An Analysis of Heterogeneity in Futuristic Unmanned Vehicle Systems

C.E. NEHME
M.L. CUMMINGS

MASSACHUSETTS INSTITUTE OF TECHNOLOGY*

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Humans and Automation Laboratory

http://halab.mit.edu
e-mail: halab@mit.edu

*MIT Department of Aeronautics and Astronautics, Cambridge, MA 02139

ABSTRACT

Recent studies have shown that with appropriate operator decision support and with enough automation aboard unmanned vehicles, inverting the multiple operators to single-vehicle control paradigm is possible. These studies, however, have generally focused on homogeneous teams of vehicles, and have not completely addressed either the manifestation of heterogeneity in vehicle teams, or the effects of heterogeneity on operator capacity. An important implication of heterogeneity in unmanned vehicle teams is an increase in the diversity of possible team configurations available for each operator, as well as an increase in the diversity of possible attention allocation schemes that can be utilized by operators. To this end, this paper introduces a resource allocation framework that defines the strategies and processes that lead to alternate team configurations. The framework also highlights the sub-components of operator attention allocation schemes that can impact overall performance when supervising heterogeneous unmanned vehicle teams. A subsequent discrete event simulation model of a single operator supervising multiple heterogeneous vehicles and tasks explores operator performance under different heterogeneous team compositions and varying attention allocation strategies. Results from the discrete event simulation model show that the change in performance when switching from a homogeneous team to a heterogeneous one is highly dependent on the change in operator utilization. Heterogeneous teams that result in lower operator utilization can lead to improved performance under certain operator strategies.

INTRODUCTION

Increasing use of automation in unmanned vehicle systems has shifted the human operator's responsibility from manually controlling vehicles to managing vehicles at the supervisory control level. At the supervisory control level, implementation details of higher-level tasking initiated by the human is delegated to the automation onboard these vehicles (Sheridan, 1992). The reduced workload afforded by supervisory control has several implications. One such ramification is an increase in operator idle time, which can be used as a force multiplier that allows operators to supervise multiple vehicles simultaneously, hence inverting the current many-to-one ratio of operators to vehicles. Inverting the operator to vehicle ratio can also be used to reduce manning in situations where the number of vehicles needed to accomplish missions exceeds that of available operators, which is currently a significant problem in the Predator community.

An increasing body of literature has examined the capacity of single operators to supervise multiple unmanned vehicles (Cummings et al., 2007; Olsen & Wood, 2003). This research has mainly focused on the supervision of a homogeneous set of unmanned vehicles. However, as unmanned vehicle system mission goals become increasingly demanding, the composition of unmanned vehicle (UV) teams is likely to involve vehicles of varying capabilities. For example, the military has proposed future operational concepts such as Network Centric Warfare (Alberts et al., 1999) and the Future Combat System (FCS) (Feickert, 2005) that require interoperability among unmanned vehicles of varying attributes.

In addition to heterogeneity across vehicle types, even a single unmanned vehicle can have multiple payloads. Thus multiple mission objectives can drive heterogeneity in a system, which will ultimately lead to heterogeneity for operator tasks.

These multiple dimensions of heterogeneity introduce a number of problems in applying previous models of homogeneous UVs to the heterogeneous case. The different vehicle types that the team could be composed of, and the different tasks that those vehicles could be assigned present a complex and mathematically intractable problem. Moreover, the method by which operators allocate their attention to the heterogeneous vehicles and/or tasks is likely to affect system performance. Capturing the various operator management strategies and their effect on system performance is another important variable that must be considered.

This paper will address these problems by introducing a framework that utilizes resource allocation to describe the process of heterogeneous unmanned vehicle team creation, as well as the operator's attention allocation strategies that define the operator's interaction with the UV team. Using a discrete event simulation model that incorporates the framework considerations as well as a performance model, an experiment that addressed the impact of different heterogeneous vehicle team compositions and the choice of operator strategies on system performance will be discussed.

BACKGROUND

Previous research that examined the capacity of operators supervising multiple homogeneous robots by Olsen and Goodrich (2003) introduced several temporal-based metrics for describing operator interaction with unmanned vehicles. Neglect time (NT) was defined as the expected amount of time that a robot (which is representative of any unmanned vehicle) can be ignored before its performance drops below some acceptable threshold. Interaction time (IT) was defined as the average time it takes for a human to interact with the robot to ensure it is still working towards mission accomplishment. Olsen and Wood (2003) went on to propose that the number of homogeneous robots or vehicles a single human can effectively control, termed “fan-out”, can be given by:

$$FO = \frac{NT + IT}{IT} = \frac{NT}{IT} + 1 \qquad (1)$$

By the fan-out estimation, the total number of robots a single human operator can control makes use of the neglect time of the one robot and converts it into ITs for additional robots. The timeline presented in Figure 1a can be seen as composed of segments, each of length NT+IT. In the single robot example, the operator interacts with the robot for length of time IT and then ignores it for length of time NT during each segment. In order to maximize the number of robots controlled, the NT time partition is replaced by ITs for additional robots (Figure 1b).

While the fan-out estimate of Equation 1 represents a theoretically perfect system, in terms of human-automation interaction, the original fan-out approach makes several assumptions that need to be addressed:

- Requests for human interaction from vehicles are serial and instantaneously met, so that no queues develop while robots are waiting on the operator.
- The operator is perfectly efficient and does not lie idle while vehicles need attention.
- The operator appropriately allocates his/her attention to the vehicle in need.

Because these assumptions cannot hold, an additional critical variable is needed when modeling human control of multiple vehicles, which is the concept of Wait Time (WT). Although it is possible for human beings to multi-task, humans act as serial processors in that they can only solve a single complex task at a time (Broadbent, 1958; Welford, 1952). While operators can rapidly switch between cognitive tasks, any sequence of tasks requiring complex cognition will form a queue and consequently, wait times will build (Cummings et al., 2007). Wait time can occur when 1) a vehicle is neglected while the operator is busy interacting with another vehicle, or 2) when an operator requires re-orientation time while switching between vehicles, or 3) when a vehicle is neglected due to lack of operator situation awareness. Since wait times can negatively affect the actual number of vehicles that can be effectively controlled, Cummings et al. (2007) proposed a modification to Equation 1 to include the concept of wait times as shown in Equations 2 and 3.

$$WT = \sum_{i=1}^{X} WTI_i + \sum_{j=1}^{Y} WTQ_j + \sum_{k=1}^{Z} WTSA_k \qquad (2)$$

$$FO = \frac{NT}{IT + \sum_{j=1}^{Y} WTQ_j + \sum_{k=1}^{Z} WTSA_k} + 1 \qquad (3)$$

Equation 2 categorizes total system wait time as the sum of:

- The interaction wait times, which are the portions of IT that occur while a vehicle is operating in a degraded state (WTI) while the operator is attempting to service it.
- Wait times that result from queues due to near-simultaneous arrival of problems (WTQ) and the inability of an operator to instantaneously solve a problem.
- Wait times due to operator loss of situation awareness (WTSA), which occurs when an operator does not realize a vehicle needs servicing.

An example of WTI is the time that an unmanned vehicle idly waits while a human re-plans a new route. WTQ occurs when a second vehicle sits idle, also waiting for operator interaction, and WTSA accumulates when the operator doesn’t even realize a vehicle is waiting for service.

Although Equation 3 is more conservative than Equation 1 because it captures wait times, both these equations do not link fan-out to measurable effective performance. In both of these equations, performance of each individual vehicle is guaranteed through the thresholds set for NT/IT as well as by ensuring that each vehicle is neglected for a period no greater than NT and serviced for a period no less than IT. There is, however, no system performance metric that the equations utilize to ensure that the vehicle capacity level predicted ensures optimal system level performance.

