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AGENT-BASED SIMULATION OF UNMANNED SURFACE VEHICLES: A FORCE IN THE FLEET

by

Melissa J. Steele

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Thesis Advisor:	Susan M. Sanchez
Second Reader:	Russell Gottfried

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The Navy is considering the use of unmanned surface vehicles (USVs) to reduce risk to personnel in maritime interdiction operations, and to conduct intelligence, surveillance and reconnaissance (ISR) and force protection (FP) missions. In this thesis, alternative configurations of the prototype and operational uses of the USV are explored using agent-based simulation for three scenarios. An efficient experiment design alters settings of ten factors for the two ISR scenarios and 11 factors for the FP scenario. Some factors varied in the experiment are uncontrollable during operations, such as the total number of contacts, threat density, their maneuvering characteristics, and the sea state. The USV sensor range and endurance are also considered as well as factors set by the decision-maker for a particular mission: namely, USV speed and numbers to deploy. The results provide several operational and tactical insights with implications for patrolling and combat radius, and form the basis for a recommendation to use the USV in an active role in maritime missions. The results also support the guidance on the benefits of improving USV sensing and endurance capabilities, and find that simply increasing USV numbers is not necessary for attaining high mission performance.

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AGENT-BASED SIMULATION OF UNMANNED SURFACE VEHICLES: A FORCE IN THE FLEET

Melissa J. Steele
Ensign, United States Navy
B.S., The Pennsylvania State University, 2003

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June 2004

Author: Melissa J. Steele

Approved by: Susan M. Sanchez
Thesis Advisor

LCDR Russell Gottfried
Second Reader

James Eagle
Chairman, Department of Operations Research

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ABSTRACT

The Navy is considering the use of unmanned surface vehicles (USVs) to reduce risk to personnel in maritime interdiction operations, and to conduct intelligence, surveillance and reconnaissance (ISR) and force protection (FP) missions. In this thesis, alternative configurations of the prototype and operational uses of the USV are explored using agent-based simulation for three scenarios. An efficient experiment design alters settings of ten factors for the two ISR scenarios and 11 factors for the FP scenario. Some factors varied in the experiment are uncontrollable during operations, such as the total number of contacts, threat density, their maneuvering characteristics, and the sea state. The USV sensor range and endurance are also considered as well as factors set by the decision-maker for a particular mission: namely, USV speed and numbers to deploy. The results provide several operational and tactical insights with implications for patrolling and combat radius, and form the basis for a recommendation to use the USV in an active role in maritime missions. The results also support the guidance on the benefits of improving USV sensing and endurance capabilities, and find that simply increasing USV numbers is not necessary for attaining high mission performance.

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EXECUTIVE SUMMARY

The Navy is considering distributed means of conducting surveillance and reconnaissance using unmanned surface vehicles (USVs) (Ricci, 2002). An attack on 24 April 2004 against Sailors in a Rigid Hull Inflatable Boat (RHIB) makes the notion more relevant. During maritime interdiction operations (MIO) in the Arabian Gulf, a 7-member crew RHIB proceeded to intercept and board an unidentified dhow for investigation. As the RHIB approached the dhow, it exploded—killing two Sailors and wounding four others. Two other unidentified dhows also exploded the same day (Navy Newsstand, 2004). These incidents give solid motivation for the USV to be integrated into daily operations in the Fleet.

Using agent-based simulation to analyze information, surveillance, and reconnaissance (ISR) and force protection (FP) missions, each model depicts USVs, enemies, neutrals, and a high value unit (HVU). The USVs leave the HVU in pursuit of accurate identification of contacts in its field of view. There are two ISR models: a Waypoint scenario which provides a predetermined path for each USV to follow, and an Interceptor scenario, in which the USV is free to move on any path. The FP Model has two types of enemies: threatening and non-threatening. This model assesses the ability of each USV to prevent threatening enemies from reaching the HVU.

This thesis looks at ten factors for the ISR Models:

- USV speed,
- Enemy speed,
- Neutral speed,
- Sea state,
- Number of USVs,
- Number of Contacts,
- Percentage of contacts that are enemy,
- Sensor range,

- Tactical radius from the HVU, and
- Time on station.

