Developing a Decision Tool to Evaluate Unmanned System's Command and Control Technologies in Network Centric Operations Environments

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***Abstract*—Expert systems that evaluate new Command and Control (C2) technologies are necessary to determine their adequacy for Network Centric Operations (NCO) missions. New technologies for complex C2 NCO scenarios are currently being developed. However, little has been done to evaluate these new technologies for specific sets of mission requirements. There is neither a standard methodology to evaluate these new technologies, nor a research environment to test these technologies under realistic assumptions. This paper will introduce an expert system that will help decision makers evaluate these technologies and determine whether they can transition into practical applications for the Navy, and under which limitations.**

Keywords-operator capacity; supervisory control; expert systems; unmanned vehicles.

I. INTRODUCTION

The Department of Defense's future vision for NCO is intended to increase combat control by networking relevant entities across a battlefield [1]. This new vision implies large amounts of information sharing and collaboration across different entities. An example of a futuristic NCO mission scenario is one in which a group of heterogeneous Unmanned Vehicles (UVs) are supervised by a single operator using NCO technology. In this type of complex C2 scenario, UV operators will be subjected to vast amounts of information as compared to today's command and control scenarios. Therefore, this vision brings with it a new problem that must be addressed: How to maintain an adequate workload to avoid information overload and resulting loss of situation awareness. Currently, C2 technologies that allow the operator to control multiple UVs in a NCO scenario are rapidly increasing. The development of these new C2 technologies generates the tendency to exponentially increase the ratio of UVs to operators. However, if systems are inadequately designed or are used beyond their design capabilities, they will not adequately control for increased workload, which in turn will cause the operator to become overloaded and lose situation awareness. It is critical that military decision makers develop predictive models of human and system performance to evaluate the adequacy of a system's design to satisfy specific mission requirements.

This paper will start by discussing previous research in the area of UV operator capacity, to later explain the project goals, methodology and experimental results. Finally, it will end with a brief discussion of the future research plans and the implications of this study on future human-UV interaction research.

II. BACKGROUND

Mental workload is a limiting factor in deciding how many UVs an operator can control or supervise. In the case of one operator supervising multiple vehicles, the operator's workload is measured by the effort required to supervise each vehicle and the overall task. The effort required to supervise an individual UV in a team depends on the efficiency of the system to reduce workload and increase situation awareness. Moreover, workload also depends on the complexity of the mission scenario. Some of the characteristics of a complex mission scenario as defined by military standards include: mission time constraints, precision constrains, repeatability in tasks (i.e., navigation, manipulations, etc.), level of collaboration required, concurrence and synchronization of events and behaviors, resource management (i.e., power, bandwidth, ammunition), rules of engagement, adversaries, and knowledge requirements [2]. The degree to which these characteristics are required also define workload. Consequently, if the system is not designed to achieve specific types of requirements, then when it is tested for those requirements the system may not perform them adequately.

Previous attempts to model operator capacity were developed to display temporal constraints associated with the system. The complexity of these measures progressed from measuring operator capacity in homogenous UVs controlled by one operator [3-7], to scenarios in which teams of heterogeneous UVs are supervised by one operator [8]. The first equation developed to predict operator capacity in homogenous UVs suggested that the operator capacity is a function of the Neglect Time (NT), or the time the UV operates independently, and Interaction Time (IT), or the time the operator is busy interacting, monitoring, and. making decisions with the system [3]. Critics of this method suggested that the equation lacked two critical considerations: 1) the importance of including Wait Times (WTs) caused by human-vehicle interaction, and 2) how to

 ISBN: 978-1-61208-155-7

link this equation to measure effective performance [6]. Hence, WT is added to the equation to account for the times the UV has to perform in degraded state because the operator is not able to attend to it or is not aware of a new incoming event. Three WTs were identified: Wait Times due to Interaction (WTI), Wait Times due to Loss of Situation Awareness (WTSA), and Wait Times due to Queue (WTQ).

