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Control of Multiple Unmanned Vehicles: A Capacity Model from a Meta-Analysis

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How many unmanned systems can the operator effectively control and/or supervise before the operator begins to experience higher mental workload, thus losing SA and degrading overall mission performance? In this paper we describe the results of a literature search that was undertaken to identify factors of particular importance to the control of unmanned systems. We present the architecture for a computational model of the controller of multiple UVs that accounts for the diminishing gains in overall mission productivity and eventual loss in productivity that appears to occur as the number of vehicles under supervision, N, increases.

A question asked with increasing frequency in advanced aviation is "how many unmanned air vehicles" can a human supervise? The challenge here is that as the number of unmanned air vehicles (UVs) grows, a single human operator who must both supervise an overall "fleet" and service each individual vehicle when required becomes taxed to the limit of his or her capabilities and beyond, thus diminishing the overall performance of the fleet. Our task in this research was to undertake a review of the literature on the supervision of UVs to identify both computational models and empirical data that could help to address this question, as well as those data that would identify mitigating factors to such a limit; particularly the degree of automation or autonomy provided per vehicle, (Wickens Dixon & Chang, 2003, Dixon Wickens & Chang, 2005) or overall automation decision support (Nehme et al, 2008).

As part of a larger literature review (See Appendix A of Gosakan, 2011 for more details), the goal of the research we report here was to identify empirical studies that had varied the number of USs under supervision, N, and provided objective outcome measures of overall mission performance. Our goal was to synthesize these results into a plausible model of the human controller of MUVs. Many of the concepts underlying this model are attributed to the extensive empirical research carried out by Cummings and her laboratory at MIT (e.g., Domneez et al, 2010, Cummings et al, 2010; Nehme et al, 2008); along with a smaller amount of research carried out by the first author at the University of Illinois (e.g., Wickens Dixon & Chang, 2003; Dixon Wickens & Chang, 2005, Wickens Levinthal & Rice, 2009, Wickens Dixon & Ambinder, 2008).

Results of Meta Analysis

The graph in Figure 1 presents an overview of the data from studies that had varied N and assessed some global measure of mission performance; such as the percentage of territory surveyed within a fixed amount of time, the number of targets destroyed, or the number of enemy discovered. The individual studies are identified by number in the box, and these numbers can be cross referenced to the citation list at the end of this paper. In the citation list, the number identification of each study (seen in figure 1) is boldfaced at the end of the citation. The performance metric on the Y axis is normalized to the maximum possible value within each study. The most striking aspects of this figure are the general non-linear increase in global mission performance with N, and the fact that some studies actually show an inverted U shaped pattern, suggesting that mission success has an optimum N, and that adding further UAVs (referred to as assets in sections below) to the skies actually diminishes overall performance.

An Asset-centric Model

In order to understand the causes of the general form of the data shown in figure 1, we present a model of the influences on mission performance as a function of N. In doing so, we distinguish between two important metrics: a **global performance** (GP) metric such as that depicted on the Y axis of figure 1, and a unit **asset productivity** (AP) metric, that characterizes the productivity of each individual asset. As N grows, global performance is generally expected to grow (with the exception of the high level down turn, accounted for by our model), but AP may not follow this pattern. In the following sections, we distinguish four different influences on AP, as they may be mediated by both N and by AP. The model we present first is one that is "asset-centric" in that it focuses on the performance of specific assets, to create the global performance metric. We then turn to defining an operator-centric model, based in part upon components of the asset model.