The FP model enables consideration of eleven factors, including all of those in the ISR analysis with the exception of the time on station and with the addition of threatening enemy speed and percentage of enemies that are threatening. The measures of effectiveness (MOEs) are the proportion of enemies detected. The FP scenario has two additional MOEs: the proportion of threatening enemies detected and the number of threatening enemies that reach the HVU.

One factor that is significant in each of the five analyses is the number of USVs. USV speed is significant in all analyses except the FP-number that reach the HVU. Sensor range and time on station are important in the two ISR scenarios. Finally, the percentage of threatening enemies is significant in each of the FP analyses. USV speed, the number of USVs available to the HVU, sensor range, and time on station are all controllable factors. Percentage of threatening enemies is the only common factor that is not controllable. This analysis shows that the Navy can make a decision to deploy the USV in one of the three proposed scenarios without having to rely on intelligence or make assumptions regarding inaccessible information. This is not to say that the models' other significant factors are trivial; only that if, for example, the situation at hand would evolve from an Interceptor scenario to a FP scenario, some important information is already known about the impact of the number of USVs, the USV speed, and the sensor range.

Preventing fatal incidents such as the lethal April 2004 event is an advantage to implementation of the USV into the Fleet. Multiple linear regression and regression trees are coupled with an experimental design that analyzes up to 11 factors simultaneously. This provides insights into USV configuration into the Fleet putting a stop to fatal MIO operations. These insights include working toward covering a 1600 sq-nm area with 16-20 USVs per HVU, enabling the platforms to be able to stay away from the HVU for at least 7.5 hours, and designing either an increased range that the USVs can travel from the HVU or an improved sensor range to increase the proportion of detections.

I. INTRODUCTION

A. UNMANNED SURFACE VEHICLES

The Navy is considering distributed means of conducting surveillance and reconnaissance using unmanned surface vehicles (USVs) (Ricci, 2002). An attack on 24 April 2004 against Sailors in a Rigid Hull Inflatable Boat (RHIB) makes the notion more relevant. During maritime interdiction operations (MIO) in the Arabian Gulf, a 7-member crew RHIB proceeded to intercept and board an unidentified dhow for investigation. As the RHIB approached, the dhow exploded—killing two Sailors and wounding four others. Two other unidentified dhows also exploded the same day (Navy Newsstand, 2004). These incidents give solid motivation for the USV to be integrated with daily operations in the Fleet.

The US Navy has a prototype USV that deployed with the USS GETTYSBURG (GET). Essentially a 7-meter RHIB that has been configured for ISR, the current USV contains an electro-optical/infrared (EO/IR) camera, commercial grade radar, microphone and a loudspeaker. It is radio controlled with a current range of five nautical miles (nm) from the host ship. The USV is gas-powered with a projected endurance of six hours and a 10-foot height of eye. A picture of Spartan Scout, the prototype USV, is provided in Figure 1.

Figure 1. Spartan Scout Controlled from GET (Rich, 2003)

The US Navy is in the initial stages of procurement of the USV. Several potential uses exist. Surveillance enables the host ship to detect and identify other objects on the seas that are outside of the visual and radar range of the vessel from which the USV is operating. Along with surveillance, interception, defined as the ability to move towards the potential threatening contact, is a mission essential task especially for MIO. The combination of surveillance and maritime interdiction capabilities expected from the USV is integral to provide the Navy the ability to perform these missions while the host ship continues on operational tasking and maintains its position. Another need for the USV is Force Protection (FP), as evidenced by the April 2004 attack cited earlier. The host platform can allocate its resources in different ways to ensure proper defense. Mine warfare is another projected use of the USV, but not covered in the current study.

The operations of the prototype, Spartan Scout, tested its intelligence, surveillance and reconnaissance (ISR) capabilities. The tests occurred on December 1-2, 2003 and January 19-22, 2004. (Rich, 2003 and Quarderer, 2004). Along with ISR information, the other data collected during this live testing inform this current research in determining the benefits and shortcomings of adding the USV to missions in the fleet. Unfortunately, the possibilities for gaining insights are limited when only a single prototype is available. Instead, this thesis uses agent-based simulation to determine configurations for the USV and the unit from which the USV is deployed.

