j}^-} \sum_{t \in T_j} x_{t,v,i,j} = \sum_{k \in \{\Delta_v^+ : j \in \Delta_{v,k}^-\}} \sum_{t \in T_k} x_{t,v,j,k} \qquad \forall\ v \in V, j \in M, \tag{7}$$

$$\sum_{i \in \Delta_{v,j}^-} \sum_{t \in T_j} t x_{t,v,i,j} \le \sum_{k \in \{\Delta_v^+ : j \in \Delta_{v,k}^-\}} \sum_{t \in T_k} (t - f_{v,j,k}) x_{t,v,j,k} \qquad \forall\ v \in V, j \in M, \tag{8}$$

$$x_{t,v,i,j} \in \{0, 1\} \quad \forall\ v \in V, j \in \Delta_v^+, i \in \Delta_{v,j}^-, t \in T_j, \tag{9}$$

$$z_j \in \{0, 1, \ldots, u_j^{\min}\} \quad \forall\ j \in M. \tag{10}$$

Constraint (1) states that each task $j \in M$ must be performed by at least $u_j^{\min}$, and by no more than $u_j^{\max}$, resources. Constraint (2) ensures that constraint (1) cannot be satisfied by simply assigning the same resource to task j at multiple times; this constraint is only necessary if it is actually allowable to assign multiple resources to the task (i.e., if $u_j^{\max} \ge 2$). Constraint (3) prohibits vehicles from being assigned to more than one node during any given time interval. Constraint (4) ensures that each vehicle departs from its initial location, Δ_v^0, and begins its first task at a feasible time. Constraints (5) and (6) require vehicles to visit a base location prior to exhausting fuel supplies. Constraint (7) states that the number of times a vehicle visits a node must equal the number of times the vehicle leaves the node. Constraint (8) states that if vehicle v travels from j to k, then it must have previously traveled from i to j. Finally, Constraints (9) and (10) describe the definitions of the necessary decision variables.

V. Operator Scheduling

In addition to routing UAVs to targets, human operators must also be scheduled to activities. The set H represents the collection of human operators that are available for the mission. In this paper we consider three distinct types of activities that may be performed by human operators:

1) **Control aircraft during the execution of a task (on-target)**. This may involve remotely piloting the aircraft, configuring on-board sensors, or managing communications between on-ground forces. For example, if an aircraft's task is to bomb an enemy target, an operator's activity could be to move the aircraft into position and manually fire the weapons. Let $M^C \subseteq M$ represent the set of all tasks that require human control.
2) **Control aircraft that are en-route from one task to another (on-path)**. Here, the UAV is not actively engaged in the performance of a task. However, perhaps due to hazardous conditions, it may be necessary for the aircraft to be manually piloted or monitored. To capture the complexity of this on-path activity, we let Γ represent a set of tuples, each of the form $\langle v, i, j \rangle$. Each tuple represents a distinct combination of a vehicle $v \in V$ that requires human control when traveling from node i to node j.
3) **Analyze data collected from aircraft**. Much of the raw data captured from UAVs – such as video, sensor readings, or audio transmissions – must be interpreted by human operators. These operators might not be actively

engaged in controlling the aircraft. Let $M^A \subseteq M$ represent the set of all tasks that require human analysis.

For the first two types of activities, in which operators control the aircraft, one or more humans must be assigned during the performance of the UAV task simultaneously. However, for "analysis" activities, humans may be assigned to address the UAV task within some pre-defined lag period after the UAV task is completed. For example, if a UAV captures video of a target, it may be permissable for an analyst to study this footage after the fact. Like aircraft, it is assumed that each human operator performs these activities without preemption.

A. Operator Control of UAVs on Task

Operator control of UAVs requires the simultaneous assignment of human and aircraft. Let $e^C_{h,j} > 0$ represent the effectiveness of human operator $h \in H$ while controlling a UAV performing task $j \in M^C$. This parameter acknowledges the fact that some operators may be more highly-skilled at performing certain tasks, and thus will be more effective. Let $E^C_j > 0$ represent the total required human effectiveness for controlling a UAV as it performs task $j \in M^C$. If a task requires a relatively large amount of human supervision (e.g., authorizing and firing a missile at a target) the value of E^C_j should be larger than for tasks that require little supervision (e.g., verifying that the UAV has successfully performed a task). We define d^C_j to be the number of time intervals required for an operator to control UAVs performing task j, such that $d^C_j = d^T_j$. Because the human operator must perform the control activity simultaneously with the UAV, the allowable time window for these activities is given by $T^C_j = T_j$ for all $j \in M^C$.

Fig. 1 shows a possible assignment of one human operator, h, to control aircraft v while performing task j. Note that the allowable time window (represented by the lightly-shaded box) defines allowable *start* times for beginning the task. Therefore, it is acceptable for both the UAV and the human operator to continue performing the task after the time window has closed (provided that the activity started within the time window).

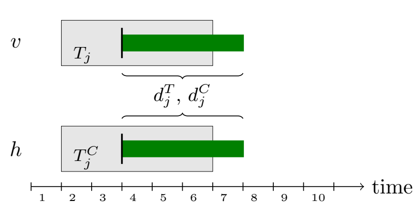


Figure 1: Operator control of UAV on target.

Two types of decision variables are required to describe the assignment of operators to control activities. The first, binary variable $o^C_{t,h,j}$, equals one if human operator $h \in H$ is assigned to control a vehicle while it performs task $j \in M^C$ during time interval $t \in T^C_j$. In the event that there is an insufficient supply of human operators, we define the integer decision variable $z^C_{t,j}$ to represent the "infinite" human operator (IO) needed to perform a control activity on task $j \in M^C$ during time interval $t \in T_j$. To discourage its use, this decision variable is highly-penalized in the objective function. A positive value of $z^C_{t,j}$ in the optimal solution would indicate to a decision-maker that additional human operators are required to adequately supervise certain tasks in the mission.

The necessary constraints for UAV control on a task are given by:

$$\sum_{h \in H_j} e^C_{h,j}\ o^C_{t,h,j} + z^C_{t,j} \geq \sum_{v \in V} \sum_{i \in \Delta^-_{v,j}} E^C_j\, x_{t,v,i,j} \quad \forall\ j \in M^C, t \in T^C_j, \tag{11}$$

$$o^C_{t,h,j} \leq \sum_{v \in V} \sum_{i \in \Delta^-_{v,j}} x_{t,v,i,j}\ \forall\ h \in H, j \in M^C, t \in T^C_j, \tag{12}$$

$$o^C_{t,h,j} \in \{0,1\} \quad \forall\ h \in H, j \in M^C, t \in T^C_j, \tag{13}$$

$$z^C_{t,j} \geq 0 \quad \forall\ j \in M^C, t \in T^C_j. \tag{14}$$

Constraint (11) requires that each vehicle performing task $j \in M^C$ is supported by a minimum total effectiveness level across all operators. In the event that an insufficient number of skilled operators are available to begin the control activity at time t, an IO is included. Constraint (12) prohibits operators from being assigned to control activities during times when no vehicle is beginning performance of task j. Constraints (13) and (14) describe the nature of the required decision variables.