Using a discrete event simulation, a research study attempted to create a link to performance by using a proxy to measure workload and situation awareness. In this model, the researcher intended to model heterogeneity in UV systems in order to evaluate the system's design [8]. The human was modeled as a server attending to vehicle-generated tasks – both exogenous and endogenous tasks – as defined by their arrival and service processes. The concept of utilization was introduced as a proxy for measuring mental workload. Utilization Time (UT) refers to the percentage of time the operator is busy. The concept of WTSA was used as a proxy to measure Situation Awareness. The UT and WTSA measures were computed as a type of aggregate effect of inefficiencies in information processing rather than being computed as individual measures of workload and situation awareness. The author of this model suggested that many other sources of cognitive inefficiencies, besides these two proxies, are manifested through cognitive delays. He emphasized that measures of UT and WTSA are extremely critical to determine supervisory performance and suggested that better methodologies to measure these variables need to be developed.

III. Project Goals

This study aims to develop a model of operator capacity in a complex mission scenario that will serve to help decision makers determine whether a particular technology is adequate for an NCO mission scenario. Moreover, this study aims to develop a model of operator capacity that is more comprehensive. This model is intended to fill in the gaps of current research by introducing new variables and relationships to previous models. The model will be constructed in a way so prior knowledge about the relationship between variables will serve to better predict missing data, such as workload and situation awareness. Moreover, the model will be structured in a way that will make it easy to determine which areas in the system design need improvement. The ultimate goal of this study is to develop a decision-making tool that will serve to evaluate and determine the effectiveness and limitations of a particular NCO technology in a complex mission scenario.

IV. Methodology

A. Approach

The approach taken by this research study was to model the decision-making process required to decide whether to increase a particular team size. This approach was taken in order to present decision makers with a decision-support tool that will ensure that knowledgeable decisions are made in regards to the adequacy of a given team size with a particular NCO technology. Modeling the decision-making process, as opposed to the environment, allows for more knowledgeable decisions because not only are the most important factors in the decision taken into account, but optimization of the recommended decision's outcome is also possible. This approach provides adequate information to the user to make a decision. And while the model is based on answering this particular question, the nature of the situation is manifested in the model, thus allowing users to draw more conclusions than only the adequacy of the team size.

B. The Decision Network Model

A decision network was developed to model the decision-making process required to decide whether to increase a given team size with the selected NCO technology. Netica Bayesian Belief Network (BBN) software [9] was used to develop a decision network that incorporates quantitative and qualitative information about the model. This software was chosen mainly because it provides an effective display of quantitative and qualitative data and it can accommodate missing or incomplete data. Using a BBN allows researchers to compute unobservable variables (i.e., missing data) based on measures that are observed (i.e., prior knowledge). This feature is very important to determine variables such as Situation Awareness and Workload that were only computed as proxies in previous models.

A decision network consists of nature, decision, and utility nodes. Nature nodes represent variables over which the decision maker has no control (see yellow nodes in Fig. 2). Decision nodes represent variables over which the decision maker can make a decision (see blue nodes in Fig. 2). Utility nodes represent a measure of value, or the decision maker's preferences for the states of the variables in the model (see pink nodes in Fig. 1). In this network, the outcome of a decision node is maximized by finding a configuration of the various states of the sets of variables that maximize the values of the utility node. Therefore, based on a series of requirements, or utility values, a decision network provides the user with the correct decision. Additionally, the arrows in the model represent reasoning relationships and are detailed in the conditional probability tables (CPTs) of the nature and utility nodes. In the CPT, the distribution of each node will be determined *a priori* based on the relationships specified in each conditional probability table.

This model makes several assumptions. First, the type of UV system addressed by this model is one in which a single human operator is responsible for supervising a team of heterogeneous UVs. The human operator is assumed to act in a supervisory control style, interacting with the system at discrete points in time (i.e., there is no manual control). Second, in this model, the human operator is responsible for supervising a team of heterogeneous UVs defending an oil

 ISBN: 978-1-61208-155-7

platform from potential enemies. Third, the human operator could be situated in a ground-based, sea-based, or airborne control station. Fourth, the model was built in a way such that decision makers will use this model to help them decide if a particular technology is adequate for specific mission requirements. Finally, the model assumes that the decision making process required to make this decision is hierarchical; therefore, later decisions are based on earlier ones. The model captures attributes from the Operator Performance Model, the System Performance Model, and the Operator Capacity Model as shown in Figure 1.