An agent-based simulation is used to evaluate the performance of configurations and operational use of the USV. The simulation varies these current characteristics of the prototype among the missions expected of a USV in the Navy. The results form the basis for a recommendation to the US Navy to use the USV in an active role in maritime missions. The simulation looks at the type of mission as well as the sea state in which the mission is to be performed in. In order to fully capture the essence of agent-based simulation, the model experiments with the number of USV's to be deployed per High Value Unit (HVU) throughout simulations so that activity differences can be detected with low and high numbers of USV's.

B. PURPOSE AND MOTIVATION

The Navy has only recently begun to procure these assets, and it has not yet developed operational procedures for the USV(s). Determining whether or not the USV benefits fleet operations is desirable. Being able to emulate actual scenarios that would be useful to the ships in the fleet in an agent-based simulation is an objective of this study as well. Three scenarios of interest are:

- Maintaining a recognized maritime picture (RMP) of a large number of vessels;
- Sorting out and tracking a specific contact of interest out of a number of routine vessels; and,
- Detecting, identifying and tracking a high-density group of contacts of interest among a number of contacts.

Another intention is to estimate USV performance under a variety of situations with a confidence that is acceptable to the Navy. These performance estimates provide information and insights that can assist decision-makers or lead to further research involving specific areas of interest, tactical applications, or operational scenarios.

Undertaking this topic came as a function of the author's future as a Surface Warfare Officer in the Navy. Since the USV is in its beginning stages of development and testing, it appears to be a great place to begin research for a thesis as well as background for a future SWO. Knowing that this thesis has the potential for further developments within the fleet or even for further research is inspiring and encouraging.

C. SCOPE AND METHODOLOGY

This study uses an agent-based simulating platform PYTHAGORAS to model the performance of the USV with respect to its current capabilities. Agent-based simulations are those in which the entities and objects that make up the model behave disjointedly (Sanchez and Lucas, 2002). Each entity of a squad, for example, is defined in the exact same manner. The entities, or agents, act independently of other agents in the squad. For military applications, this logic seems applicable. Training in the military is, for all intents and purposes a constant factor for the members, but each member takes what is commanded and, in conjunction with the environment, makes decisions separately from the other members in the group. More detailed explanations of agent-based simulation and analysis can be found in Sanchez and Lucas (2002). The models developed in this thesis are able to capture the way USVs act under a variety of circumstances. Factors that are varied throughout the modeling include:

- Sea state,
- Speed of USV and targets,
- How close the USV must get to a target for accurate identification,
- Number of USVs to send out for particular mission, and
- Combat radius (the length of time to and on station) under the various factors.

Among the factors that are varied, experiments determine with statistical significance whether the manner of deploying USVs should be on a given patrol pattern as opposed to the USV choosing the closest enemy to pursue. Another desired outcome of this thesis is to see if the factors examined yield evidence whether the USV is the best solution to the tactical problem. Varying these factors, in conjunction with operational scenarios, covers some ground to provide useful insights to the Navy, but it is optimistic to expect this study to enable the necessary decisions for full implementation of the USV into the Fleet under all circumstances.

Every problem needs answers. Therefore it is necessary to define the correct questions and specific problem statements to be answered. The organization of the remainder of this encompasses an approach toward answering each of the following questions and statements. Chapter II contains an overview of the assumptions made to develop the models, the models' capabilities, and descriptions. Chapter III is the design of experiments explaining the design process, the factors analyzed throughout analysis, and the tactical interpretation. The analysis of each model, verification and validation, and results are included in Chapter IV. The final chapter consists of the conclusions of the analysis, lessons learned regarding the use of agent-based simulation for analyzing USV deployment and recommendations for further research on this topic.

D. PAYOFFS AND BENEFITS

This thesis benefits the researchers and supporters of the USV, and it seeks to support Fleet-wide decisions on whether the USV should be implemented into tactical operations. One series of experiments in this study could aid in determining whether the current configuration of the USV should be altered, including whether weapons should be added or if any of the other four capabilities, (force protection, surveillance, maritime interdiction or mine warfare) should be fully implemented to obtain optimal performance. As a direct link to disseminate information for the benefit of USV researchers and supporters, the results of this thesis are implemented into a TACMEMO (Statement of Work, 2003). The best benefit that the Fleet can have is preventing the death and injury of Sailors. The MIO incident on 24 April 2004 is an example of why USVs are necessary in the current tactical environment.