B. Operator Guidance of UAVs Between Tasks

UAVs traveling between tasks may require a degree of human interaction that differs from the control of a UAV on a fixed target. As each UAV task has time windows in which the task may be performed, it is likely that the UAV may be forced to loiter if it arrives before the task's time window has opened. We assume that, as a UAV travels from task i to task j, any required loitering will take place at the location of task i, and that no operators are required to oversee the loitering. Thus, an operator is required only while the vehicle is en route. Recall that the parameter $f_{v,i,j}$ includes the time required for vehicle v to perform task i, d^T_i, as well as the time required for v to travel from i to j. Therefore, the allowable time window for which human operators may begin guiding a particular UAV between nodes i and j is given by $T^P_{v,i,j} = [\min\{T_j\} - (f_{v,i,j} - d^T_i), \max\{T_j\} - 1]$ for all $\langle v,i,j \rangle \in \Gamma$. The maximum value of $T^P_{v,i,j}$ is equal to the maximum value of T_j minus one to account for the fact that path control is not required once the vehicle arrives at node j and begins service. Thus, $\max\{T^P_{v,i,j}\}$ represents the latest possible time that path control would be required. Fig. 2 demonstrates the relationship between UAV travel and operator assignments.

For each $\langle v,i,j \rangle \in \Gamma$, the required total operator effectiveness is given by parameter $E^P_{v,i,j}$, where human operator h is capable of providing $e^P_{h,v,i,j}$ units of effectiveness when assigned to this activity. Two new decision variable types, similar to those described above, are required for path-control activities. The first type, binary decision variable $o^P_{t,h,v,i,j}$, assumes a value of one if operator h is assigned to perform a path-control activity of vehicle v along arc (i,j), with the

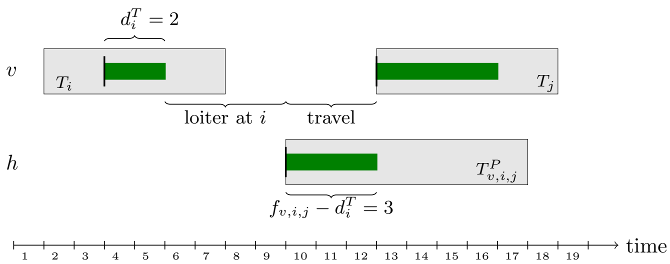


Figure 2: Operator control of UAV traveling between nodes i and j.

activity beginning at time t. The second type of decision variable, $z^P_{t,v,i,j}$, represents the IO.

The constraints required for path control are given by:

$$E^P_{v,i,j} x_{t,v,i,j} \leq \sum_{h \in H} e^P_{h,v,i,j} o^P_{t-(f_{v,i,j}-d_i^T),h,v,i,j} + z^P_{t-(f_{v,i,j}-d_i^T),v,i,j} \quad \forall \ \langle v,i,j \rangle \in \Gamma, \ t \in \{T_j : t-(f_{v,i,j}-d_i^T) > t_0\} \tag{15}$$

$$o^P_{t,h,v,i,j} \leq x_{t+f_{v,i,j}-d_i^T,v,i,j} \quad \forall \ h \in H, \langle v,i,j \rangle \in \Gamma, t \in T^P_{v,i,j} \tag{16}$$

$$\sum_{t \in T^P_{v,i,j}} o^P_{t,h,v,i,j} \leq 1 \quad \forall \ \langle v,i,j \rangle \in \Gamma, h \in H \tag{17}$$

$$o^P_{t,h,v,i,j} \in \{0,1\} \quad \forall \ \langle v,i,j \rangle \in \Gamma, h \in H, t \in T^P_{v,i,j} \tag{18}$$

$$z^P_{t,v,i,j} \geq 0 \quad \forall \ \langle v,i,j \rangle \in \Gamma, t \in T^P_{v,i,j} \tag{19}$$

Constraint (15) ensures that the required total skill level of operators assigned to control v along path (i,j) is observed. If the UAV begins performing task j at time t, then the path guiding begins at time $t-(f_{v,i,j}-d_i^T)$. The IO is included to maintain mathematical feasibility. Constraint (16) prevents operators from being assigned to control the path of v either too early or too late. Constraint (17) prohibits h from re-performing the path-guiding for this particular vehicle along this particular path at a later time. Constraints (18) and (19) describe the decision variable definitions.

C. Operator Analysis of UAV-gathered Data

UAVs capture enormous quantities of data, only a small fraction of which is analyzed in real-time. Although there have been efforts to automate data analysis activities, it is expected that this process will remain manual in the immediate future. Unlike the previously-described "control" and "path-guiding" activities, the "analysis" activity may allow for looser synchronization between UAV and operator. In other words, it may be permissible for UAV-gathered data to be analyzed after the fact. As such, we define $L_j^{\min}$ ($L_j^{\max}$) to be the minimum (maximum) allowable number of time intervals that may pass between the time that a UAV begins performance of task j and the time that an operator begins analysis activities of that task. If $L_j^{\min} = L_j^{\max} = 0$ then the analysis must be performed simultaneously with the task itself. Thus, the allowable time window for data analysis is given by: $T_j^A = \left[\min\{T_j\} + L_j^{\min}, \max\{T_j\} + L_j^{\max}\right]$ for all $j \in M^A$. The time required for human analysis of task $j \in M^A$ is given by d_j^A. This duration is not required to equal d_j^T, which is the duration of task j.

Fig. 3 shows an example assignment involving one UAV and two operators. Note that v begins performing task j at time interval 5. Therefore, analysis activities may begin as early as time $5 + L_j^{\min} = 6$, or as late as time $5 + L_j^{\max} = 10$. Also note that the allowable time window for analysis, T_j^A, represents allowable *start* times for analysis. Thus, if $d_j^A > 0$, it is possible that the analysis activity may extend beyond the time window.

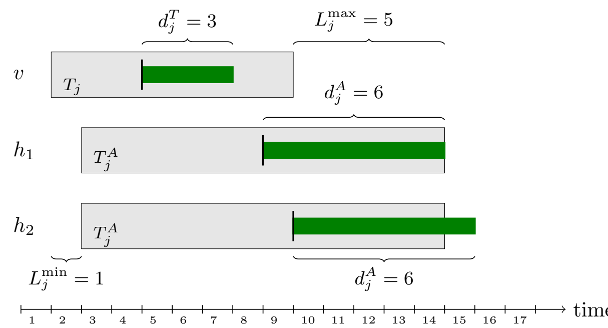


Figure 3: Data analysis assigned to two operators.

The binary decision variable for assigning operators to analysis activities is $o^A_{t,h,j}$, such that $o^A_{t,h,j} = 1$ if human operator $h \in H$ is assigned to analyze data during time interval $t \in T_j^A$ from a vehicle's performance of task $j \in M^A$. The constraints governing operator analysis activities are given by:

$$\sum_{v \in V} \sum_{i \in \Delta^-_{v,j}} E_j^A x_{t,v,i,j} \leq \sum_{h \in H} \sum_{\substack{t' \in T_j^A \\ t+L_j^{\min} \leq t' \leq t+L_j^{\max}}} e^A_{h,j} \ o^A_{t',h,j} + z^A_{t,j} \quad \forall \ j \in M^A, t \in T_j, \tag{20}$$

$$o^A_{t,h,j} \leq \sum_{v \in V} \sum_{i \in \Delta^-_{v,j}} \sum_{\substack{t' \in T_j \\ t-L_j^{\max} \leq t' \leq t-L_j^{\min}}} x_{t',v,i,j} \quad \forall \ h \in H, j \in M^A, t \in T_j^A, \tag{21}$$

$$\sum_{t \in T_j^A} o^A_{t,h,j} \leq \sum_{v \in V} \sum_{i \in \Delta^-_{v,j}} \sum_{t \in T_j} x_{t,v,i,j} \forall \ h \in H, j \in M^A \tag{22}$$

$$o^A_{t,h,j} \in \{0,1\} \quad \forall \ h \in H, j \in M^A, t \in T_j^A, \tag{23}$$

$$z^A_{t,j} \geq 0 \quad \forall \ j \in M^A, t \in T_j. \tag{24}$$

Constraint (20) ensures a sufficient total effectiveness level of operators assigned to perform analysis of task j no earlier than $L_j^{\min}$, and no later than $L_j^{\max}$, time intervals after the time that v starts performing task j. The parameter $e^A_{h,j}$ represents the effectiveness level of operator h while performing analysis of task j, and E_j^A represents the total required effectiveness of operators assigned to analyze task j. The IO, represented by $z^A_{t,j}$, is again included for mathematical feasibility. Constraint (21) prevents analysis activities from being performed too early or too late. Constraint (22) prevents h from excessively re-performing the same analysis activity. Constraints (23) and (24) describe the nature of the decision variables for analysis activities.