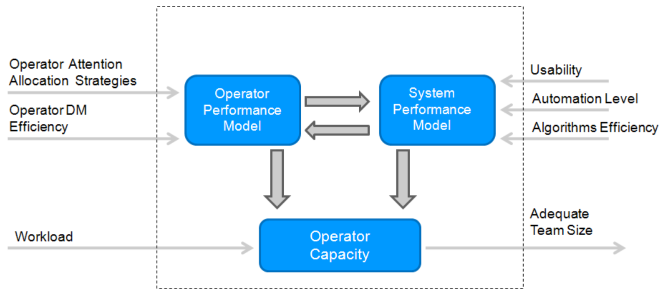

Figure 1. A high level representation on the attributes the model captures. Notice that variables of interest in Operator Performance Model are Operator Attention Allocation Strategies and Operator Decision Making Efficiency, while in the System Performance model are Usability, Automation Level and Algorithm Efficiency. The output of the operator capacity model is to determine an adequate team size.

The attributes captured in Figure 1 represent three major areas of relevance for the decision to increase the team size: system performance, operator performance, and cognitive workload (see Figure 2). These areas of relevance are represented in the model as sub-models; each of them contains one or more decision nodes that correspond to the decisions that must be made by the operator in each area to ensure that they are working adequately. The order in which the decision nodes have been organized represents the way in which decisions should be made (see blue nodes on Figure 2). The model represents a sequence of decisions in which later decisions depend on the results of earlier ones. In this model, the last decision is shown at the end of the sequence. The last decision determines whether a particular team size should be increased.

The first sub-model, system performance, includes three decision nodes with the followings decisions: 1) Is the interface effective? 2) Does the system have an adequate level of automation? 3) Are the system algorithms efficient for the task? These three decisions were included in this sub-model because they represent areas that are important to ensure good system performance. Some of the utility nodes for each of these decision nodes were identified from the literature, while some others were included to ensure that specific mission requirements are satisfied. For example, if the system has good interface usability, the situation awareness of the operator will be high. Moreover, if the situation awareness is high, the system's automation level must be somehow effective to avoid loss of situation awareness and/or complacency. Then, to ensure that the mission requirements are satisfied, the algorithms used must be working efficiently toward achieving the mission goal. This efficiency is measured by the number of times the operator reassigns a mission that was previously assigned by the system, with a lower number signaling higher efficiency. Note that algorithm efficiency is defined in this model only as a result of the operator's perceived trustworthiness of the system. If the system is not perceived as trustworthy, then the operator will tend to override the system frequently and the algorithm efficiency will be low.

The second sub-model, operator performance, needs to ensure that the operator performs effectively with the system being evaluated, as more UVs are introduced to the team, and the mission scenario becomes more complex. Since this is a supervisory control environment, operator performance is defined in terms of the operator's decision making. There are two decisions (decision nodes) that are important to evaluate whether the operator's performance is adequate for the task: 1) Is the operator's task management strategy efficient? 2) Is the operator's decision making efficient? The first decision is necessary to evaluate whether operators will efficiently prioritize different tasks that arrive simultaneously.

The second decision is necessary to evaluate whether the operator will successfully achieve the goals of the mission (i.e., protecting the asset from enemy attack). Together these two decisions summarize what is important to ensure a satisfactory operator performance. Please note that by measuring task management efficiency, an attention inefficiency component is included in this model.

Finally, the last sub-model, cognitive workload, includes the final decision node: "Increase Team?" For this decision, it is important to ensure that operators are not overloaded, but instead their workload is adequate to successfully complete the mission scenario. This final decision node is the end of a sequence of decisions and therefore it depends on the outcomes of the previous decisions made in the system performance and operator performance sub-models. Hence, in order to avoid cognitive overload, not only does the system have to efficiently perform in the mission scenario, but the operator also has to perform efficiently to ensure that tasks are adequately managed and do not overload the operator. The cognitive workload and operator performance sub-models are strongly associated. If cognitive workload is too high, then the operator performance will be low. Therefore, the more inadequate management and tactical decisions operators make, the higher their workload will be.