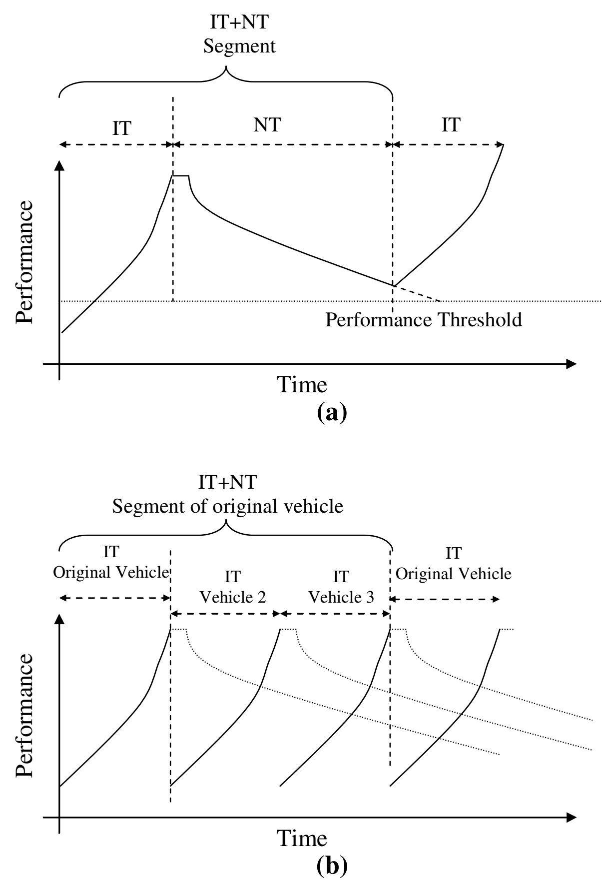

Figure 1. The relationship of NT and IT for (a) a single vehicle, and (b) multiple vehicles

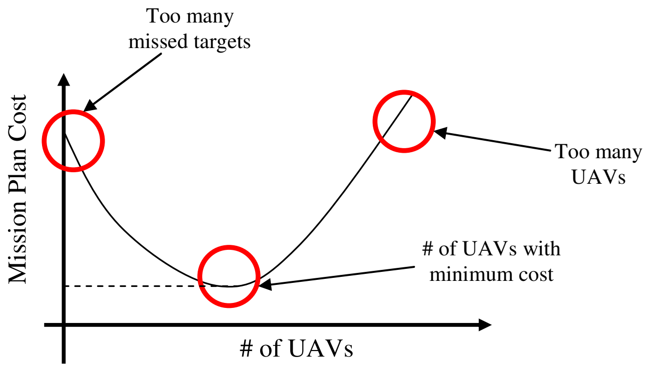

Figure 2. Cost vs. Number of Vehicles

Further work by Cummings et al. (2007) proposed a cost performance model that, instead of achieving maximum limit prediction, is designed to find a satisficing interval of vehicle team sizes such that mission performance is maximized. As a performance metric, Cumming et al. (2007) suggested the use of a system performance metric that evaluates overall mission performance based on the mission objectives. By linking a cost equation to the number of vehicles that the operator would be supervising, an optimized performance metric was utilized to derive a robust interval of vehicle team sizes that best achieves the mission objectives, as represented in Figure 2. The cost equation included the cost of missed targets as well as the operational cost of UAVs.

In order to model wait times, Cumming et al. (2007) proposed a queuing model of the human operator servicing multiple homogeneous UVs. In the single-server queuing network, the events that arrive are vehicles that require intervention to bring them above some performance threshold (Figure 3). Although this model is effective in providing a cost-performance trade space for evaluating the effectiveness of vehicle team sizes, the model does not address the heterogeneity dimensions as previously discussed.

HETEREOGENEITY FRAMEWORK

In order to develop better estimates of both human capacity for heterogeneous UV teams as well as the impact of varying mission tasks and vehicles on operator performance, we first created a framework that captures the processes by which unmanned vehicle teams are created and assigned to human operators. It was also important to define any human interaction with unmanned vehicle teams that might be affected by heterogeneous vehicles/tasks.

Based on the idea of resource allocation, this framework is presented in Figure 4. The framework incorporates the allocation of three hierarchical resources: vehicles, human operators, and human attention. The first two resources, vehicles and human operators, are tangible physical assets that are allocated during mission planning, and it is through the allocation of these assets that vehicle teams are defined and

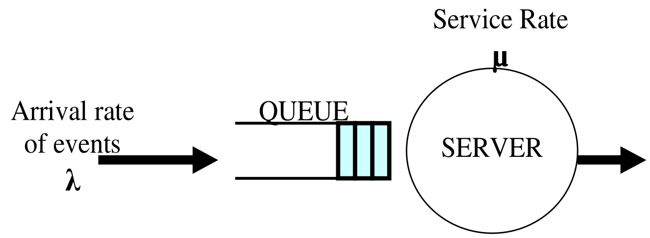

Figure 3. Queuing Model

assigned to operators. The third resource, operator attention, is an intangible asset whose allocation strategy defines the interaction of the operator with the team of unmanned vehicles. This framework is not meant to be a detailed description of every aspect of unmanned vehicle assignment, but is instead meant to highlight the role of resource allocation strategies in influencing the effectiveness of human-vehicle/task interaction.

Starting from the top left of Figure 4, a vehicle allocation strategy is depicted as the method by which vehicles, based on their capabilities (which includes payloads, vehicle specifications, operational domain, and levels of automation), are assigned mission-based tasks that collectively satisfy the mission objectives. The objective of the vehicle allocation strategy is to break down the mission objectives into tasks that can be allocated to the different vehicles. The choice of vehicle allocation strategies depends on the vehicle capabilities, the mission objectives, and the timing/control constraints imposed by the mission specification.

Next, a personnel allocation strategy is utilized in order to allocate an operator unit (at the organizational and individual level) to one or more mission task(s). The choice of personnel allocation strategies depends on the capabilities of the operators, as well as the interfaces available to them.

Together, a vehicle allocation strategy and a personnel allocation strategy identify the particular vehicles and mission tasks that will be the responsibility of each operator unit. These initial two steps in the framework proposed in the preceding discussion are not the only possible format. It is possible for example to assign vehicles to personnel instead of assigning them to mission tasks. The main theme, however, across any allocation strategy combination is that, vehicles, tasks, and personnel need to be assigned to each other in order to define the vehicle/task team that each operator unit will be supervising.

The third and final strategy in the framework, the human-attention allocation strategy, is a function of the level at which the operator interacts with each vehicle/task, as well as the order by which the different vehicles/tasks are serviced. Operator resource allocation strategies are depicted in Figure 4 as dependent on the operator-task assignment, the importance of the mission tasks, and the urgency of the mission tasks.