D. Human Workload during Multi-tasking

The mathematical representations of operators' multi-task workloads and workload capacity limit constraints in this study are predicated upon existing mental workload theories and methods, specifically: the resource theories, the visual, auditory, cognitive and psychomotor (VACP) method, and the "cost of concurrence" concept.

The resource theories [51]–[54] propose that the human has a limited capacity (resources) for processing information and this capacity can be allocated in graded amounts to different activities. Also, these theories view performance decrement as a shortage of resources. Thus, if an operator simultaneously performs multiple tasks and their combined demands exceed the operator's capacity, the performance of some or all of the tasks may suffer. The resource theories have been supported by numerous empirical studies and have served as a basis for developing human mental workload prediction tools [35].

The VACP method [55], [56] provides a computational framework for aggregating individual workloads of multiple simultaneous activities to represent the combined workload. The method assumes that individual workloads of multiple simultaneous activities at a time instant can be linearly added together to represent the instantaneous combined workload. Each activity's workload is assumed to be pre-estimated based on subject matter experts' subjective ratings. The combined workload is compared with a predetermined workload threshold to determine if the operator is overloaded. The improvement performance research integration tool (IMPRINT) developed by Army Research Laboratory uses the VACP method in predicting operators' workload-time profiles based on discrete event simulations [35].

In addition to the linear sum of individual workloads of simultaneously performed activities, our representation of the total mental workload also considers the "cost of concurrence" component [53], which represents the additional workload purely due to having to manage or supervise multiple activities. The act of time-sharing itself pulls resources away from the simultaneous activities above and beyond the resources that each activity demands by itself [53]. The cost of concurrence is also consistent with the "switching cost" concept in cognitive psychology [57], [58]. In most circumstances, switching activities is known to result in a sizable decrement in performance [59].

Operators' multitask workloads and workload capacity limits are mathematically expressed in Constraint (25) below, which ensures that each operator is not assigned a workload that exceeds the threshold at any time. Each human operator is assumed to possess a maximum workload threshold, represented by $W_h^{\max}$; this corresponds to the mental capacity concept of the resources theories. At a time instant, each activity that an operator performs induces some measure of workload, where w_{hj}^C represents the amount of workload experienced by operator h when performing a control activity for task $j \in M^C$. Similarly, $w_{h,v,i,j}^P$ represents the workload on h when performing path-control of vehicle v along arc (i, j)

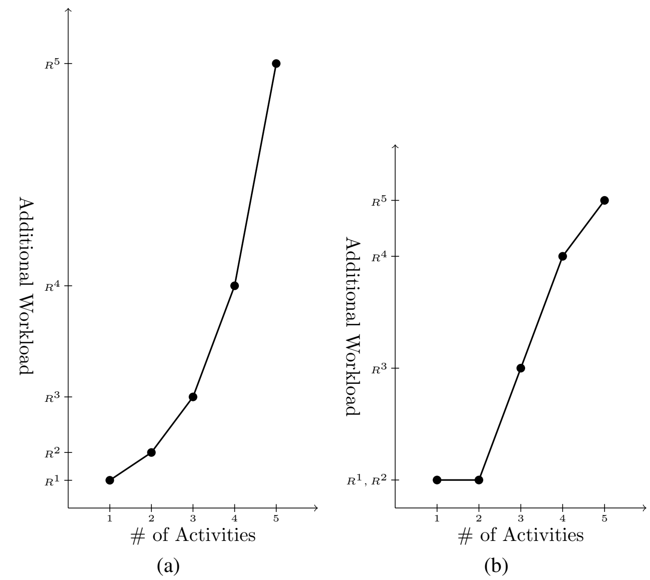


Figure 4: Two possible forms of additional workload.

(such that $\langle v, i, j\rangle \in \Gamma$), and $w_{h,j}^A$ represents the workload on h when performing analysis of task $j \in M^A$. Each of these workload measures is assumed to be pre-determined by subject matter experts in a manner similar to the workload estimations in the VACP method [55], [56]. Also, it is assumed that when an operator performs multiple activities, the corresponding individual workload measures can be linearly added to represent the combined effect, again similar to the computation in the VACP method.

$$
\begin{aligned}
&\sum_{j \in M^C} \sum_{\substack{t' \in T_j^C \\ t-d_j^T+1 \le t' \le t}} w_{h,j}^C o_{t',h,j}^C \\
&\quad + \sum_{\langle v,i,j\rangle \in \Gamma} \sum_{\substack{t' \in T_{v,i,j}^P \\ t-(f_{v,i,j}-d_i^T)+1 \le t' \le t}} w_{h,v,i,j}^P o_{t',h,v,i,j}^P \\
&\quad + \sum_{j \in M^A} \sum_{\substack{t' \in T_j^A \\ t-d_j^A+1 \le t' \le t}} w_{h,j}^A o_{t',h,j}^A \\
&\quad + \sum_{n=1}^{n_h^{\max}-1} R^n \left(q_{t,h}^n - q_{t,h}^{n+1}\right) + R^{n_h^{\max}} q_{t,h}^{n_h^{\max}} \le W_h^{\max} \\
&\qquad \forall\, h \in H, t \in T
\end{aligned} \tag{25}
$$

The cost of concurrence is expressed using the scaling parameter R^n; it represents the additional workload due to "supervising" or "switching" activities when an operator performs n activities simultaneously (Constraint (25)). The cost of concurrence may increase in a linear or nonlinear manner as operators are burdened with more tasks. Empirical testing is required to determine the exact functional form for the additional workload, but two representative forms are depicted in Fig. 4.