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II. SCENARIO DESCRIPTION

A. ASSUMPTIONS AND CAPABILITIES

The scenarios included in this study are the prototype of the Spartan Scout (Scenario-P), two proposed Information, Surveillance and Reconnaissance (ISR) scenarios and one proposed Force Protection (FP) scenario. The ISR models include a Waypoint scenario (Scenario-W) and an Interceptor scenario (Scenario-I). The proposed scenarios are explained in more detail later. Analyzing a tactical problem using simulation requires abstraction of a scenario using tactical information while seeking to retain a sufficient level of resolution. For this thesis, several basic assumptions enable the problems to be implemented on the PYTHAGORAS simulation platform and make the results comprehensible. Because this is an abstraction of a tactical scenario, the model needs to be verified and validated so that the results are credible (Law and Kelton, 2000). The verification and validation are expanded in Chapter IV.

An important concept underlying all three scenarios is that USVs deploy from High Value Units (HVUs). The HVUs can be a Carrier or Expeditionary Strike Group, (CSG and ESG, respectively), or any generic HVU. The HVU is composed of a number of ships, or even a single defended asset, responsible for the each USV. It is not correct to assume that the HVU has direct control of each USV, but that individual units within the CSG or ESG are responsible for their respective USVs. For simplicity, the USVs in the ISR and FP scenarios are not represented as deploying from individual ships. Instead the group controls the USVs. When viewed within the context of a tactical situation, ISR assets are typically treated as common resources for the entire task group. Therefore, the assumption that each USV is controlled by any unit is realistic, and emulates how the chain of command may evolve.

Another abstraction of the PYTHAGORAS models is that some meteorological factors are not included in the development of the simulations, including wind, current, tides, and sea surface temperature. These are factors that the meteorology and oceanographic (METOC) community predict would have an effect on a USV (Joint METOC Handbook, 2000). While these factors are omitted from the simulation for simplicity, their effects on visibility and maneuverability do exist. Sea state is another factor important by the METOC community and it is included in the simulation. This is discussed in more detail in Chapter III.

One final factor not incorporated into the simulations is latency. Latency is the delay as data are relayed from each USV to the HVU so the operator can control the vehicle or identify a contact. The average latency from live USV prototype experimentation was 0.204 seconds with a standard deviation of 0.037 (Quarderer, 2004). Since each simulation time step is 72 seconds, this small amount of time for data latency essentially becomes absorbed within the time step. Therefore the simulation models are slightly optimistic because the data latency does affect control of the USV. PYTHAGORAS can model these effects by increasing the "hold fire desire" property in the "engagement desires" in the simulation. "Hold fire desire" can be thought of as a probability that the agent has to wait to act. This defines whether each USV takes action or not with a certain non-zero probability. An area for further research is rescaling the problem so that the time steps are less than one second, enabling effective modeling of latency.

B. SCENARIOS

Scenario-P closely represents the results from several prototype exercises conducted onboard the USS GETTYSBURG (GET). The model is based on a single USV operating within a five nautical mile (nm) radius, limited by the controlling Radio Frequency (RF) from its host ship. The range drives the overall dimension of the scenario, which is 10 nm by 10 nm. The USV has radar with a range of 16 nm and an Electro-Optical/Infra-Red (EO/IR) camera for visual detection, and sends its data to the host via a real-time link to shipboard video consoles. The USV pursues contacts that require closer investigation. The contacts are neutral merchant ships and contacts of interest. Scenario-P serves as the base scenario for verification that the simulation models are in compliance with the tactical situation. The only run done on this scenario is confirmatory, to verify its concurrence with the live prototype results.

The three experimental scenarios are designed with the purpose of emulating operational possibilities for the USV. The scope of the proposed scenarios is an area of interest of 1600 square-nm in the open seas near possibly high-traffic regions. Scenarios-W and -I are similar except in one way—the USV movement patterns. In Scenario-W, each USV has predetermined patrol patterns, or waypoints. Each USV is initially placed at the HVU and patrols along the prespecified paths. Scenario-I explores ISR operations when each USV takes a closer look at nearby contacts of interest as designated by the CSG or ESG. The scenario begins with the USV departing the HVU and traveling to the nearest enemy.

In PYTHAGORAS, in order for one agent to be able to investigate another agent, it is necessary that they be on opposing sides. In each of the two ISR scenarios, there are two types of opposition, representing ships that are merchant ships (a noise factor), as well as the contacts from which the friendly force is truly looking to gather intelligence. The experiments (discussed in detail in Chapter III) are set up so that each model provides information on the proportion of enemies detected in each scenario and compares outcomes between the two ISR scenarios.