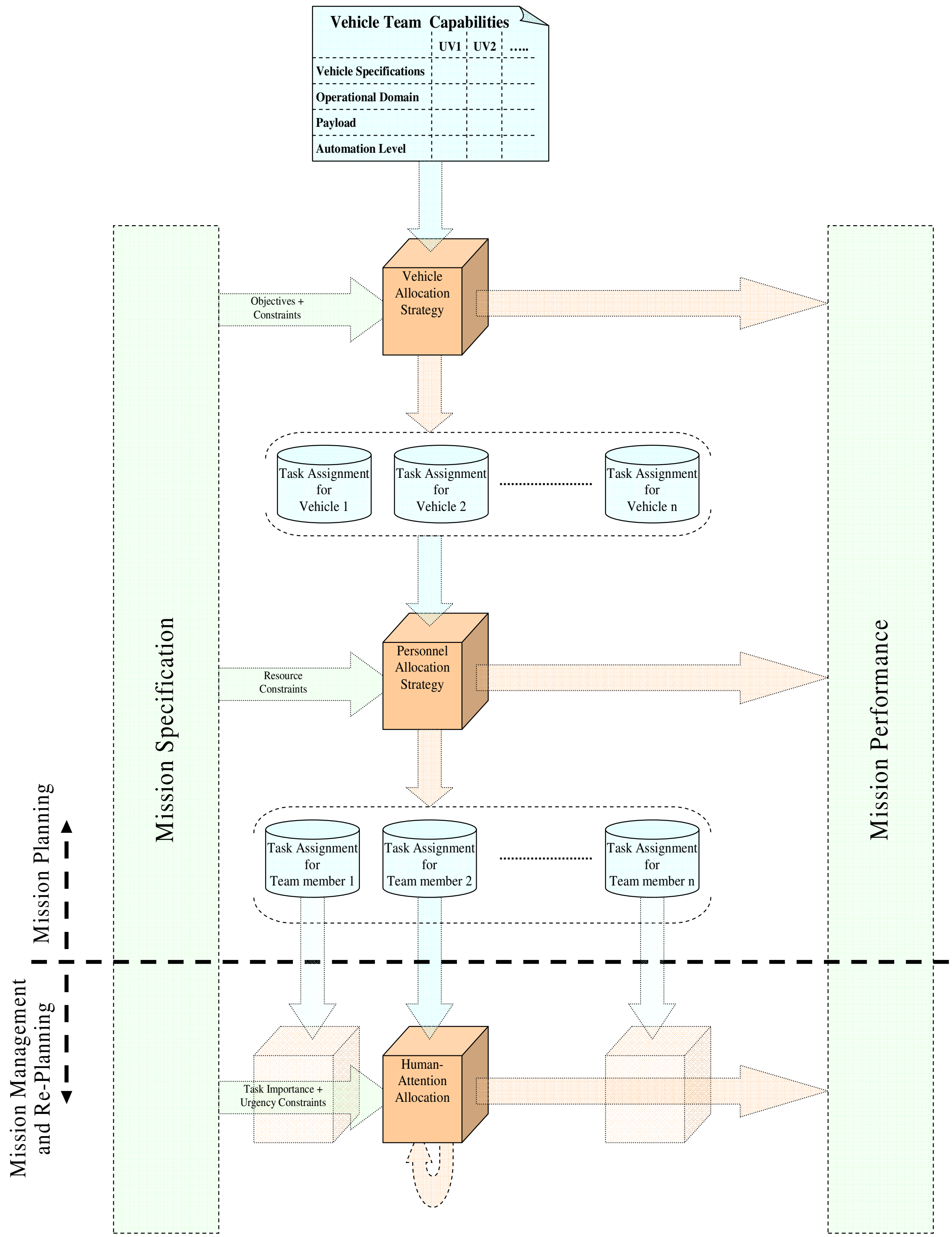

Figure 4. Human-Vehicle(s)/Task(s) Interaction Framework

The significance of the overarching mission description block on the left hand side of Figure 4 represents the constraints imposed on the different strategies throughout the mission planning and re-planning phases. An example of this is a time on target (TOT) constraint that requires that an ISR task be assigned to a UAV over a UUV due to the latter vehicle being unable to reach the area of interest in time.

The right hand side of Figure 4 represents the possible effects of the allocation strategies for all three resources on overall mission performance. For example, in a two-operator mission that requires the completion of two surface imagery tasks as well as two other target designation tasks, alternate personnel allocation strategies are possible. Assigning each operator two of the same tasks will result in mission performance that likely differs from that resulting from assigning each operator to one of each task type. The extent of the effect of alternate human-attention allocation strategies on overall mission performance is the subject of interest in this paper, and will be discussed further in the experiment section. First, a more detailed analysis of human-attention allocation is presented.

Human Attention Allocation

This part of the framework represents the attention allocation strategies that are available to the operator for attending to the different vehicles/tasks. Whereas vehicle and personnel allocation is normally the result of careful advanced planning, human-attention is allocated in real-time once the mission is underway. Human-attention allocation strategies are also likely to be dependent on operator training and experience, which could provide greater consistency in attention allocation.

In supervising an unmanned vehicle mission, the operator's role is that of a mission manager whose task is to increase the performance of the unmanned vehicle mission. The operator can interact with an unmanned vehicle when either a) the automation is acting sub-par and the operator believes that interaction can increase performance, or b) when an event occurs that requires human judgment and reasoning, something the automation is incapable of handling. For example, in the case of an unmanned aerial vehicle that is assigned a laser designation task, the operator could re-plan the vehicle path generated by automation in order to better meet a time-on-target restriction. The operator's judgment is also critical in deciding whether a specific target is the one that should be designated. When supervising multiple unmanned vehicles, the operator attention allocation strategy will dictate the method by which the operator will supervise the different vehicles.

An overall attention allocation strategy can be dissected into four main components, which will be discussed in greater detail below: a) a neglect strategy, b) an interaction strategy, c) a switching order strategy, and d) a complexity mitigation strategy.

Neglect Strategy. The first component of human-attention allocation is the operator neglect strategy. The neglect strategy affects the duration of time for which the operator neglects the unmanned vehicles; i.e., the frequency by which the operator attends to the vehicles. The neglect strategy can vary per vehicle, and can be thought of as the scheme by which the operator distributes his/her attention across the different vehicles. A strategy where the operator services the vehicle only when necessary, and otherwise allows the vehicle's automation to undertake tasks can be referred to as a neglect-macro-management strategy. On the other hand, a strategy where the operator constantly interferes with the vehicle's automation can be referred to as a neglect-micro-management strategy. Other neglect strategies can exist between these two extremes.

Interaction Strategy. The second component of human-attention allocation is the operator interaction strategy. The interaction strategy affects the duration of time the operator services the unmanned vehicle. A strategy where the operator uses any provided automated decision support to achieve increased vehicle performance can be referred to as an interaction-macro-management strategy. On the other hand, a strategy where the operator services the vehicle for a period longer than that needed by the vehicle can be referred to as an interaction-micro-management strategy. An example of an interaction-micro-management strategy is one where an operator insists on manually planning a vehicle path when an automated path planner is available. Other interaction strategies can exist between these two extremes.

Complexity Mitigation. The third component of human behavior that influences attention allocation is the mitigation of system complexity through the use of cognitive abstractions. For example, operators can use mental abstractions to form vehicle groupings based on one or more criteria in order to reduce the complexity of supervising all the vehicles (Goodrich et al., 2007; Histon et al., 2002). Examples of criteria for grouping vehicles include the similarity of vehicle capabilities or task types. The result of such grouping abstractions is to organize the vehicles into relevant groups in order to simplify the task of managing them. For example, an operator that is supervising multiple unmanned vehicles in a mission that includes coastal and inland surveillance might elect to divide the vehicles into two groups depending on their region of operation.

Switching Order. Finally, the fourth component of human-attention allocation is the order by which the different vehicles are serviced. When multiple vehicles require operator attention simultaneously, the operator must select the next vehicle to be serviced. Whereas this selection process is relatively simple in the homogeneous case, it is much more involved in the heterogeneous case. In the heterogeneous case, the difference in vehicles capabilities and their assigned tasks allows for more diverse selection strategies. For example, an operator that is supervising two UAVs with heterogeneous tasks can service the vehicles on a first come, first serve basis (FIFO) or allocate attention to the UAVs based on the priority of their tasks (the latter scheme is formally known as preemptive priority queuing). The order by which the vehicles are serviced affects the total time that vehicles spend in the system, including the time they spend waiting for service as well as their processing time. In addition to having an effect on wait times, when a human operator switches between two different tasks, this is accompanied by a mental model switch that comes at a time cost, i.e., a switch cost (Goodrich et al., 2005; Squire et al., 2006). Thus switching between different combinations of heterogeneous vehicles can lead to different switch costs.

OPERATOR MODEL

To examine the impact of attention allocation strategies on overall system performance, a discrete event simulation (DES) model of a heterogeneous unmanned vehicle system was developed. The DES model, notionally shown in Figure 5, includes a) a queuing model of the human operator supervising multiple UVs, and b) a component for the ability to measure overall system performance, which will be discussed in the next section. In order for the queuing model to represent the ideas developed in the framework in Figure 4, two ideas needed to be incorporated. First, due to the different team configurations possible through the vehicle and personnel allocation strategies, the queuing model needed to support teams with heterogeneous vehicle capabilities, heterogeneous vehicles tasks, and variable team sizes. Second, in order to study the effect of alternate attention allocation strategies on mission performance, the ability to modify the strategies was included in the model. Finally, the model captured all three wait time components, WTQ, WTSA, and WTI in order to provide realistic data to the performance model. For equations and a more detailed description of the calculations, see the Appendix.