Constraint (25) makes use of binary decision variable $q_{t,h}^n$, which equals one if human $h \in H$ performs at least n activities at time $t \in T$. Appropriate values for $q_{t,h}^n$ are determined by the following constraints:

$$\sum_{n=1}^{n_h^{\max}} q_{t,h}^n = \sum_{j\in M^C} \sum_{\substack{t'\in T_j^C \\ t-d_j^T+1\le t'\le t}} o^C_{t',h,j} + \sum_{j\in M^A}\sum_{\substack{t'\in T_j^A\\ t-d_j^A+1\le t'\le t}} o^A_{t',h,j} + \sum_{\langle v,i,j\rangle\in\Gamma} \sum_{\substack{t'\in T^P_{v,i,j}\\ t-(f_{v,i,j}-d_i^T)+1\le t'\le t}} o^P_{t',h,v,i,j} \quad \forall\ h\in H, t\in T, \tag{26}$$

$$q_{t,h}^n \le q_{t,h}^{n-1} \ \forall\ h\in H, t\in T, n\in\{2,3,\ldots,n_h^{\max}\}, \tag{27}$$

$$q_{t,h}^n \in \{0,1\} \ \forall\ h\in H, t\in T, n\in\{1,2,\ldots,n_h^{\max}\}, \tag{28}$$

where parameter $n_h^{\max}$ represents the maximum possible number of activities that may be performed at a given time by operator h, and is calculated as follows:

$$n_h^{\max} = \left\lfloor \frac{W_h^{\max}}{\min\left\{\min_{j\in M}\{w^C_{h,j}\cup w^A_{h,j}\}\cup \min_{\langle v,i,j\rangle\in\Gamma}\{w^P_{h,v,i,j}\}\right\}} \right\rfloor \quad \forall\ h\in H.$$

Note that $n_h^{\max}$ serves solely to establish the solution space for $q_{t,h}^n$. Constraint (26) states that the sum of the binary $q_{t,h}^n$ decision variable values equals the number of activities assigned to operator h at time t. Constraint (27) ensures that the $q_{t,h}^n$ values are sequential over n. In other words, if operator h is assigned to exactly two tasks at a particular time, t, then $q_{t,h}^1 = q_{t,h}^2 = 1$ and $q_{t,h}^n = 0$ for all $n > 2$. Finally, Constraint (28) describes the nature of these decision variables.

While excessive workloads can result in decreased operator performance, it has also been observed that operators perform best with some degree of stimulation [35], [60]–[62]. In fact, [35] stated that "…decrements in performance may occur if workload is either too low or too high." Therefore, we incorporate the notion of a target workload level. Deviation from this target level will result in a penalty in the objective function, to be described shortly.

To capture the absolute deviation from the target workload level, represented as τ_h for each operator h, two new decision variables are required. Let $r^+_{t,h}$ ($r^-_{t,h}$) represent the amount by which the actual workload level experienced by operator h at time t exceeds (falls below) the target level, as illustrated in Fig. 5.

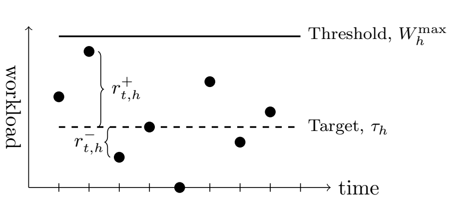


Figure 5: Deviations from the target workload.

Constraints to establish proper values for $r^+_{t,h}$ and $r^-_{t,h}$ are as follows:

$$\begin{aligned} r^+_{t,h} \ge{}& \sum_{j\in M^C} \sum_{\substack{t'\in T_j^C \\ t-d_j^T+1\le t'\le t}} w^C_{h,j} o^C_{t',h,j} \\ &+ \sum_{\langle v,i,j\rangle\in\Gamma} \sum_{\substack{t'\in T^P_{v,i,j}\\ t-(f_{v,i,j}-d_i^T)+1\le t'\le t}} w^P_{h,v,i,j} o^P_{t',h,v,i,j} \\ &+ \sum_{j\in M^A}\sum_{\substack{t'\in T_j^A\\ t-d_j^A+1\le t'\le t}} w^A_{h,j} o^A_{t',h,j} \\ &+ \sum_{n=1}^{n_h^{\max}-1} R^n\left(q^n_{t,h} - q^{n+1}_{t,h}\right) + R^{n_h^{\max}} q^{n_h^{\max}}_{t,h} - \tau_h \\ &\forall\ h\in H, t\in T \end{aligned} \tag{29}$$

$$\begin{aligned} r^-_{t,h} \ge{}& \tau_h - \sum_{j\in M^C} \sum_{\substack{t'\in T_j^C \\ t-d_j^T+1\le t'\le t}} w^C_{h,j} o^C_{t',h,j} \\ &- \sum_{\langle v,i,j\rangle\in\Gamma} \sum_{\substack{t'\in T^P_{v,i,j}\\ t-(f_{v,i,j}-d_i^T)+1\le t'\le t}} w^P_{h,v,i,j} o^P_{t',h,v,i,j} \\ &- \sum_{j\in M^A}\sum_{\substack{t'\in T_j^A\\ t-d_j^A+1\le t'\le t}} w^A_{h,j} o^A_{t',h,j} \\ &- \sum_{n=1}^{n_h^{\max}-1} R^n\left(q^n_{t,h} - q^{n+1}_{t,h}\right) - R^{n_h^{\max}} q^{n_h^{\max}}_{t,h} \\ &\forall\ h\in H, t\in T \end{aligned} \tag{30}$$

$$r^+_{t,h} \ge 0 \quad \forall\ h\in H, t\in T \tag{31}$$

$$r^-_{t,h} \ge 0 \quad \forall\ h\in H, t\in T \tag{32}$$

E. Objectives

In such a complex problem, a variety of objectives are conceivable. We describe several applicable objectives and demonstrate how these may be considered simultaneously. The first objective involves maximizing the overall task effectiveness by assigning higher priority tasks to the most effective UAVs as early within the allowable time window as possible. An overall task effectiveness value, Z_{TE}, may be calculated as follows:

$$Z_{TE} \equiv \sum_{j\in M}\sum_{v\in V}\sum_{i\in\Delta^-_{v,j}}\sum_{t\in T_j} p_j e_{v,j}\left(1-\left(\frac{t-\min\{T_j\}}{|T_j|+1}\right)\right) x_{t,v,i,j}.$$

Similarly, it is desirable to assign the most effective operators to the highest priority tasks. An operator effectiveness value, Z_{OE}, may be determined as follows for each of the three types of operator activities:

$$\begin{aligned} Z_{OE} \equiv{}& \sum_{h\in H}\sum_{j\in M^A}\sum_{t\in T_j^A} p_j e^A_{h,j} o^A_{t,h,j} \\ &+ \sum_{h\in H}\sum_{j\in M^C}\sum_{t\in T_j^C} p_j e^C_{h,j} o^C_{t,h,j} \end{aligned}$$

$$+\sum_{h\in H}\sum_{\langle v,i,j\rangle\in\Gamma}\sum_{t\in T^P_{v,i,j}}\max\{p_i,p_j\}e^P_{h,v,i,j}o^P_{t,h,v,i,j}.$$

To encourage operator assignments near target workload levels, we define

$$Z_W\equiv\sum_{h\in H}\sum_{t\in T}\left(\phi r^+_{t,h}+\theta r^-_{t,h}\right)$$

to be the weighted sum of deviations from the target, where $\phi\geq 0$ represents a penalty for exceeding the operator's target workload level at any time, and $\theta\geq 0$ represents a similar penalty imposed when the operator's workload level falls below the target value.