This study also uses PYTHAGORAS to implement Force Protection capabilities as well as ISR capabilities. Scenario-FP is a scenario where the ratio of attackers to defenders is high. The Force Protection scenario has three classifications of enemies, for PYTHAGORAS purposes. As mentioned for the ISR scenarios, there are both neutral contacts and opposing forces within the USV field of regard that are not possible threats to the HVU. The additional force of enemies is threatening, and these hostile contacts act nearly simultaneously to attack the HVU. Each USV opposing forces looks for their nearest enemy to investigate. The neutral contacts and non-threatening enemies act as noise factors for this scenario. The experiment is set up so the model will provide information on the proportion of enemies detected, the proportion of threatening enemies detected, and the number of enemies that reach the HVU.

C. SCENARIO DESIGN

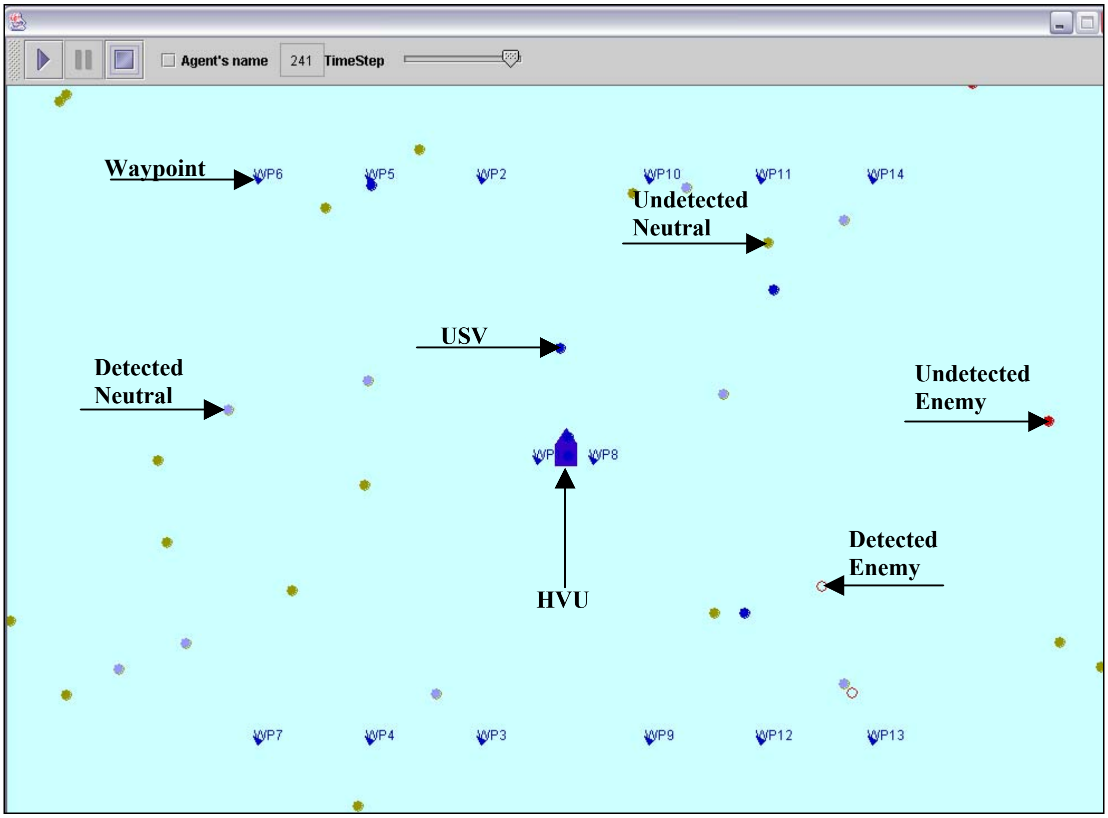

Figure 2. Screen Shot of Waypoint Scenario in PYTHAGORAS

These models require translation into the language of PYTHAGORAS in order to be compatible with the real world scenario. The modeling platform uses pixels for distances, and speed is in pixels/time step. Properties such as the speed of the individual agents determine the agent's position and state after each time step. Every scenario has agents representing three forces: friendly, neutral, and enemy. Figure 2 displays the agents in the Waypoint scenario. Each force has its unique properties that determine movement and activity. The friendly force consists of the HVU and all of the USVs. Neutrals, such as merchant vessels, represent those ships that are simply moving randomly throughout the area, interacting with neither the enemy nor the friendlies. Although this force is neutral, PYTHAGORAS represents these contacts as enemies, so the USV has reason to approach them.