Overview

The operator model is based on the single server queue with multiple input streams (Figure 6). Each input stream is associated with one of the unmanned vehicles in the team. A team of size *n* is therefore modeled with *n* input streams. In the model, each vehicle is represented by an NT/IT pair. NT represents the expected value of the distribution of the duration of time for which the vehicle can be neglected before its performance drops below some acceptable threshold. IT represents the expected value of the distribution of the duration of time needed for a single interaction between the operator and that vehicle in order to raise performance to some acceptable threshold level.

Since the vehicles belonging to the *n* input streams have different neglect and interaction distributions, the rates at which the operator will actually neglect and attend to the vehicles could vary from vehicle to vehicle. This is captured by the separate arrival streams which allow distinct arrival and service rates for each stream. These arrival rates include both exogenous events (event arrivals from the external environment) and endogenous events (those events the operator chooses to attend to). Both the arrival rates and

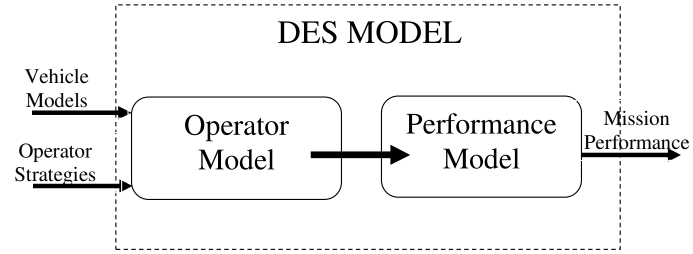

Figure 5. DES Model for Heterogeneous UV System

service rates of events depend on a) the operator's attention allocation strategies, and (b) wait times.

Event Arrival Rate

The arrival rate of events from stream *i,* which represents the rate at which the operator intends to service the vehicle associated with stream *i*, is a random process. The expected value of this random process is NT_i', which is the average duration of time for which vehicle *i* is neglected following an interaction. Note that the operator's decision to service a vehicle does not necessarily signify the beginning of an interaction. The period between the end of a neglect period and the beginning of an interaction depends on queuing wait times which are captured separately as a dependent variable. NT' is a function of two main components; a) the operator's neglect strategy and, b) loss of situational awareness (Equation 4).

$$NT_i^{'} = LON * NT_i + \chi * NT_i \qquad (4)$$

where LON (level of neglect) represents the operator's neglect strategy taking on values between 0 and ∞, and χ represents the operator's loss of situational awareness taking on values between 0 and 0.25.

Neglect Strategy. The first term in Equation 4 represents the period for which the operator neglects vehicle *i*, excluding any effect due to loss of situational awareness (SA). This term is a product of two variables, LON and NT_i. NT_i is the neglect time associated with the vehicle represented by stream *i*. By definition, this is the average length of time that the operator should interact with vehicle *i* for in order to bring performance up to some acceptable threshold. The product of LON and

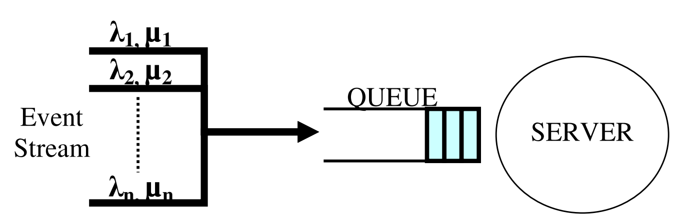

Figure 6. Human-Vehicle(s)/Task(s) Interaction Framework

NT_i, however, represents the average rate at which the operator actually neglects the vehicle, which is not necessarily equivalent to NT_i.

The LON variable, which can take on any positive real number, represents the operator's neglect strategy. For example, an LON of 1 would result in a neglect macro-management strategy where the operator attempts to service vehicle *i* at a frequency equivalent to NT_i, the rate at which vehicle *i* needs attention. A neglect micro-management strategy on the other hand, is represented by an LON less than 1 which means the operator services the vehicle more often than the vehicle needs attention.

Wait Times due to Loss of Situational Awareness. The second term in Equation 4 represents the effects due to loss of situational awareness (SA). SA is defined as the combination of perception of elements in the environment, the comprehension of their meaning, and the projection of the their status in the future (Endlsey, 1995). The effect of low SA is to create additional vehicle wait time (WTSA) which increases NT', due to the operator taking longer to notice the vehicle (Cummings et al., 2007).

In order to capture SA, this model builds on an assumption that SA is related to operator utilization (Endsley, 1993). When operators are under high levels of utilization, it is assumed that they are too busy to accumulate the information that is required to build SA. At the same time, when operators are under-utilized, it is presumed that due to a low level of arousal, they could overlook information from the environment, which would also lead to low SA.

The χ variable in Equation 4 is related to operator utilization through a parabolic function that is concave upwards (see Appendix for the specific formulation). This implies that at both high and low operator utilization, χ increases according to a quadratic law and therefore increases NT' correspondingly. The parabolic relationship is inspired by the Yerkes Dodson Law (Yerkes & Dodson, 1908), which relates operator utilization to performance. The χ variables is multiplied by NT in order to capture the fact that the effect on NT' due to loss of SA is a function of the vehicle's neglect time. The reasoning behind this is that vehicles with larger neglect times are serviced less often, and are therefore more likely to be overlooked than vehicles that are serviced more frequently.

Event Service Rate

Also associated with each input stream is a service rate which is based on the length of time it takes the operator to interact with a particular vehicle, corresponding to the arriving event. The expected value of this random process is IT_i', which is the average length of time for which vehicle *i* is serviced. IT_i' is a function of two main components; a) the operator's interaction strategy, and b) wait times due to context switching (Equation 5).

$$IT_i^{'} = LOI * IT_i + (\varphi + \tau) * IT_i \qquad (5)$$

LOI (level of interaction) represents the operator's interaction strategy, taking on values between 0 - ∞. φ is a coefficient for calculating the time penalty due to switching between vehicles with heterogeneous capabilities, and τ is a coefficient for calculating the time penalty due to switching between vehicles with heterogeneous tasks.

Interaction Strategy. The first term in Equation 5 represents the length of time for which an operator interacts with a vehicle excluding any wait times due to context switching. This term is a product of two variables, LOI and IT_i. IT_i is the interaction time associated with the vehicle represented by stream *i*. By definition, this is the expected amount of time for which the operator needs to interact with vehicle *i* in order to raise performance above some acceptable threshold.

The LOI variable, which can take on any positive real number, represents the operator's level of interaction. For example, an LOI of 1 would result in an interaction macro-management strategy where the operator services vehicle *i* for lengths of time equivalent to IT_i, the expected length of interaction time required by vehicle *i*. The interaction strategy can vary from the operator interacting with vehicle *i* for a length of time much larger than that a priori designed vehicle IT_i (such as is the case when the operator spends a lot time interacting with a vehicle each time that vehicle is serviced) to a strategy where the operator services vehicle *i* for a length of time equivalent to a fraction of IT_i (such as is the case when the operator underestimates vehicle *i*'s need for operator attention and therefore services vehicle *i* for shorter periods than required).

Wait Times due to Context Switching. The second term in Equation 5 is a function of the context switching times that arise when servicing a specific vehicle. When a human operator switches between two different tasks, this is accompanied by a mental model switch that comes at a time cost, also known as a switch cost. The switch cost is not limited to switching between cognitively complex tasks, but exists even when humans switch between cognitively simple ones (Rogers & Monsell, 1995). For example, Goodrich et al. (2005) demonstrated that the existence of context switching costs in multi-vehicle control is unavoidable, and that the amount of time required to switch between vehicles can be substantial. As a consequence, longer switching times can dramatically decrease the upper bound on the number of manageable robots (Goodrich et al., 2005). For this DES model, context switching was accounted for whenever the current vehicle's capability or its task type differed from that of the last vehicle serviced (these effects are captured by the φ and τ variables respectively). The effect of switching times creates additional interaction wait times (WTI) which increases ITi', due to the operator taking longer to interact with the vehicle. The (φ + τ) factor is multiplied by IT in order to capture the fact that the context switching time effect on IT' is a function of the vehicle's interaction time.