Finally, we wish to minimize the use of infinite resources and operators, particularly for high-priority tasks. This penalty is given by

$$Z_{IR}\equiv\sum_{j\in M}p_jz_j+\sum_{j\in M^C}\sum_{t\in T_j}p_jz^C_{t,j}$$
$$+\sum_{\langle v,i,j\rangle\in\Gamma}\sum_{t\in T^P_{v,i,j}}\max\{p_i,p_j\}z^P_{t,v,i,j}+\sum_{j\in M^A}\sum_{t\in T_j}p_jz^A_{t,j}.$$

We incorporate these individual objectives as follows:

$$Z=\frac{Z_{TE}}{Z^{\max}_{TE}}+\frac{Z_{OE}}{Z^{\max}_{OE}}-\frac{Z_W}{Z^{\max}_W}-Z_{IR} \tag{33}$$

where the first three terms are scaled by their maximum values such that

$$Z^{\max}_{TE}\equiv\sum_{j\in M}\max_{v\in V}\{p_je_{v,j}u^{\max}_j\},$$
$$Z^{\max}_{OE}\equiv\sum_{j\in M^A}\max_{h\in H}\left\{p_je^A_{h,j}n^{\max}_h\right\}$$
$$+\sum_{j\in M^C}\max_{h\in H}\left\{p_je^C_{h,j}n^{\max}_h\right\}$$
$$+\sum_{\langle v,i,j\rangle\in\Gamma}\max_{h\in H}\left\{\max\{p_i,p_j\}e^P_{h,v,i,j}n^{\max}_h\right\},\text{ and}$$
$$Z^{\max}_W\equiv\sum_{h\in H}\sum_{t\in T}\left\{\max(W^{\max}_h-\tau_h,\tau_h)\right\}.$$

The complete mathematical programming formulation for the operator assignment model is given by:

Max	(33)	Mission Effectiveness
s.t.	(1) – (10)	UAV Assignments
	(11) – (14)	Operator control of UAVs on task
	(15) – (19)	Operator control of UAVs along paths
	(20) – (24)	Operator analysis activities
	(25) – (32)	Operator workload constraints

VI. Numerical Example

A small-scale example is presented to show the impact of incorporating human factors considerations in the routing of UAVs. Although the proposed mathematical model accommodates multiple operators, heterogeneous UAVs, and three types of operator activities, for ease of explanation and greater clarity this example features only a subset of the model's features. Five surveillance tasks, each with a duration of $d^T_j=4$, must be performed by two identical UAVs, such that the effectiveness of vehicle v performing task j is given by $e_{v,j}=1$. The allowable time windows and priority values of each task are given in Table I, where it is shown that tasks 1, 3, and 5 are of higher priority.

Table I: Task parameters

Task j	**Time Window** $[T^{\min}_j, T^{\max}_j]$	**Priority** p_j
1	$[\ 1,\ 7]$	3
2	$[\ 1,14]$	1
3	$[\ 1,13]$	3
4	$[\ 8,19]$	1
5	$[16,30]$	3

Each UAV task requires two operator activities: control of the UAV over the target and analysis of the surveillance data. Each analysis activity must be performed within four time units of the completion of the UAV task (i.e., $L^{\min}_j=0$ and $L^{\max}_j=4$). A single operator is available, whose effectiveness values for all control and analysis activities are given by $e^C_{h,j}=e^A_{h,j}=1$. The total required operator effectiveness for these activities are given by $E^C_j=E^A_j=1$. Each control activity is assumed to impose a workload of $w^C_{h,j}=0.5$, whereas each analysis activity has a workload of $w^A_{h,j}=1.0$, indicating the relative difficulty of two activities. Additional workload values associated with the performance of multiple activities simultaneously are given by $R^1=0.25$, $R^2=0.5$, $R^3=1$, $R^4=2$, and $R^5=4$.

The sensitivity of the model with respect to changes in operator workload thresholds was tested by varying these threshold levels and obtaining optimal operator and UAV assignments. Five threshold levels were tested, as shown in Table II. For each threshold level, an optimal solution was obtained by CPLEX version 12.2.0 (a commercial integer programming solver) on an HP 8100 Elite desktop PC with a quad-core Intel i7-860 processor running Ubuntu Linux 10.10 in 64-bit mode.

Table II: Operator threshold and target workload values.

	Model				
Parameter	**A**	**B**	**C**	**D**	**E**
$W^{\max}_h$	20	1	1.5	2	2.5
τ_h	0	0.5	0.75	1	1.25

Fig. 6 contains details of optimal UAV and operator assignments when the operator workload threshold value is essentially infinite. To obtain this particular mission plan, the routing algorithm was first solved without any human factors considerations (i.e., the only objective was to maximize the overall effectiveness of the UAVs). Using the resulting UAV assignments as inputs, the algorithm was re-executed, this time maximizing the human effectiveness. Given the effectively non-existant workload threshold, the operator is tasked to perform 6 activities simultaneously during time intervals 10 – 13.

In Model B (Fig. 7), the operator's workload threshold is decreased to $W^{\max}_h=1$. Due to the workload requirements of the control and analysis activities, as well as the R^1 value, this threshold allows the operator to perform only control activities. The resulting mission plan, therefore, does not include any

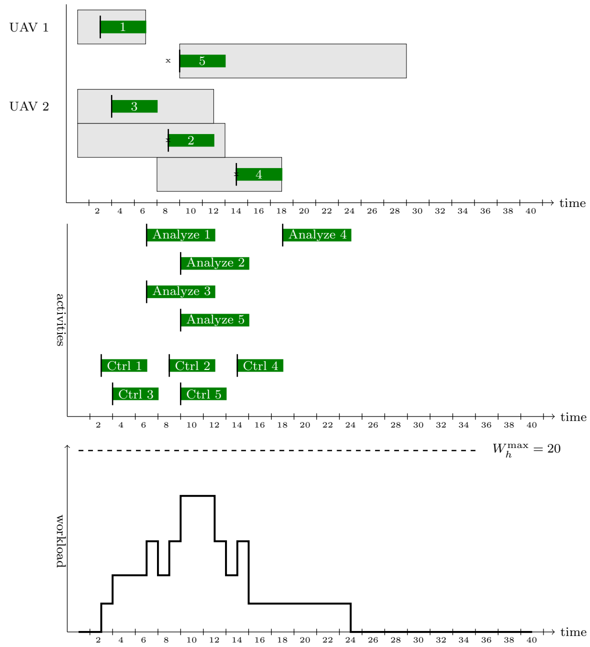


Figure 6: Model A – UAV routes ignore human factors considerations.

data analysis although all UAV tasks are assigned. Because the operator cannot multitask due to the low workload threshold, the mission duration is extended from that of Model A.

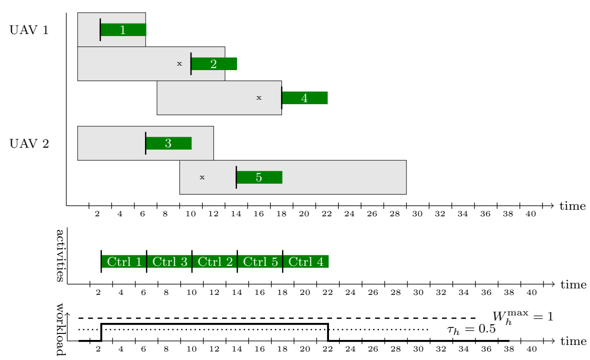


Figure 7: Model B ($W_h^{\max} = 1$, $\tau_h = 0.5$).

In Model C, the workload threshold is increased to $W_h^{\max} = 1.5$. Again, the operator is unable to multitask, as shown in Fig. 8. However, this threshold is now large enough to allow analysis activities. In this case, control and analysis activities may be performed, but only on three of five tasks. As a result, only one of the UAVs is employed. Note that, while this UAV could begin task 3 at time interval 10 (indicated by an "x" in the UAV Gantt chart), it is delayed until time 13 to accommodate the operator. A similar delay is observed for task 5. Also of interest is the fact that the UAV skips from task 1 to task 3, bypassing task 5, because task 3 is of a higher priority and it is desirable to perform this task earlier. In Model D (Fig. 9), the workload threshold has been increased to a level that allows all tasks to be performed, as the operator may simultaneously perform a control activity and an analysis activity (although it is still infeasible for the operator to perform two control activities simultaneously).