Enemy agents are different depending on the desired mission, ISR or FP, for analysis. Enemy movements for ISR scenarios are as follows, in descending order of their desire:

- Move away from nearest enemy if closer than two nm,
- Maintain last course,
- Move randomly about the space.

The enemies in the FP scenario act more hostile in order to get to the HVU. This is explained in detail later. The only movement desire the neutral agents possess is to move in a random direction. All agents have the ability to possess sensors and weapons, and specific speeds, and movement desires. Movement desires can be selected by four different methods: highest desire, average desire, random desire, or the top two desires (Bitinas, 2004).

PYTHAGORAS requires each agent to possess a weapon and a sensor. However, to model agents without a sensor or weapon, the platform can use dummy weapons which have they have a zero-probability of kill. Each agent type in these scenarios possesses a sensor so a dummy sensor is not necessary. For all scenarios explored, the HVU inhabits the center. To reduce the simulation models' complexity, movements of each agent (USV, enemy or neutral) are considered relative to the motion of the HVU; therefore, the effect is that of a maneuvering board or a radar display onboard the HVU.

Other features of the simulation models include the inputs into PYTHAGORAS that remain constant throughout the simulation replications while varying factors and scenarios. Incorporated features are weapon and sensor ranges, kill and detection probabilities in the scenarios, some agents' color state values, and movement desires.

Weapons, firing and kill behaviors in PYTHAGORAS emulate detection and identification. "Weapon range" defines the distance an agent possessing the weapon must be from the contact in order to fire the weapon. This equates to a detection. Along with the range of the weapons, the modeler must specify the probability of kill, $P_{k,}$ once the weapon is used. For all scenarios in this thesis, the range and the P_k are constant. The maximum range of the weapon is 1 nm. The reason a USV has to be so close to "kill" is related how kills equate to positive identification. Once a USV is within 1 nm of the contact, it is "hit," and the identification process is complete.

The P_k is set at 1.0 for any range, calculated in PYTHAGORAS through interpolation. Since the time step is 72 seconds, randomness is overrun by the time step. For simplicity, the P_k and the maximum range of the weapon are constant. The probability of detection, P_D, is similar to the P_k but relates to the ability for the sensor to detect a contact. The optical sensor has a maximum range of 4 nm and the radar sensor has a maximum range of 16 nm (Rich, 2004), that of a commercial radar system. Plots in Figures 3 and 4 show the explicitly stated probabilities by range for optical sensor and radar, respectively. The probabilities are an abstraction to show the relationship of the ability of each USV to detect contacts with these sensors. The program linearly interpolates any range that is not at the stated distances to determine the correct probability.