Switching Between Events

In order to model the switching strategy of the operator, the type of queue can be varied to represent different strategies Examples of switching strategies that can be modeled include the first-in-first-out (FIFO) queuing scheme as well as the highest attribute first (HAF) strategy. The HAF strategy is similar to a preemptive priority scheme in that high priority events are serviced first except that there is no pre-emption. Therefore if an event is generated with a priority higher than any of the events already in the system, it will be moved to the front of the queue but will not preempt a lower priority vehicle that is already being serviced.

PERFORMANCE METRIC

The model just described allows for the manipulation of team heterogeneity as well as the strategies utilized by operators in allocating their attention. In order to evaluate the effectiveness of alternate strategies while supervising teams with different levels of heterogeneity, a system performance metric was developed.

Initial research on operator capacity in supervising homogeneous vehicle teams focused on individual vehicle performance metrics. In some cases, acceptable levels of performance were defined as occurring when vehicles were not neglected beyond their predefined neglect time.

Later work (Cummings et al., 2007) proposed using a mission performance metric that is focused more towards system performance than individual vehicle performance. In this case, metrics focused on cost equations that measured completion of mission objectives. The benefit of utilizing a system performance metric is that it measures the combined performance of all the vehicles towards the mission goal which is a better indicator to mission commanders of overall mission progress. However, evaluating systems based on such performance metrics tends to focus on just the reward for objectives completed, and hence overlooks any unacceptable individual vehicle performance.

For this research effort, we have developed a cost performance model that captures system performance, but also ensures a heavy penalty when individual vehicle performance falls below a certain threshold. This performance metric measures different variables from the operator model in order to evaluate system performance (Equation 6).

$$Performance = \frac{1}{priority_1 + priority_2 + \cdots} * \left(priority_1 * P_1 * MIN(1, \Delta_1) + priority_2 * P_2 * MIN(1, \Delta_2) + \ldots\right) \tag{6}$$

Each vehicle's contribution to the performance metric is captured through one term in Equation 6. The P_i factor in each term represents the quality of the operator's interaction with that vehicle. The MIN(1, Δ_i) factor represents the timeliness of the operator's interaction, and therefore ensures that the value added due to the operator's interaction is weighted by the punctuality of that interaction. The metric therefore reflects both the timeliness of interaction as well as the quality of interaction. Finally, each term in the equation is weighted by the priority of that vehicle, which is dependent on the value of that vehicle's task as a proportion of the overall mission objective. These priorities can also be predefined during mission planning and might be dictated by rules of engagement. Mission performance is therefore most sensitive to operator performance in supervising vehicles whose assigned tasks have significant value to the mission objective. A vehicle that underperforms on an individual basis will negatively impact the performance metric, and at the same time, the metric measures the total contribution of all vehicles which serves as an overall mission performance indicator.

One important factor that influences both operator and mission performance is the quality of the human-computer interface and associated decision support. By comparing performance resulting from alternate strategies, a conclusion can be made as to what strategies promote the best performance trends. This can encourage system designers to design interfaces that amplify these strategies and mute those that result in less effective performance. A study was therefore conducted to provide as a preliminary investigation of the effects of alternate resource allocation strategies on system performance.

EXPERIMENTAL STUDY

The focus of this experiment was to determine the effects of a subset of operator resource allocation strategies on mission performance, as the level of heterogeneity in the unmanned vehicle team is varied. Three independent variables were of interest in this experiment: team-heterogeneity, level of neglect (LON) strategy, and the operator switching strategy.

Team-Heterogeneity Factor

For the team-heterogeneity factor, four levels were utilized. One of those levels was a homogeneous team, and the other three each represented different heterogeneous team configurations.

The first level, team1, was representative of a homogeneous team which consisted of three UAVs each doing a surface imagery task. The NT for each vehicle was drawn from a normal probability distribution with a mean of 60 seconds and a standard deviation of 6 seconds, or 10% of the mean.

The second level, team2, was a heterogeneous team that was created by replacing a single UAV from the homogeneous team with an unmanned surface vehicle (USV). This heterogeneous team therefore consisted of two UAVs and a USV all assigned surface imagery tasks. The mean of the NT distributions for the UAVs was 60 seconds, whereas the mean of the distribution for the USV was 30 seconds which represented the fact that a surface vehicle might be more susceptible to detection than a UAV, and therefore needed extra attention from the human operator. The NT standard

Table 1. Team Configurations

	Vehicle1		Vehicle2		Vehicle3	
	NT	IT	NT	IT	NT	IT
Team1	60	10	60	10	60	10
Team2	30	10	60	10	60	10
Team3	60	10	60	10	120	10
Team4	30	10	60	10	120	10

deviation for the two UAVs was 60 seconds and 30 seconds for the USV (the standard deviations were chosen to be 10% of the corresponding NTs).

The third team, team3, was a heterogeneous team that was created by replacing the task of a single UAV in the homogeneous team with a communications task. This heterogeneous team therefore consisted of three UAVs, two of which were each doing a surface imagery task, with the third vehicle served as a communications relay. The means of the NT distributions for the UAVs doing the surface imagery task were 60 seconds, whereas the mean of the distribution for the UAV doing the communications task was 120 seconds, which represented the fact that a vehicle performing a communications task would require modest operator intervention. The NT standard deviation for the first two UAVs was 60 seconds and 120 seconds for the communications UAV.

Finally, team4 was a heterogeneous team that was created by having three different vehicle/task pairs, each having a different mean for their NT distributions. Team4 consisted of a USV and a UAV each assigned a surface imagery task, as well as a UAV assigned a communications task.

For all four factor levels, all vehicles had a mean IT of 10 seconds and an IT standard deviation of 3 seconds. The above data is summarized in Table 1.

The general team assignments represent increasing heterogeneity. In team2, heterogeneity was induced by introducing a low NT vehicle that is likely to increase overall operator task load. In team3 on the other hand, heterogeneity was induced by introducing a high NT vehicle that is likely to be less demanding than the low NT vehicle added in team2. In team4, just like the homogeneous team, the mean NT across all three vehicles was 60 seconds. Unlike the homogeneous team however, there was a spread in NTs for team4.

LON Factor

For the experiment, the operator level of neglect factor consisted of three levels; Macro, Macro/Micro, and Micro. The three factor levels represented alternate operator neglect strategies. The neglect strategy was represented by the LON variable in the operator discrete event simulation model. The Macro neglect strategy was that corresponding to an LON of 1. This, in essence, represented a situation where NT' was equivalent to NT, excluding any effects due to loss of situational awareness. In the Macro case therefore, the operator decided to service vehicles exactly at the NT mark

Table 2a. Test matrix for sub-experiment #1

FIFO			
	Macro	Macro/Micro	Micro
Team1	o	o	o
Team2	o	o	o
Team3	o	o	o
Team4	o	o	o

Table 2b. Test matrix for sub-experiment #2

FIFO			
	Macro	Macro/Micro	Micro
Team2	o	o	o
Team3	o	o	o
Team4	o	o	o
HAF			
	Macro	Macro/Micro	Micro
Team2	o	o	o
Team3	o	o	o
Team4	o	o	o

(whether the operator does so depends on any wait times that could precede the interaction). The Macro/Micro strategy was represented by setting NT' to be equivalent to ¾ NT. This strategy represented an operator that is partly attempting to micromanage the vehicles, but doing so at a moderate level. Finally, the Micro strategy represented an extreme case of micromanaging and was quantified by an NT' equivalent to ½ NT.

Switching Factor

The switching factor consisted of two factors: The FIFO and HAF queuing strategies discussed previously. The two factor levels represented alternate switching strategies by which the human operator can service vehicles when there is more than one request at the same time, and the operator is faced with the choice of selecting which vehicle to service. Under the FIFO strategy, operators service vehicles on a first-come basis. The HAF strategy relies on events having a specific criterion and the operator selects the vehicle with the highest criteria value. The priorities for this experiment were as follows: The USV performing an ISR task was assigned the highest priority, followed by the UAV performing the ISR task, and the UAV assigned the communications task having the lowest priority. Alternate priority-assignment schemes were not investigated in this experiment.