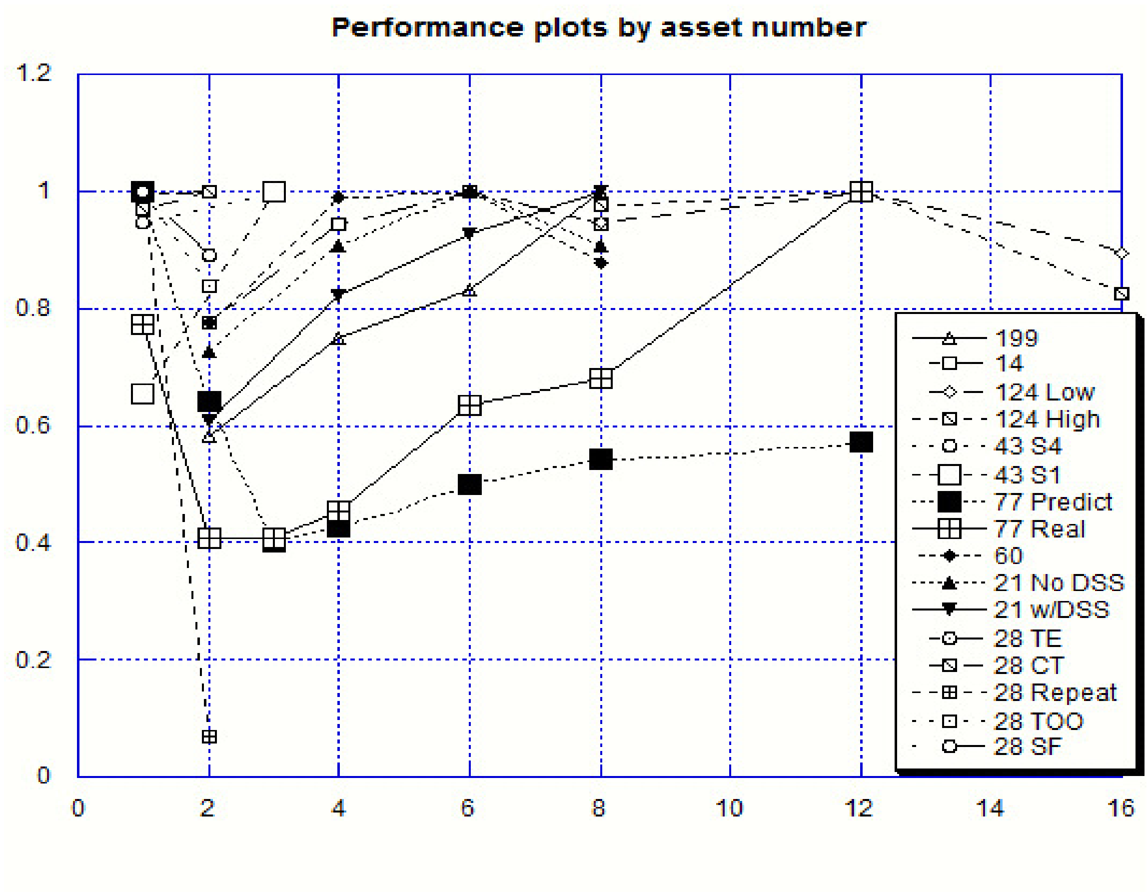

Figure 1: Global mission performance as a function of N (number of UVs).

First, as N increases this increases the total **power** of the fleet in a relatively linear function. For example as more surveillance vehicles are placed in the air, careful coordination will assure linearly increasing amounts of terrain covered, per unit time. Indeed some of the studies in Figure 1 appear to reflect this relationship (.e.g., study 199**).**

Second, this increase is not necessarily linear, as a pure fleet power function would predict, but often logarithmic in its approach to maximum. To account for this, we partition individual asset performance (AP) time into three separate components, following Nehme et al (2008) and Cummings & Mitchell, 2007 (see figure 2).

1. Service time (ST) is the amount of time it takes each asset to be "serviced" by the human supervisor; that is for example, directed on its next trajectory, or performing some maintenance function upon it. Assuming the operator can only service one asset at a time, an observation consistent with empirical data (Dixon & Wickens, 2003), then time servicing one asset must preclude servicing any other asset simultaneously.
2. Productive time (PT). This is time when the asset can operate autonomously in a way that is productive for the overall mission (e.g., capturing ground video along a designated track), and hence contribute to GP.
3. Wait time (WT). This is non-productive time when the asset must wait until servicing becomes available (Nehme et al, 2008). One can then define asset productivity as the ratio of PT to [PT +ST + WT). This ratio can also be defined as an **asset percent utilization.**

Given this ratio, and the single server nature of the queue, it then follows that as N increases, WT will increase linearly as NxWT, as a given asset must wait longer while a given number (N-1) of assets must be serviced. Hence the percent utilization of each asset will decrease, predicting the logarithmic increase in GP generally shown by the left side of the functions in Figure 1. We can see this influence of N near the top of Figure 2.