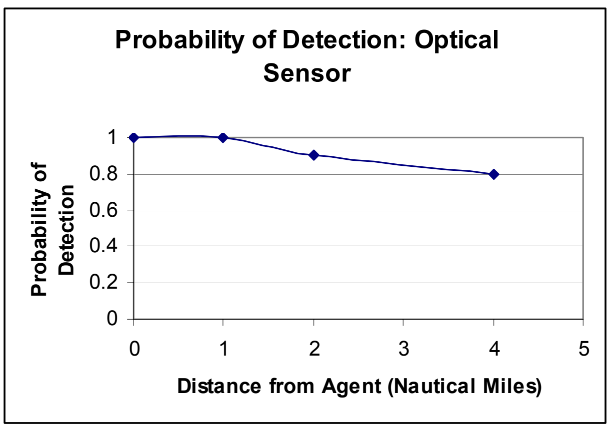

Figure 3. Probability of Detection for Optical Sensor

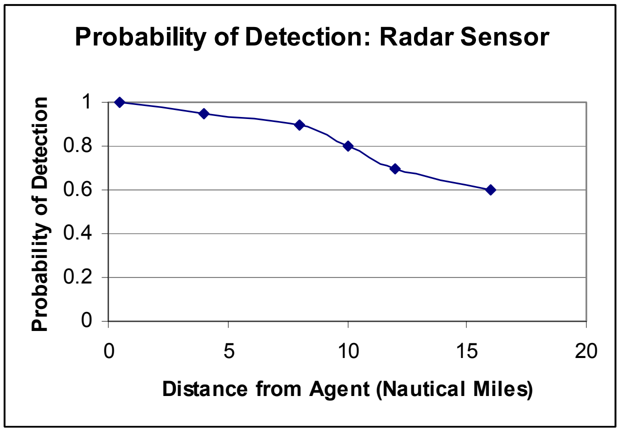

Figure 4. Probability of Detection for Radar Sensor

PYTHAGORAS distinguishes among friendlies, enemies and neutrals using color properties. Each of the three forces has the same distinct color for every scenario. Friendlies are blue; the unidentified or alive enemy are solid red; "killed" Enemy are red circles; and neutrals start out as brown and turn light blue after being identified. Color or state changes occur only when a USV shoots neutral agents. A neutral agent's color changes so it is no longer seen as a potential enemy contact, but it is not "killed." This equates to a circumstance in which contacts, once identified, remain so throughout the remainder of the scenario. This may be optimistic. These color properties are the same for each model to facilitate comparisons.

Agent movement, as previously mentioned, has values from 0-100. The value entered is a number that relates the particular desire to the other desires. Obviously, if the movement desire is 0, that particular desire has no effect on the agent and is omitted from this discussion. This value is only a relative relationship with respect to the agent it is describing. The values are chosen only so that the relationships among the competing movement desires can be shown. The relative importance of the movement is the desired relationship in the modeling.

1. Scenario-P

The area of operation for this scenario represents a 10 nm x 10 nm area of ocean relative to the HVU. In PYTHAGORAS, only the USV has weapons to "kill" a contact. The HVU, enemy and neutral agents do not posses any weapons. A kill represents correctly identifying the contact, and the likelihood of obtaining a kill varies with a probability of kill (P_k). P_k is 0.85 in Scenario-P (Quarderer, 2004). The feedback from prototype testing also indicated latency in the data-link back to the HVU, modeled by delaying the time that the weapon can kill.

The sensors in the scenario are optical and radar. The USV possess both the optical and radar sensor, the HVU only has radar, and the enemy and neutral agents only possess the optical sensor. The USV optical sensor represents the EO/IR camera, and has perfect vision for 45 degrees directly in front and some peripheral vision, whereas the neutral and enemy sensors are merely visual cues. The probability of detection (P_d) decreases as the range to the contact increases. The maximum range is 2 nm. The radar sensor has 360-degree coverage with a maximum range of 10 nm due to communications.

As observed for the prototype, the RF range for the USV is a 5 nm radius from the host platform. This limits the USV to travel only in a 5 nm area around the HVU. The movement desires of the USV are, in decreasing order:

- Away from leader (HVU) if closer than 0.5 nm,
- Toward leader if farther than 5 nm,
- Toward nearest enemy if farther than 0.2 nm,
- Toward next waypoint,
- Maintain last course.

The prototype scenario does not have a design matrix with replicating runs. A confirmatory run is made in order to verify the scenario is representing the data from GET.

2. Scenario-W

Scenario-W implements a scenario where each USV patrols in pre-determined tracks, via waypoints. Tactically, each should simply be able to vigorously patrol sectors rather than follow specific paths, but the limitations of PYTHAGORAS did not permit this Sector Scenario to be developed. The waypoints make a “bow-tie” patrolling pattern near the HVU. The total area represented is 40 nm x 40 nm. As in Scenario-P, the only agent that has a weapon is the USV, which “kills,” or in the terms of the thesis accurately detects, the enemy. All three sides, friendly, enemy, and neutral, have an optical sensor that has a 45-degree frontal view with a view probability of 1.0 and a 0.0 view probability for any other angle.

The HVU agent possesses a radar sensor with a range of 16 nm, equivalent to a commercial navigational radar system (Rich, 2004) and that information is broadcast to each USV. The broadcast range represents how far the HVU can cue the USV with information from its radar. This property constrains each USV to be within the broadcast range in order to receive the information that the HVU is sending. This is simply a modeling aspect that is not intended to represent the actual HVU sends information at precise ranges. The radar has a 360-degree view with a view probability of 1.0.