System performance, operator performance, and cognitive workload are the foundation of this model. Most of the knowledge about the model relationships between variables was acquired from a literature review. Variables such as "Information Overload" and "System Interruption" were included to emphasize the need to evaluate these aspects of the usability of the system (see Figure 2) in complex

 ISBN: 978-1-61208-155-7

supervisory control tasks. These variables are relevant because they contribute to design interfaces, especially in the supervisory control environment in which large amounts of information, and large event queues can result in information overload and frequent system interruptions.

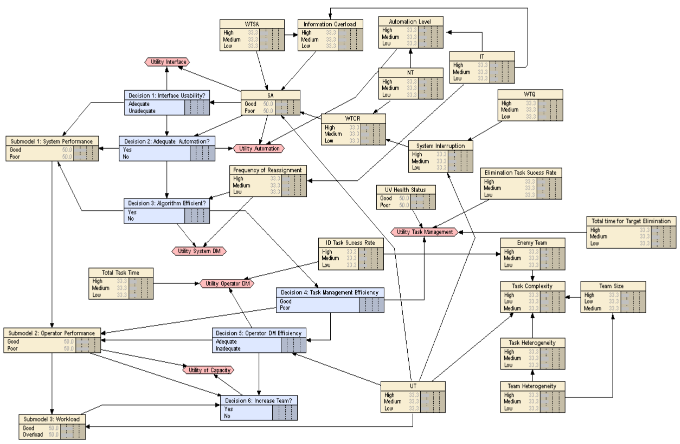

Figure 2**.** Decision network representing the decision process involved in deciding whether to increase a particular team size. Notice that this picture displays the model with no data. When data are introduced into the model, the system provides the user with a recommended course of action that will be displayed as a percentage (i.e., Yes 90%).

C. Performance Measures

The model allows for measurement of several output variables. These variables include those implemented in the previous models [3-7], as well as specific user-defined metrics that the model allows to capture. Temporal measures such as UT and WT are used because they are critical in a system where the operator has limited attention resources that must be divided across multiple tasks. UT is used to capture the effects of alternate design variables on operator workload. Some researchers indicate that average UT and WT can allow for benchmarking and comparison to be made across applications [8, 10]. The level of autonomy in the model is captured through the NT. In addition to the basic metrics inherently captured by previous models, this model also captures mission-specific metrics. Some of the mission-specific metrics include the rate at which tasks are successfully completed, the UVs' health status and the total time to complete the mission scenario. Furthermore, other measures being captured by the model include Information Overload, System Interruption, and Reassignment Rate. These three measures are important to evaluate the system performance. Information Overload and System Interruption are shown to be related to SA; therefore, they are used to help determine Situation Awareness (SA). For example, when the operator is overloaded with information, he/she is not able to focus on what is important, therefore vital SA is lost. Moreover, when the system is constantly interrupting the operator at any point in time, it drives the operator's attention away from one task to focus on another, therefore affecting their SA. The system's Frequency of Reassignment measure is used to evaluate the number of times the operator overrides the system. Identifying the amount of times the system has been overridden will help us determine how trustworthy the system is for the operator. The underlying assumption is that the more the operator overrides the system, the less reliable the algorithm for the system is. See Figure 3 for a list of the performance measures used as input in the model.

PERFORMANCE MEASURES	DEFINITION
Wait Times due to lost of Situation Awareness(WTSA)	Represents the amount of time the operator is not aware that the vehicle requires his attention.
Wait Times due to Queue (WTQ)	Represents the amount of time resulting from queues due to near simultaneous arrivals of tasks.
Interaction Times (IT)	Represents the amount of time the operator interacts with the vehicle. Includes monitoring and decision making time.
Neglected Times (NT)	Represents the amount of time each vehicle operates independently.
Utilization Times (UT)	Represents the amount of time the operator actively interacted with the display over the course of the experiment.
Total Task Time	Represents total time to complete the trial.
Information Overload	Represents information overload in the interface.
System Interruption	Represents the amount of time the operator was interrupted to attend a different task.
Target Elimination Task-Success Rate	Represents the ratio of eliminated enemies to the total number of identified enemies.
Identification Task-Success Rate	Represents the ratio of identified enemies to the total number of detected vehicles.
Frequency of Reassignment	Represents the operator's trust in the system. Accounts for the times the operator reassigned a vehicle once that it was assigned by the system.
UV Health Status	Represents the amount of damage experienced by the vehicle.