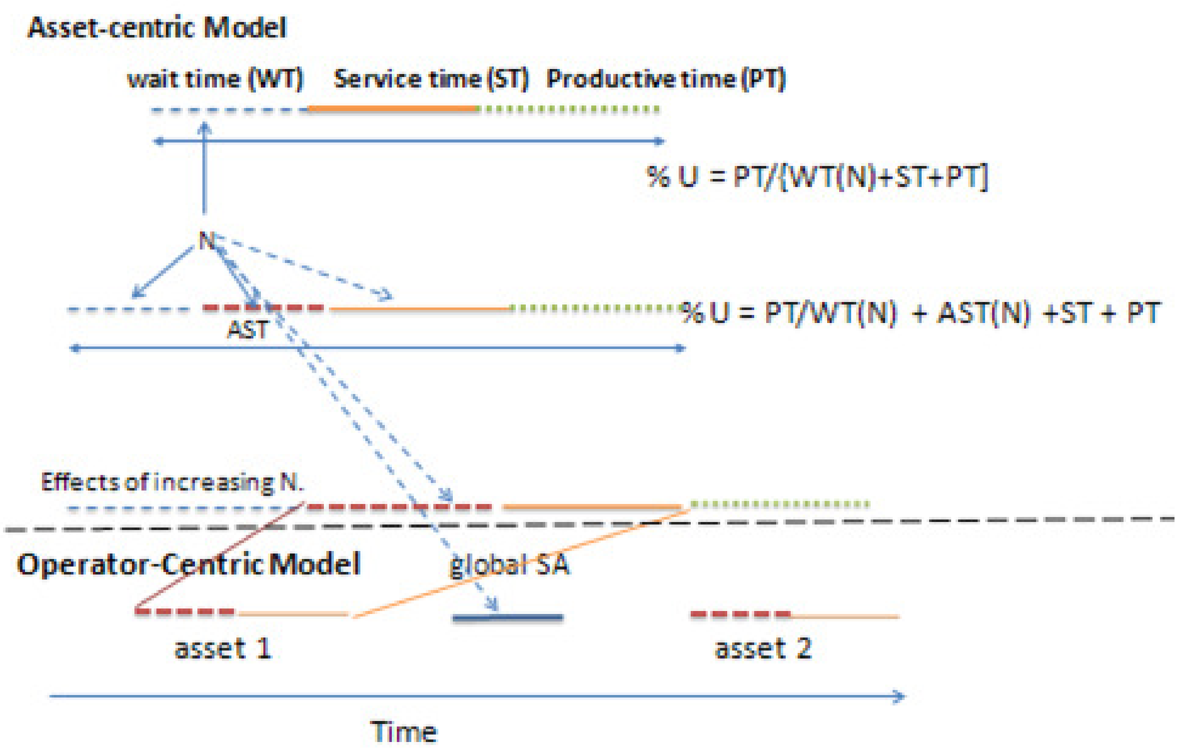

Figure 2. Components of the time cycle for each asset. The influence of N on these components is shown by comparing the second and third time line, where it can be seen that in the third time line the percent Utilization (productive time to total time) is diminished. On the bottom the foundations of the operator-centric model are depicted, showing the servicing of two assets and the time required to maintain global SA (the solid line).

A **third** influence on this timing cycle is shown in the middle of Figure 2. Here **attention switch time** (AST) is added as the time between when an asset appears for servicing, and when the supervisor can turn his full attention to servicing it. (Wickens Dixon & Chang, 2003). In the time line in Figure 2, AST is assigned between the waiting time period, and the servicing time period, reflecting the fact that when a new asset is "noticed" it may take some time for the supervisor simply to orient to the asset ("which asset is that, and where is it located?"), as well as to restore his or her memory for the mission of that particular asset, and how that mission should be altered (e.g, a change in trajectory, altitude, etc.). Importantly, we see that both aspects of this cognitive component will be influenced by N. As more units are present, the supervisor will spend increasingly more time identifying which unit is in need of servicing (or which is the unit requesting servicing), as well as choosing the nature of the service (e.g., the next mission segment). This choice will take longer to the extent that it has been longer since a given asset was serviced, because memory for what it was doing before, will have declined. And this time of operator neglect of a particular asset will grow with N. Both the nature of the increase in AST with N, and its slope remain unclear. As a default, it may be considered to be linear with N.