The Simulation

There were 21 treatments in total with three missing treatments due to the incompatibility of the HAF queuing scheme and the homogeneous team factor levels (Table 2).The discrete event simulation modeling language used was Arena®, and the simulations were run on a Fujitsu T4000 series tablet with a 1.80 GHz Intel Pentium processor.

Thirty simulation replications were conducted for each treatment condition. In each replication, data on two

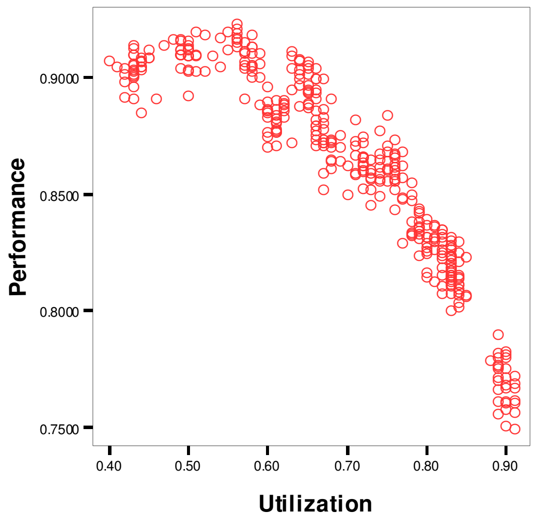

Figure. 7. Performance vs. average Operator Utilization

dependent variables was collected. The first dependent variable ζ, the performance metric introduced in the previous section, measured average vehicle performance for the whole mission. The second dependent variable measured was operator utilization.

RESULTS

In this section, the results from the experimental study described in the previous section are presented. Due to the fact that a discrete event simulation was used and is therefore lacking the variance that real subject data would have, a family-wise significance level of 0.001 was used wherever needed.

Sub-Experiment 1

The first of these studies was a two factor study with the switching factor fixed at the FIFO level. Data from the 12 treatments that included the FIFO factor level were utilized. Using the Pearson correlation test, the dependent variables were found to be highly correlated to each other (utilization-performance -.901). Plotting performance as a function of utilization, Figure 7, it is evident that a curvilinear relationship exists between these two variables and that the linear correlation calculated is likely to be the result of a lack of points at lower utilization levels. The curvilinear relationship seen here can be associated with the parabolic dependence of NT' on utilization described previously in Equation 4. NT' was described as being dependent on operator utilization, with higher utilization levels causing loss of SA and an ensuing rise in NT'.

At a significance level of 0.001, a 4x3 MANOVA (team-heterogeneity x LON) revealed through the Wilk's Lambda test significant main effects for both factors, as well as a significant two-factor interaction ($p < 0.001$). It was also determined through a univariate analysis that the two-way interaction was significant for both DVs. The next step was therefore to compare simple effects for each of the DVs.

The box plots for the performance DV are presented in Figure 8. For the treatment means that had the smallest differences between them, nine simple contrasts using the Bonferroni procedure were conducted in order to check for significance. All mean contrasts were significant (highest p-value < 0.0001) except for the contrasts between the Team3 treatment means for Macro and Macro/Micro (p-value = 0.0003), as well as the Macro treatment means for Team1 and Team3 (p-value = 0.0006).

The box plots for the utilization dependent variable are presented in Figure 9. For the treatment means that had the smallest difference between them, three simple contrasts using the Bonferroni procedure were conducted in order to check for significance. All contrasts resulted in significant differences (highest p-value < 0.0001).

Sub-Experiment 2

In the second sub-experiment, the switching factor was varied and so the team1 level for the team-heterogeneity factor was dropped since it was incompatible with the HAF queuing scheme (3x3x2 study). At a significance level of 0.001, a 3x3x2 MANOVA (team-heterogeneity x LON x switching) revealed through the Wilk's Lambda test significant main effects for all three factors ($p < 0.001$). The test did not reveal significance for the three way interaction ($p = 0.418$), the LON x switching 2-way interaction ($p = 0.033$), or the team-heterogeneity x switching 2-way interaction ($p = 0.011$). There was, however, a significant team-heterogeneity x LON 2-way interaction ($p < 0.001$). A univariate analysis revealed that the team-heterogeneity x LON two-way interaction was significant for both DVs ($p < 0.001$), and that the switching main effect was significant only for the utilization DV (utilization: $p < 0.001$; performance: $p = 0.0031$). Since the effect of the team-heterogeneity x LON interaction on the DVs was investigated in the first sub-experiment, the focus for this sub-experiment was on the switching factor main effect on the

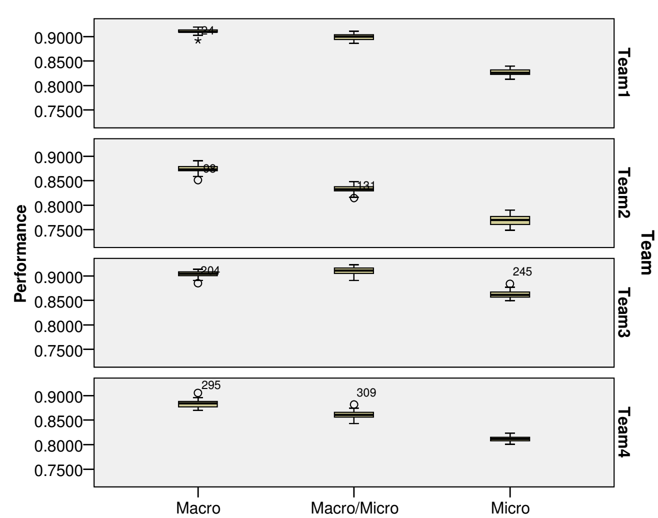

Figure. 8. Box plot for Performance DV

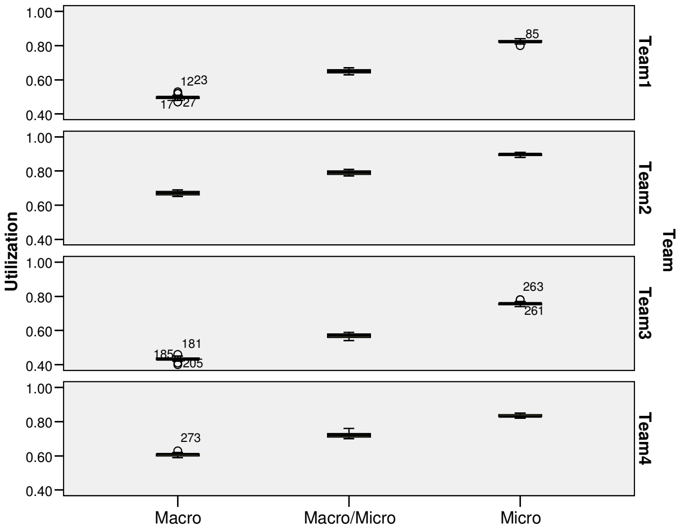

Figure. 9. Box plot for Utilization DV

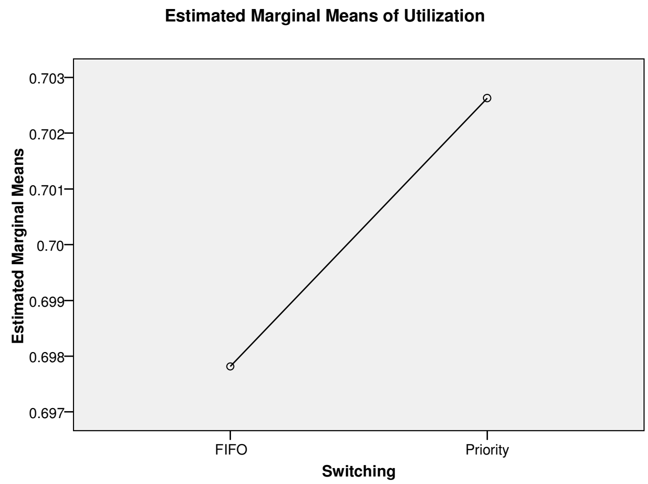

Figure. 10. Estimated Marginal Utilization Means

utilization DV. It was found that under the HAF strategy, average operator utilization was significantly higher than under the FIFO strategy (p-value < 0.001). The estimated marginal means plot for the utilization DV is shown in Figure 10.