Figure 3. Performance measures collected during the experiment.

D. Experimental Apparatus

Since there is no test bed available that portrays all the complexities of a futuristic mission scenario, the Research Environment for Supervisory Control of Heterogeneous Unmanned Vehicles (RESCHU) developed by the Massachusetts Institute of Technology (MIT) was acquired and later modified to be used as a test bed in this study. The RESCHU simulator [8] is a test bed that allows operators to supervise a team of Unmaned Aerial Vehicles (UAVs) and Unmanned Underwater Vehicles (UUVs) while conducting surveillance and identification tasks. This simulation was modified for this study to include the following requirements: 1) a complex mission scenario with an asset to protect and multiple simultaneous enemies to attack, 2) a highly automated system such as mission definition language (MDL) and 3) a highly heterogeneous team that is made of at least three different types of UVs. The new version of the simulation is called RESCHU SPAWAR or RESCHU SP.

It is important to mention that the Unmanned System technology selected as an example of a NCO's technology that allows one operator to supervise multiple UVs is the Collaborative Sensing Language (CSL) developed at the

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University of California, Berkeley. The CSL [11] is a high-level feedback control language for mobile sensor networks of UAVs. This system allows an operator to concentrate on high-level decisions, while the system takes care of low-level decisions, like choosing which UV to send for a particular type of task. A framework for the CSL was designed to integrate this technology into the complex mission scenario portrayed by the RESCHU SP simulator. The CSL version displayed in this simulation is only intended to illustrate one way to portray how this technology may work in more complex mission scenarios and with supervisory control of multiple heterogeneous UVs (see Figure 4).

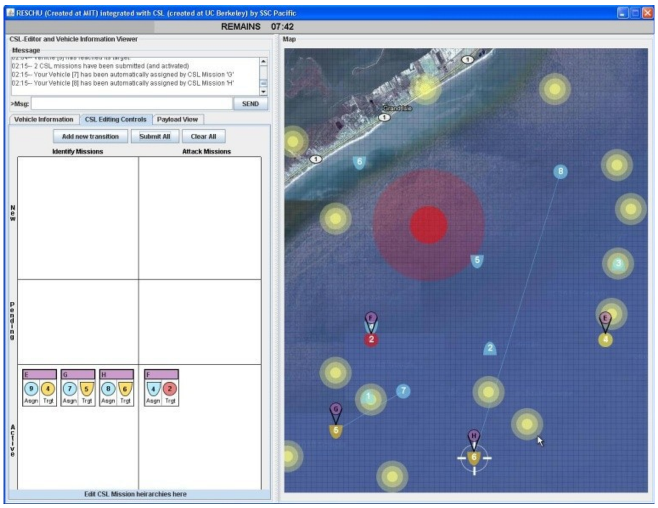

Figure 4. RESCHU SP simulator displays a mission scenario with a team size of nine UVs (blue icons in the map), three potential enemies (dark yellow icons in the map), and one identified enemy (red numbered icon in the map). The CSL tab shows missions that are currently active and other missions that are not yet submitted.

The team of UVs in the RESCHU SP simulator is composed of UAVs, UUVs, and Unmanned Surface Vehicles (USVs). There are two types of UAV, the MALE UAV and the HALE UAV; both travel to areas of interest to detect potential enemies. When a UAV detects a potential enemy, a USV is sent to the detection area to identify the vehicle (i.e., the unidentified vehicles appear as dark yellow numbered icons in map). Engaging the video payload that arrives at a detection area requires the operator to decide whether the vehicle detected is a potential enemy. If an enemy is identified, a UUV travels to the location to target the enemy. UUVs are slower than USVs and UAVs. UAVs are the fastest UVs.