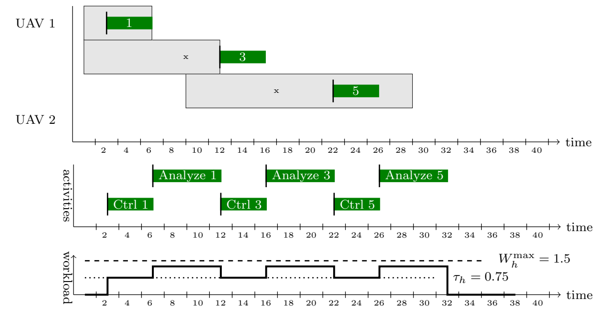


Figure 8: Model C ($W_h^{\max} = 1.5$, $\tau_h = 0.75$).

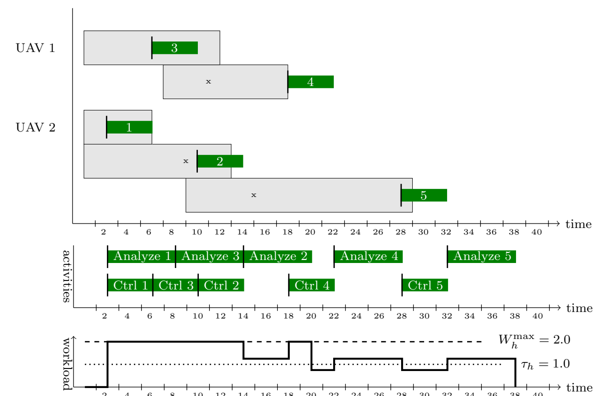


Figure 9: Model D ($W_h^{\max} = 2$, $\tau_h = 1.0$).

Finally, in Model E, the operator may now perform two control activities simultaneously. As a result, high-priority tasks 1 and 3 may be performed early (Fig. 10). This increases the overall task effectiveness. While UAV 1 flies past task 5 en route from 1 to 4, the operator is too busy to perform task 5 until later. Thus, the model has successfully balanced operator workload, despite UAV routes that would appear suboptimal if human factors considerations were ignored. In this small example, five different workload thresholds produced five unique UAV routes, as shown in Fig. 11.

We conclude this section with some brief remarks on the model's complexity. As demonstrated in Table III, where Model A reflects only the determination of optimal UAV routes (ignoring operator assignments), the incorporation of human factors considerations increases both the model size and solution times. The numbers of constraints and decision variables is also affected by the particular workload threshold values, as larger thresholds require larger models. While the CPLEX solution times for optimally solving these small-scale problems is reasonable, large-scale problems will benefit from customized solution approaches that exploit the model's structure. This presents an opportunity for further research efforts, particularly for applying this framework to dynamic asset re-allocation problems requiring near real-time solutions.

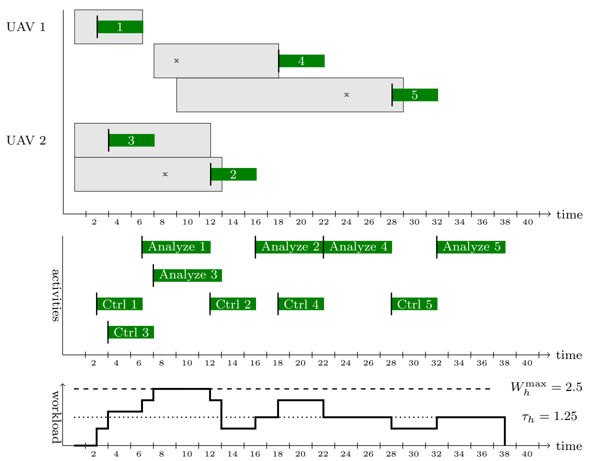
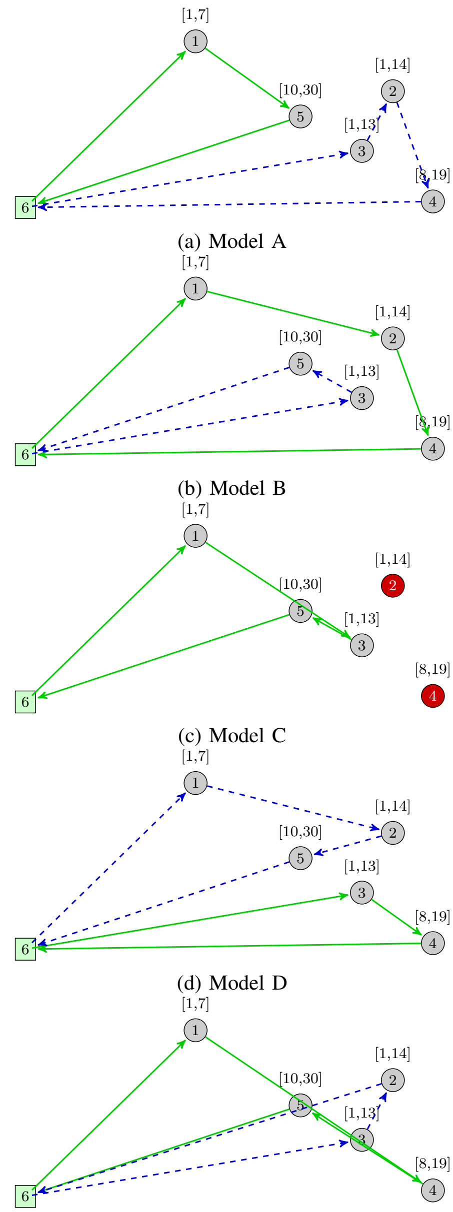


Figure 10: Model E ($W_h^{\max} = 2.5$, $\tau_h = 1.25$).

Table III: Comparison of model sizes and solution times.

Model	Constraints	Dec. Vars.	Soln. Time [sec]
A	104	687	0.19
B	637	1403	0.25
C	685	1451	1.32
D	733	1499	1.03
E	781	1547	3.27



(a) Model A

(b) Model B

(c) Model C

(d) Model D

(e) Model E

Figure 11: Optimal UAV routes for each model.

VII. Summary and Future Research Directions

Most previous human factors studies related to UAV mission tasks made efforts to address the human operator workload and performance issues at the single operator level. Many existing UAV routing studies describe optimization approaches for tasking a fleet of aircraft to time-sensitive targets. However, few studies have explored the possibilities of coordinating multiple human and machine assets at the global system level to optimize the complex system's overall performance while simultaneously meeting human operators' workload requirements. This article presented a task scheduling model based on mathematical programming for such system level integration and optimization. It is thought to be the first of its kind.

Specifically, an integer programming formulation for the problem of scheduling a fleet of heterogeneous UAVs to time-sensitive targets is proposed. This model recognizes that UAVs, while unmanned, require significant human supervision. As such, optimal mission effectiveness can be realized only when man and machine are scheduled in harmony. Three hybrid operator activities have been modeled, including control of UAVs on targets, control of UAVs between targets, and analysis of data captured during surveillance of a target. Assignments of operators to activities must not exceed human workload limitations.

Admittedly, one limitation of the proposed model is that it employs a uni-dimensional representation of workload and resources, rather than a multi-dimensional (visual, auditory, cognitive and psychomotor) representation, as found in [35], [36], [55], [56]. This uni-dimensional approach was employed for the sake of mathematical tractability, as the aforementioned models did not incorporate the UAV routing optimization (which is itself a challenging problem). Nonetheless, efforts to extend the proposed model to allow for multi-dimensional representations are ongoing.