DISCUSSION

Using the results from the sub-experiment 1, the effects of two different elements on system performance and operator utilization will be addressed, including the effects of team heterogeneity, and the effects of alternate LON strategies. Then, using the results from the second experiment, the effect of switching strategies on operator utilization will be addressed.

Team Heterogeneity and Level of Neglect

The first sub-experiment showed that the effect of heterogeneity in UV teams on system performance and operator utilization depends on the type of heterogeneity present. When heterogeneity was created by replacing one of the vehicles in a homogeneous team with another vehicle/task pair that had a smaller NT (team2), performance decreased and operator utilization increased. This can be attributed to the fact that the lower overall NT in team2 created an increase in operator utilization, which likely led to increased wait times and degraded performance. Team2 also experienced context switching times, which did not exist for the homogeneous team, and this further exacerbated the performance reduction.

However, when heterogeneity was created by replacing one of the vehicles in the homogeneous team with another vehicle/task pair that had a larger NT (team3), the results were different. When operators had a Macro level of neglect strategy, there was no statistically significant difference in performance between the two teams. Although, the introduction of the high NT vehicle/task pair significantly reduced operator utilization for team3, the drop in utilization was not enough to counteract the context switching times experienced when supervising team 3. However, under more Micro LON strategies, the utilization drop was even larger when supervising the heterogeneous team which created significantly better performance. This suggests that by introducing certain forms of heterogeneity that decrease the average NT of the team, it is possible to reduce utilization and even increase performance at certain levels of LON.

Finally, team4, which had the greatest heterogeneity across NTs, yielded both significantly higher utilization and lower system performance. One explanation for this result is that although the average NT across vehicles was the same for both teams 1 and 4 (60 s), heterogeneity was only present in team4 which made it underperform due to the existence of context switching times. Deeper analysis however should be conducted in order to realize whether or not the size of the spread in NTs across vehicles has any effect on the increased utilization and reduced performance.

It is also important to note that for all four teams, when going from a Macro to a Macro/Micro strategy or from a Macro/Micro to a Micro strategy, average operator utilization increased significantly, as expected.

It was also the case that the increase in utilization was accompanied by a significant drop in system performance with the exception that in team3, when going from Macro to Macro/Micro LON, there was no significant performance change. For the cases where there was a significant performance drop, there are two likely explanations. First, increased operator utilization likely led to reduced situation awareness (or increased wait time due to loss of situational awareness). Second, the increased rate of interaction with vehicles in the more Micro levels resulted in saturated operators. This, in effect, created a large increase in queuing wait times which were measured in this study but not analyzed as a DV. Both, increased WTQ and WTSA, are detrimental to performance due to the fact that vehicles were likely to be serviced at periods greater than their assigned NT.

In the case of team 3, although utilization increased significantly when going from Macro to Macro/Micro, utilization was not likely to increase too greatly since utilization was already low in the Macro case. Therefore the increase in utilization was unlikely to cause a reduction in situational awareness, which according to the χ variable occurs as utilization increases much higher than 50% (see Appendix). In addition, any increase in queuing wait times was likely to impact the vehicle with the longer neglect time which was a lower priority vehicle (the assumption that high NT vehicles are lower priority was just an assumption for this study and will change in future studies). Since lower priority vehicles have a lower impact on performance (according to the model described earlier), any wait times experienced by the high NT vehicle/task did not cause a significant decrease in performance.

Switching Strategy

In sub-experiment 2, utilization increased significantly when going from a FIFO to an HAF switching strategy. This can be attributed to the fact that by moving high priority (low NT) vehicles to the top of the queue, average queuing wait times for the low priority vehicles increased (since they would always have to wait behind the high priority vehicles). Since the length of time it takes an operator to interact with a vehicle (IT') is proportional to the size of queuing wait times (according to the current model, see Appendix), this resulted in longer interaction times and hence higher average operator utilization.

Although there was a significant increase in utilization, the results showed no significant change in performance under the two switching strategies. Although it was hypothesized that the HAF strategy would increase performance by reducing the queuing wait times for the highest priority vehicles that have the largest contribution on performance, this was not realized. A possible explanation for this is that since the size of the vehicle teams in this experiment was small, the reduction in queuing wait times was not likely to be substantial. For example, in the FIFO, strategy, the highest priority vehicle would, in the worst case, be waiting in a queue with 2 other vehicles ahead of it.

The important message from this analysis is that when considering the effects of alternate switching strategies, the number of vehicles is an important consideration. When the team size is too small, it is unlikely that an HAF strategy will likely result in significant performance gains and could instead lead to a significant increase in average operator utilization.

CONCLUSIONS AND FUTURE WORK

A framework was presented that identified the resource allocation strategies that are fundamental in defining the type of heterogeneity that will be present in vehicle teams, as well as the different attention-allocation strategies that are available to the human operator in supervising such teams. A discrete-event simulation model that was developed to investigate the effect of alternate operator strategies in supervising the different forms of team heterogeneities was also presented. Finally the results of an experimental study conducted using the discrete-event simulation model were analyzed. It was shown that when comparing heterogeneous teams to their homogeneous counterparts, the average NT across vehicles is decisive in predicting significant performance and utilization changes. Heterogeneous teams with an average NT across vehicles lower than that of homogeneous teams were likely to result in a significant increase in operator utilization. On the other hand, a heterogeneous team with a larger average NT across vehicles could cause a reduction in utilization and an increase in performance under certain LON strategies. It was also noted that further investigation needs to address the effect of the size of the spread of NTs across vehicles on average operator utilization and performance. Finally, the effect of varying the switching strategy was shown to be absent in the case of small-sized vehicle teams.

Future work will involve using the lessons learned through this study to improve the model and make predictions which will be validated against results from human-subject experiments. The arrival process of events to the queue will be modified in order to separate out operator-induced events from vehicle-enerated events. In addition, an arrival stream will be added to model the arrival of events that are exogenous to the system and therefore represent the unpredictable environment. Varying the arrival rate of exogenous events in future experiments will help test for the robustness of the queuing model. Other changes involve comparing the current dependence of NT' on utilization to existing experimental data and improving the model accordingly. A simulation game that allows participants to supervise multiple simulated heterogeneous unmanned vehicles is under development, and once completed, will then be used to validate the predictions from the updated model.

ACKNOWLEDGEMENTS

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APPENDIX

This appendix describes the main elements in the DES model introduced in the body of this paper.

Calculation of NT'

NT_i' represents the length of time before which the operator will next decide to service vehicle i. In the DES model, the operator waits for a length of time equivalent to NT_i' before deciding to service the vehicle again. NT_i' is updated each time vehicle i completes an interaction with the operator. After an event belonging to a vehicle i is serviced, the neglect time, NT_i, for the next time period is generated. NT_i' is based on NT_i which is itself calculated by drawing from a normal distribution with a predefined mean and a standard deviation specific to vehicle i. NT_i is then the length

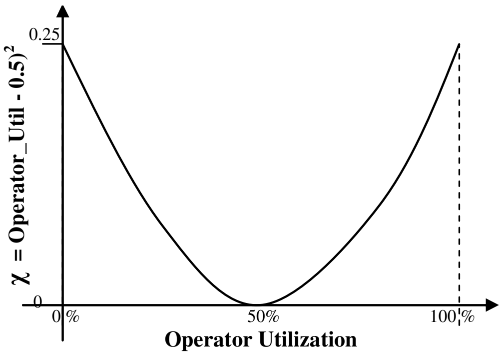

Figure. 11 χ curve

of time before which vehicle i will next require interaction from the operator.

After NT_i is calculated for vehicle i, NT_i' is calculated, which is the length of time that the operator ignores vehicle i before he/she decides to service it again.

$$NT_i' = LOI*NT_i + \chi *NT_i \quad (1)$$

where $0 <= LOI <= \infty$

The first term in (1) is a product of an LOI term and NT_i where LOI varies between 0 and ∞. When LOI is equal to 1, the operator is essentially neglecting vehicle i for a length of time equal to NT_i, such as when the operator intends to service a vehicle only when an alarm for that vehicle appears. An LOI less than 1 implies that the operator is servicing the vehicle prior to vehicle i requiring service which would be the case when the operator is micro managing the vehicle.