The operator's main task is to identify and target potential enemies while protecting an asset (i.e., oil platform). At the same time, the operator is responsible for supervising the path of the UVs, in order to avoid traveling through potential threat areas (bright yellow areas on the map). Threat areas are zones that operators should avoid in order to protect the health of their vehicles. Moreover, operators are also responsible for following chat messages which provide them with the necessary Intelligence and guidance to complete their missions. When a UAV detects a potential enemy, a visual flashing alert is issued to warn the operator. This alert indicates that the operator should command the CSL system to assign a UV to complete the task. The operator commands the CSL to complete the task through a right-click interaction. The CSL system chooses a UV that is appropriate for the task and one that is also in close proximity to the potential target. The operator is in charge of approving the CSL selection by submitting the task through the *Submit All* button in the *CSL Editing Controls* tab. In the case of multiple identification tasks submitted to the CSL at the same time, the operator's task is to approve the CSL selection, and if applicable, determine the order in which the tasks should be conducted. For example, in a situation in which there is only one UV available for the task, the operator has to determine the order in which tasks should be conducted to ensure a good mission performance. Once the order of tasks has been determined, the operator needs to submit the commands so that the CSL can complete the tasks. Once that a task has been submitted, a selected UV is sent to location, when it arrives, a visual flashing alert warns the operator that the video payload is ready to engage. Then, the operator engages the video payload through a right-click interaction. The detected vehicle is viewed through the video image displayed in the *Payload View* tab to determine whether the detection is identified as the enemy. The operator identifies the vehicle by clicking on the *Yes* or *No* button below the payload view. A supervisor will inform the operator via chat whether the identification is correct or not. If the operator correctly identifies the vehicle as an enemy, the vehicle icon on the map becomes red. If the operator incorrectly identifies a detected vehicle as the enemy, the supervisor will override the operator; therefore, the icon will not change to red. The next step for the operator is to inform the CSL that a vehicle should be assigned to complete the target mission. Once again, the CSL system chooses a UV and sends it to the target location. When on target, a visual flashing alert is issued to inform the operator that the UV is ready to engage. The operator confirms this through a right-click interaction, and the target is eliminated. In this way, the operator is responsible to identify all detections and eliminate all enemies in order to protect the asset.

E. Participants, Experimental Design and Procedure

Experiments were designed to be completed in two phases: 1) the software and performance measures program verification phase, and 2) the model validation phase. First, it is desired to ensure that the requirements of the simulation and performance measures computation program are met. Second, it is desired to obtain data associated with the different levels of team size, in order to build confidence in the model's accuracy at replicating human-UV-interaction under different conditions. Having team size as the independent variable, the model's ability to replicate statistically significant effects on the operator performance and/or mission performance could be evaluated. Finally, having data sets associated with the different levels of team size allows for predictive validation by selecting a single data set associated with one of the conditions and predicting the results observed for a second condition. The recruited participants for the first experimental phase are students from the Naval Postgraduate School (NPS). The online test bed includes: a background and exit survey, an interactive tutorial, a practice trial, and one of a set of possible experimental conditions.

In order to ensure the validity of the variables and relationships represented in the model, the decision network was converted into a Bayesian Belief Network (BBN) to run validation analysis. The software's Test with Cases analysis will be used to validate the network in the second phase of the experiments. The Test with Cases analysis examines if the predictions in the network match the actual cases. The goal of the test is to divide the nodes of the network into two types of nodes: observed and unobserved. The observed nodes are the nodes read from the case file, and their values are used to predict the unobserved nodes by using Bayesian belief updating. The test compares the predicted values for the unobserved nodes with the actual observed values in the case file and the successes and failures are then recorded. The report produced by this analysis has different measures that validate each node's predicted capabilities. After evaluating the validity of the model, we can determine which relationships are incorrect and we can make the network learn those relationships through the collected cases. Finally, we can run sensitivity analysis and predictive validation analysis to determine which variable has the biggest effect on team size and how each variable affects the overall result of the model.