We believe that the proposed mathematical model will be best utilized when supported by a user interface to display the complex mission plans generated as model outputs. We are currently investigating user interfaces that would effectively serve this purpose. One promising candidate is proposed by [63], which facilitates operator collaboration for teams of UAVs. Myriad additional opportunities exist for future research efforts that incorporate operator considerations within the context of UAV routing. Particularly relevant to the proposed mathematical model would be empirical studies to determine appropriate numerical values for operator workload thresholds and activity effectiveness. Solution approaches for large-scale problems would also be of value. Extensions to the proposed model, such as additional operator activities, may also be beneficial for certain mission scenarios. Finally, the model could be enhanced to consider the stochastic nature of targets and operator performance.

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References

[1] P. Stewart. (2011, December 18) Overstretched drone pilots face stress risk. [Online]. Available: http://www.reuters.com/article/2011/12/18/us-usa-drones-stress-idUSTRE7BH0VH20111218?feedType=RSS&feedName=everything&virtualBrandChannel=11563

[2] W. Chappelle, K. McDonald, and K. McMillan, "Important and Critical Psychological Attributes of USAF MQ-1 Predator and MQ-9 Reaper Pilots according to Subject Matter Experts," USAF School of Aerospace Medicine, Wright-Patterson AFB, OH, Tech. Rep. Technical Report AFRL-SA-WP-TR-2011-0002, May 2011.

[3] Headquarters, Department of the Army, ""Eyes of the Army" U.S. Army Roadmap for Unmanned Aircraft Systems 2010-2035," U.S. Army UAS Center of Excellence (ATZQ-CDI-C), Fort Rucker, AL, Technical Report, 2010.

[4] W. Chappelle, A. Salinas, and K. McDonald, "Psychological Health Screening of USAF Remotely Piloted Aircraft (RPA) Operators and Supporting Units," in *Symposium on Mental Health and Well-Being across the Military Spectrum*, Bergen, Norway, Apr 2011.

[5] J. Ouma, W. Chappelle, and A. Salinas, "Faces of occupational burnout among U.S. Air Force active duty and national guard/reserve MQ-1 predator and MQ-9 reaper operators," Air Force Research Laboratory, 711th Human Performance Wing, School of Aerospace Medicine, Wright-Patterson AFB, OH, Tech. Rep. Technical Report AFRL-SA-WP-TR-2011-0003, 2011.

[6] C. Wickens and J. Hollands, *Engineering psychology and human performance*, 3rd ed. Upper Saddle River, NJ: Prentice Hall, 2000.

[7] A. Tvaryanas, W. Thompson, and S. Constable, "Human factors in remotely piloted aircraft operations: HFACS analysis of 221 mishaps over 10 years," *Aviation, Space, and Environmental Medicine*, vol. 77, no. 7, pp. 724 – 732, 2006.

[8] A. Tvaryanas and W. Thompson, "Recurrent error pathways in HFACS data: analysis of 95 mishaps with remotely piloted aircraft," *Aviation, Space, and Environmental Medicine*, vol. 79, pp. 525 – 532, 2008.

[9] R. Parasuraman, T. Sheridan, and C. Wickens, "A model for types and levels of human interaction with automation," *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, vol. 30, pp. 286 – 297, 2000.

[10] H. Ruff, S. Narayanan, and M. Draper, "Human interaction with levels of automation and decision-aid fidelity in the supervisory control of multiple simulated unmanned air vehicles," *Presence*, vol. 11, pp. 335 – 351, 2002.

[11] M. Cummings, A. Brzezinski, and J. Lee, "The impact of intelligent aiding for multiple unmanned aerial vehicle schedule management," *IEEE Intelligent Systems: Special Issue on Interacting with Autonomy*, vol. 22, no. 2, pp. 52 – 59, 2007.

[12] S. Dixon, C. Wickens, and D. Chang, "Mission control of multiple unmanned aerial vehicles: A workload analysis," *Human Factors*, vol. 47, pp. 479 – 487, 2005.

[13] C. Wickens and S. Dixon, "Workload demands of remotely piloted vehicle supervision and control," University of Illinois, Aviation Research Lab, Technical Report ARL-02-10/MAD-02-1, 2002.

[14] J. Chen, P. Durlach, J. Sloan, and L. Bowens, "Human–robot interaction in the context of simulated route reconnaissance missions," *Military Psychology*, vol. 20, pp. 135 – 149, 2008.

[15] S. Dixon and C. Wickens, "Control of multiple-UAVs: A workload analysis," in *Proceedings of the 12th International Symposium on Aviation Psychology*, Dayton, OH, 2003, pp. 1 – 5.

[16] H. Ruff, G. Calhoun, M. Draper, J. Fontejon, and J. Abbott, "Exploring automation issues in supervisory control of multiple UAVs," in *Proceedings of the 5th Conference of Human Performance, Situation Awareness, and Automation Technology*, 2004, pp. 218 – 222.

[17] W. Chappelle, K. McDonald, and R. King, "Psychological Attributes Critical to the Performance of MQ-1 Predator and MQ-9 Reaper U.S. Air Force Sensor Operators," USAF School of Aerospace Medicine, Brooks City-Base, TX, Tech. Rep. Technical Report AFRL-SA-BR-TR-2010-0007, Jun 2010.

[18] D. of the Air Force. (2009) Afsc 1u0x1 remotely piloted aircraft sensor operator (rpa so) career field education and training plan (cfetp). [Online]. Available: http://www.e-publishing.af.mil/shared/media/epubs/CFETP1U0X1C1.pdf

[19] M. Cummings and A. Brzezinski, "Global vs. local decision support for multiple independent UAV schedule management," *International Journal of Applied Decision Sciences*, vol. 3, no. 3, pp. 188–205, 2010.

[20] K. Savla, T. Temple, and E. Frazzoli, "Human-in-the-loop vehicle routing policies for dynamic environments," in *Proceedings of the 47th IEEE Conference on Decision and Control*. Cancun, Mexico: IEEE, 2008, pp. 1145–1150.

[21] M. Prewett, R. Johnson, K. Saboe, L. Elliott, and M. Coovert, "Managing workload in human-robot interaction: a review of empirical studies," *Computers in Human Behavior*, vol. 26, pp. 840 – 856, 2010.

[22] G. Calhoun, M. Draper, J. Nelson, A. Lefebvre, and H. Ruff, "Simulation assessment of synthetic vision concepts for UAV operations," DTIC Document, Air Force Research Laboratory, Human Effectiveness Directorate Warfighter Interface Division, Wright-Patterson AFB, OH, Tech. Rep., 2006.

[23] R. Parasuraman, S. Galster, P. Squire, H. Furukawa, and C. Miller, "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.

[24] C. Smyth, "Modeling indirect vision driving with fixed flat panel displays: Task performance and mental workload," Army Research Laboratory, Aberdeen Proving Grounds, MD, Technical Report, 2002.

[25] S. Schipani, "An evaluation of operator workload during partially autonomous vehicle operations," Army Research Laboratory, Aberdeen Proving Grounds, MD, Technical Report, 2003.

[26] S. Galster, B. Knott, and R. Brown, "Managing multiple UAVs: Are we asking the right questions?" in *Proceedings of the Human Factors and Ergonomics Society's 50th Annual Meeting*, San Francisco, CA, 2006, pp. 545 – 549.