The second term in (1) is a product of χ and NT_i where χ represents the amount of over-utilization or under-utilization that the operator is experiencing from the 50% utilization point. The profile for χ is presented in Figure 11 and the corresponding equation is,

$$\chi = (Operator\_Util - 0.5)^2 \quad (2)$$

The combined effect of the two terms on NT_i' is that NT_i' decreases with decreasing LOI (more micro-management), and increases with increasing χ (Figure 12).

Calculation of Performance Weighting Factor

Before the event corresponding to vehicle i is disposed, a weighting factor is utilized to calculate the performance of vehicle i from the moment it is neglected until it is next serviced. The weighting factor is utilized in the Performance Analysis model. The weighting factor is calculated according to

$$P_i = 1/(1+EXPO(0.1)) - \chi \quad (3)$$

The first term in (3) is a number between 0 and 1 that is drawn from an exponential distribution. The randomness in this term is due to the fact that the operator's interaction with vehicle i will have a random effect in terms of performance for the ensuing neglect period. The second term represents a penalty in performance that is due to operator over or under utilization.

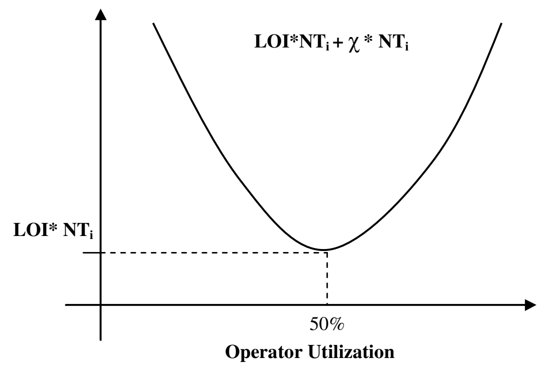

Figure 12. NT_i' profile

Calculation of IT'

IT_i is the interaction time associated with the vehicle represented by stream *i*. By definition, this is the expected amount of time for which the operator needs to interact with vehicle *i* in order to raise performance above some acceptable threshold. For each event, IT_i is drawn from a normal distribution. The length of time it takes the operator to interact with vehicle i is IT_i', where

$$IT_i' = IT_i + a* MX(0, 1- \Delta_i)*IT_i + b*(\varphi_i - \varphi') *IT_i + c*(\tau_i - \tau')*IT_i \quad (4)$$

where,
Δ_i is the ratio of NT_i to time elapsed since last service,
φ_i is vehicle i's type,
φ' is the type of the vehicle that was last serviced,
τ_i is the type of task vehicle i is completing,
τ' is the type of task that the last vehicle serviced was completing
a is the late service penalty weight,
b is the vehicle type penalty weight,
c is vehicle task penalty weight.

The second term in (4), involves Δ_i which is the ratio of NT_i to the amount of time elapsed since vehicle i was last serviced. As the time elapsed since last service increases, Δ_i decreases. The profile for curve for Δ_i is shown in Figure 13 and the equation is,

$$\Delta_i = NT_i / (TNOW - L_i) \quad (5)$$

where L_i is the time since last service and TNOW is the current simulation time, where t = 0 represents the start time of the simulation.

The profile curve for the MX(0, 1- Δ_i) term is shown in Figure 14 and the equation is,

0 when time since $L_i <= NT_i$

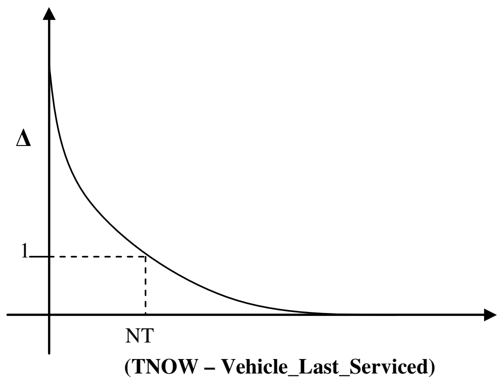

Figure. 13. Δ_i profile curve

$$MX(0, 1-\Delta_i) = \qquad (6)$$
$$1-\Delta_i \text{ when time since } L_i > NT_i$$

The second term is, therefore, the penalty in interaction time that is incurred due to an operator commencing interaction with a vehicle which is past its NT.

The third term in (4) represents the penalty in time that is incurred due to the vehicle i's type being different than the type of the last vehicle that was serviced.

The fourth term in (4) represents the penalty in time that is incurred due to the vehicle i's task type being different than the task type of the last vehicle that was serviced.

These last two terms represent the context switching time that is incurred when an operator has to reorient him/herself when switching between disparate tasks (a "task" here being the action of an operator which involves working with a specific vehicle type and a specific vehicle task type).

Calculation of System Performance Metric

The Performance Analysis model will now be explained. In this model, events are generated every half a second, with the purpose of collecting performance measures for each of the vehicles. The instantaneous performance averaged over all the vehicles is

Performance = (1/(Priority_Vehicle1+ Priority_Vehicle2+….))* (7)

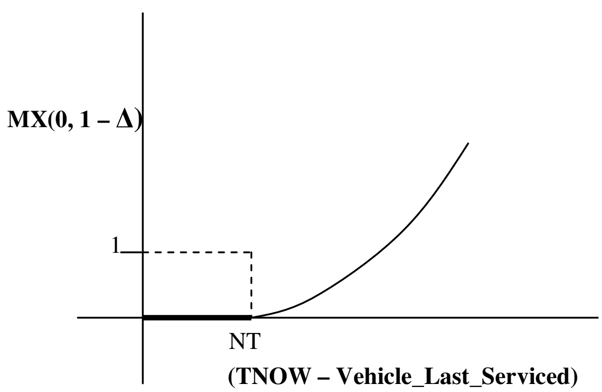

Figure. 14. MX(0, 1- Δ)

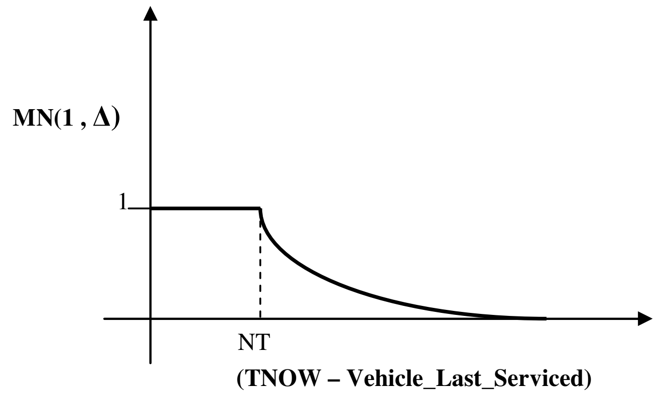

Figure. 15. MX(0, 1- Δ)

(Priority_Vehicle1 * P_i * MN(1, Δ_i) +
Priority_Vehicle2 * P_i * MN(1, Δ_i) + ...)

*Priority_Vehicle*i is the priority that is assigned to vehicle i and represents the fact that certain vehicles and the tasks they are completing will be of higher priority than others. This priority can represent the operator's priority scheme when the operator decides to prioritize the vehicles due to his/her perception of vehicle/task importance. These priorities can also be predefined during mission planning and might be handed down to the operator, in which case the priority variables would represent those priorities assuming the operator follows directions.

The P_i term was described earlier as being a performance indicator that describes the quality of an interaction and is based on operator utilization. If that interaction resulted in a low value for P_i, then the performance measure for that vehicle will be affected accordingly.

The MN(1, Δ_i) term is utilized in order to discount the contribution of a vehicle to the performance variable as vehicle i's time since last service exceeds the vehicle's NT_i (this term is represented in Figure 16).

At the end of the mission, the instantaneous performance measures are then averaged over all the measures collected resulting in a mission performance metric, ζ.

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