Within the model described so far, depending on the sub-function ***AST = f(N)***, the shape of the global performance curve in Figure 1 may reach a plateau sooner or later (e.g., at a lower or higher value of N), but also has the possibility of inverting to a downward slope at the right side, as shown by some of the functions in Figure 1. This will happen if the penalties imposed on WT and AST more than offset the gains in global productivity (GP) achieved by increasing N. However there is a **fourth** mechanism that can make this downward slope on the right side of Figure 1 even more pronounced, and this describes what may be called "**global situation awareness**"; that is, maintaining the “big picture” of who is where and how the mission is progressing. It is well known that situation awareness depends in part upon working memory (Endsley, 1995; Wickens, 2002, 2008), and that working memory demands will be heavily influenced by the number of entities which must be “kept track” of (e.g., Hess, Detweiller, & Ellis 1999). This increase in working memory demand can have two consequences: (a) to the extent that the supervisor makes some effort to sustain working memory during servicing of each item, this may impose a penalty on servicing time (shown by the dashed light arrow in figure 2). and (b) the added demands on working memory may diminish overall situation awareness (keeping track of more things is harder), and hence the overall quality of planning (e.g., optimal queuing and service order of assets; optimal assignment of assets to new tasks) will degrade, leading to an effect not on time, but on the accuracy of global performance, the Y axis of Figure 1).

In the above representation, it is important to note that, just as N will decrease asset productivity via several components in the equation, so anything that influences productivity via automation will increase this productivity. For example longer autonomous trajectories, or more artificial intelligence within the asset will reduce the frequency of required servicing and hence increase the asset productivity or utilization ratio depicted in the middle row of Figure 2. Furthermore, the presence of decision support tools to assist the supervisor during the switching period can substantially reduce this time penalty, as well as improve the overall accuracy of performance. Indeed, one study (Nehme et al, 2008) compared the presence and absence of decision support tools, and observed the inverted U pattern when such tools were absent, but a linearly increasing pattern when they were present to assist the operator in servicing choices (see study **21** in figure 1)..

An Operator-Centric Model

The top three rows of Figure 2 depicted a time line for the cycle of use of a single asset – the asset-centric model. Within this figure, the middle two components, ST, & AST were directly associated with human operator time, the first of these also being affected by N. At the bottom of figure 2 is depicted the foundations of the operator centric model. Here we have extracted the two components of human operator time from above and depicted (on a condensed time line) these as they might characterize the servicing of 2 assets by the human operator. Two features are of note here. First, in this figure, there is a good deal of unfilled (slack) time, in which the operator’s resources are idle, or “underutilized”. Second, part of this slack time is filled with a solid line time period, corresponding to the fourth mechanism described in the previous section; that is, the need to maintain **global SA** about how the mission is going, how the fleet is coordinated, and whether particular assets may need to be re-assigned to assist others.

Second, with the current demands depicted in the figure, there is ample time available to schedule this global SA task between arrivals of assets for servicing (these are the unfilled portions of the time line). However it should be apparent, that as either servicing time or AST increases (with increasing N), this free time will diminish, and eventually reach a point at which there is not enough time to develop and maintain global SA (or if it is given such time, then AST and ST will not be allocated sufficient time). Hence global performance will degrade, either because of the shortchanging of overall SA, or because adequate service and attention switch time is not available for each asset (or both) thus resulting in the operator committing errors.

According to the components of the model then, the composite inverted U shaped function revealed by the meta-analysis and portrayed in figure 1, may be seen to be made up of two additive components. One is the logarithmic function showing the increased mission power with N, but showing the diminishing gains with N, as wait time (and switching time) increases, decreasing individual asset productivity. The second component is the actual diminishing function with N, related particularly to the loss of SA, as other elements compete with this essential time demand. The precise peak of the function of course depends on the relative slopes of the two individual functions, as well as the possible mitigating role of automation (shifting that peak to the right); however the existing data suggest that it may be somewhere between 3 and 8. Continued research along these lines is necessary to better understand the quantitative role of the two critical human performance components in the model: attention switching time and SA maintenance, and the precise manner in which these are influenced by N.

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Bold faced numbers identify studies depicted in figure 1.

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