[27] K. Hendy, J. Liao, and P. Milgram, "Combining time and intensity effects in assessing operator information-processing load," *Human Factors*, vol. 39, no. 1, pp. 30–47, 1997.

[28] J. Adams, "Multiple robot/single human interaction: effects on perceived workload," *Behaviour & Information Technology*, vol. 28, no. 2, pp. 183–198, 2009.

[29] C. Wickens, S. Dixon, and D. Chang, "Using interference models to predict performance in a multiple-task UAV environment- 2 UAVs," University of Illinois at Urbana-Champaign, Technical Report, 2003.

[30] B. Hardin and M. Goodrich, "On using mixed-initiative control: A perspective for managing large-scale robot teams," in *Proceedings of the fourth ACM/IEEE International Conference on Human–Robot Interaction.*, La Jolla, CA, 2009, pp. 165 – 172.

[31] J. Luck, P. McDermott, L. Allender, and D. Russell, "An investigation of real world control of robotic assets under communication latency," in *Proceedings of the First Human Robot Interaction Conference*, Salt Lake City, UT, 2006, pp. 202 — 209.

[32] J. Chen, "Concurrent performance of military tasks and robotics tasks: Effects of automation unreliability and individual differences," in *Proceedings of the Fourth Human Robot Interaction (HRI) Conference*, La Jolla, CA, 2009, pp. 181 – 188.

[33] S. Dixon and C. Wickens, "Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload," *Human Factors*, vol. 48, pp. 474 – 486, 2006.

[34] M. Yeh and C. Wickens, "Display signaling in augmented reality: Effects of cue reliability and image realism on attention allocation and trust calibration," *Human Factors*, vol. 43, no. 3, pp. 355 – 365, 2001.

[35] D. Mitchell, "Mental workload and ARL modeling tools," Army Research Laboratory, Aberdeen Proving Grounds, MD, Technical Report ARL-TN-161, 2000.

[36] D. Duke, D. Sims, and J. Pharmer, "Reimagining workload task analysis: Applications to training system design," *Defense Acquisition Research Journal*, vol. 18, no. 4, pp. 428 –448, October 2011.

[37] D. Casbeer and R. Holsapple, "Column generation for a UAV assignment problem with precedence constraints," *International Journal of Robust and Nonlinear Control*, vol. 21, no. 12, pp. 1421–1433, 2011.

[38] S. Karaman and E. Frazzoli, “Linear temporal logic vehicle routing with applications to multi-UAV mission planning,” *International Journal of Robust and Nonlinear Control*, vol. 21, no. 12, pp. 1372–1395, 2011.

[39] C. Murray and M. Karwan, “An extensible modeling framework for dynamic reassignment and rerouting in cooperative airborne operations,” *Naval Research Logistics*, vol. 57, no. 7, pp. 634–652, 2010.

[40] L. Bertuccelli, N. Beckers, and M. Cummings, “Developing operator models for UAV search scheduling,” in *Proceedings of the Guidance, Navigation, and Control Conference*, 2010.

[41] K. Savla and E. Frazzoli, “A dynamical queue approach to intelligent task management for human operators,” *Proceedings of the IEEE*, 2010.

[42] I. Crevits, S. Debernard, and P. Denecker, “Model building for air-traffic controllers’ workload regulation,” *European Journal of Operational Research*, vol. 136, no. 2, pp. 324–332, 2002.

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

[44] S. Mau and J. Dolan, “Scheduling for humans in multirobot supervisory control,” in *Proceedings of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems*. San Diego, CA: IEEE, 2007, pp. 1637–1643.

[45] B. Norman, W. Tharmmaphornphilas, K. Needy, B. Bidanda, and R. Warner, “Worker assignment in cellular manufacturing considering technical and human skills,” *International Journal of Production Research*, vol. 40, no. 6, pp. 1479–1492, 2002.

[46] W. Tharmmaphornphilas, B. Green, B. Carnahan, and B. Norman, “Applying mathematical modeling to create job rotation schedules for minimizing occupational noise exposure,” *AIHA Journal*, vol. 64, no. 3, pp. 401–405, 2003.

[47] W. Tharmmaphornphilas and B. Norman, “A quantitative method for determining proper job rotation intervals,” *Annals of Operations Research*, vol. 128, no. 1, pp. 251–266, 2004.

[48] P. Wirojanagud, E. Gel, J. Fowler, and R. Cardy, “Modelling inherent worker differences for workforce planning,” *International Journal of Production Research*, vol. 45, no. 3, pp. 525–553, 2007.

[49] A. Otto and A. Scholl, “Incorporating ergonomic risks into assembly line balancing,” *European Journal of Operational Research*, vol. 212, pp. 277 – 286, 2011.

[50] E. Lodree, Jr., C. Geiger, and X. Jiang, “Taxonomy for integrating scheduling theory and human factors: Review and research opportunities,” *International Journal of Industrial Ergonomics*, vol. 39, no. 1, pp. 39–51, 2009.

[51] C. Wickens, *Multiple-task performance*. Washington, DC: Taylor & Francis, 1991, ch. Processing resources and attention, pp. 3–34.

[52] D. Kahneman, *Attention and effort*. Prentice-Hall Inc., 1973.

[53] D. Navon and D. Gopher, “On the economy of the human processing systems,” *Psychological Review*, vol. 86, pp. 254–255, 1979.

[54] D. Norman and D. Bobrow, “On data-limited and resource-limited processing,” *Journal of Cognitive Psychology*, vol. 7, pp. 44–60, 1975.

[55] J. McCracken and T. Aldrich, “Analyses of selected LHX mission functions: implications for operator workload and system automation goals,” U.S. Army Research Institute Aviation Research and Development Activity, Fort Rucker, AL, Technical Report ASI479-024-84, 1984.

[56] C. Bierbaum, S. Szabo, and T. Aldrich, “Task analysis of the UH-60 mission and decision rules for developing a UH-60 workload prediction model, Volume I: Summary Report,” U.S. Army Research Institute for the Behavioral and Social Sciences, Technical Report AD-A210 763, 1989.

[57] J. Rubinstein, J. Evans, and D. Meyer, “Task switching in patients with prefrontal cortex damage,” in *Annual Meeting of the Cognitive Neuroscience Society*, San Francisco, CA, 1994.

[58] J. Rubinstein, D. Meyer, and J. Evans, “Executive control of cognitive processes in task switching.” *Journal of Experimental Psychology: Human Perception and Performance*, vol. 27, no. 4, pp. 763 – 797, 2001.

[59] N. Meiran, Z. Chorev, and A. Sapir, “Component processes in task switching,” *Cognitive Psychology*, vol. 41, no. 3, pp. 211–253, 2000.

[60] D. Hebb, “Drives and the CNS (conceptual nervous system),” *Psychological Review*, vol. 62, no. 4, pp. 243 – 254, 1955.

[61] F. Nachreiner, “Standards for ergonomic principles relating to the design of work systems and to mental workload,” *Applied Ergonomics*, vol. 26, no. 4, pp. 259 – 263, 1995.

[62] M. Cummings and S. Guerlain, “Developing operator capacity estimates for supervisory control of autonomous vehicles,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 49, no. 1, pp. 1–15, 2007.

[63] F. da Silva, S. Scott, and M. Cummings, “Design Methodology for Unmanned Aerial Vehicle (UAV) Team Coordination,” MIT Humans and Automation Laboratory, Tech. Rep., 2007.