The study design is a between-subject design with three conditions: high team size, medium team size, and low team size. The high team size condition is composed of 9 UVs: 3 UAVs, 3 USVs and 3 UUVs. The medium team size condition is composed of 7 UVs: 3 UAVs, 2 USVs and 2 UUVs. Finally, the low team size condition is composed of 5 UVs: 3 UAVs, 1 USV and 1 UUV. Notice that the UAV's number was kept constant through the different conditions because the UAVs produce little interaction with the operator (i.e., UAVs only patrol for detection and operators only have to supervise their flight path to avoid flying into threat areas). The number of USVs and UUVs was gradually incremented to investigate how they affect the performance measures and therefore the model outcome. Furthermore, the baseline of a team of 5 UVs was decided after pilot testing the simulation with different team sizes.

The experimental test bed was designed for a web-based delivery, with an interactive tutorial and practice trial. A web-based experimentation was chosen in order to obtain as much data as possible. The website is Common Access Card (CAC) protected and participation is via invitation. Data collected from the simulation is being recorded to an online database. Demographic information is collected via a background survey presented before the tutorial. Participants are instructed to maximize their overall performance by: 1) avoiding threat areas that dynamically changed and therefore minimizing damage to the UVs, 2) correctly identifying enemies, 3) targeting enemies before they reach the asset, 4) overriding the system when necessary to minimize vehicle travel times and maximize mission performance, and 5) eliminating potential enemies as soon as possible.

V. Experimental Results

Pilot tests were conducted at NPS and SPAWAR to evaluate the online test bed and performance measures. The results of these pilot tests indicated that the interactive tutorial was hard to understand, the simulation had bugs and the logic used for coding the performance measures was inaccurate. The test bed and performance measures were reviewed, a framework for improvement was developed and problematic areas were fixed. The first experiment was conducted at NPS in June, 2011. Data obtained is currently being analyzed. Results will be released in a future scientific publication. Due to the complexity of the software and the number of factors to be considered in the computation of the performance measures (i.e., multiple event types, vehicle types, performance measures, start and end times, etc.), we expect the verification phase to continue through next year. It is planned to start the validation phase in May, 2012.

VI. Future Research

In the validation phase of this study, the model will be first validated with the current implemented technology. Next, the model will be validated with a different NCO technology in order to test whether the results of the model can be generalized to other NCO technologies with different system's variables (i.e., usability, automation, etc.). Furthermore, learned workload and SA curves will be incorporated into the model to strength model predictions. Finally, a decision tool package will be developed to allow decision makers and/or system designers to evaluate NCO technologies. The decision tool package will include a program that will collect performance measures from simulations and feed the model in order to evaluate new NCO technologies.

VII. Implications for Future Research

The implications of this study are various. First, the results of this study will allow a better understanding of what enables operator capacity in complex NCO mission scenarios. Second, by understanding the variables that affect operator capacity and the decision making process involved in evaluating NCO technologies, the results of this study will allow the development of specific C2 design requirements for technologies to be used in complex NCO mission scenarios. Third, by acquiring a better understanding of the dynamic between the operator capacity, the system, and the mission requirements, the results of this study will not only define performance

 ISBN: 978-1-61208-155-7

measures for these complex environments but also determine an effective logic to extract them from any simulation and place them into the model for evaluation and prediction. Finally, the overall results of this study will help future research by providing scientists with a test bed and performance measures definitions for a NCO scenario to further expand this study and/ or conduct further studies in this crucial research area.

ACKNOWLEDGMENT

The authors wish to acknowledge the support of Dr. Mary Cummings (MIT) and Dr. Luca Bertuccelli (MIT) for providing guidance on the RESCHU code, Dr. Karl Hedrick (UC Berkeley) and Dr. Raja Sengupta (UC Berkeley) for providing guidance on the functionality of the CSL, Mr. John Falby (NPS) for recruiting participants for the pilot tests, and Dr. Douglas Lange (SSC Pacific) for being a great mentor and helping us through the process.

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 ISBN: 978-1-61208-155-7