Speed in the simulation model is a function of the pixel representation as well as the length of the time step. The speed among like USV agents is set to a tolerance factor of three. The tolerance factor is input by the modeler and indicates the range of the property, such as speed, that the agents in the class can possess. For instance, if enemy speed is 10 pixels/time-step, a tolerance factor of three provides for the agents can having speeds from 7 to 13 knots. This number allows speed to vary slightly during experimentation. Since the range of speed is from 1 – 20 units, a factor of three can be used consistently over the varied speeds. Each USV starts at the HVU, the center of the modeling area, and travels toward the waypoints. Since speeds are not constant, the scenario represents average speeds.

The constant radius modeled for each USV is 20 nm. The range is just over the visual horizon and past the 16 nm radar range. Experimenting with this range shows whether it is desirable to stretch the limits beyond the line of sight. This is one of the factors that varies throughout the runs of the simulation. The movement desires of each USV are, in decreasing order of desire:

- Toward the next waypoint within a distance of 1.6 nm,
- Toward the nearest enemy if farther than 0.4 nm,
- Away from the closest unit member if closer than 1 nm,
- Away from the HVU if closer than 1 nm, and
- Toward the HVU if farther than 1 nm.

The first two desires are given equal weighting and the movement method is used "top two desires", which means that the agent only looks at the two highest desire values to execute the next movement. If conditions of the highest values are not met, the agent looks at the next highest desire value, allowing the USV to seek for enemies as well as proceed to the next waypoint. The third desire prevents the USVs from clustering together and going after the same contacts. Forcing the USVs apart makes them operate separately. The fourth desire is to "jump start" the simulation. All of the USV would otherwise start at the center and stay put without this movement desire. The last is a very low desire level and if all of the other conditions cannot be met, the USVs go back to the HVU.

3. Scenario-I

The Interceptor scenario is a representation of USV operating in a random manner, whereby each conducts cooperative searches for contacts within their optical scope or that of the HVU radar. The search area contains neutral contacts and enemy contacts, as well as the HVU. The USVs deploy from the HVU at the start of the simulation and immediately start searching for the nearest enemy. When the USV is within the stated range of identifying the contact, the contact is removed from the possible contacts that can be explored. In order for the USV agents in PYTHAGORAS to desire investigating non-threatening contacts, the neutral contact is designed as an enemy. As in tactical operations, the USV(s) would attempt to identify not only the enemies, but any unknown contact that is within the chosen zone of the HVU.

The USV agents in the scenario possess optical and radar sensors. The optical sensor has a perfect view 45-degree in front of the agent with no peripheral vision. The HVU possesses the radar sensor, which has a 360-degree view and a range of 16 nm. The neutral and enemy agents only possess the optical sensor. In descending order, the movement desires of each USV in the Interceptor scenario are:

- Toward the nearest enemy as seen in the scenario (this sends the USV after the contacts),
- Away from the closest unit member (this prevents the USV from staying in a cluster),

- Away from the leader (HVU) if closer than one nm (this jump-starts the search), and
- Toward the leader (HVU) if farther than one nm (if no other movement desires exist, this sends the USV back to the HVU).

Once again the movement method uses the “top two desires” of the values input into the simulation model. This is an ISR scenario and it follows the descriptions and assumptions of Scenario-W for the movement desires for the neutral and enemy contacts in the scenario. The verification of Scenario-I is Random Search Theory applied in Chapter IV.

4. Scenario-FP

The Force Protection scenario is designed to determine the benefits of the USV when there is an imminent threat to the HVU. As in the previous scenarios, each USV searches for the nearest contact in order to identify whether or not it is a threat. The weapons and sensors that the USV and the other contacts possess are the same as in the ISR scenarios. The difference in this scenario from the ISR scenarios is how the enemies are defined. The purpose is to see the effect of each USV when some of the enemy contacts are directly targeting the HVU. The neutral and enemy contacts in Scenario-FP are still implemented as in the ISR scenarios; however there is an additional type of enemy in the FP situation. The additional enemy is threatening and goes toward the HVU to attack. The actual attack on the HVU is not modeled, as the focus of this study is on USV activity. Modeling the attack and how the USV(s) respond could be a topic for future research.

The movement desires of the threatening enemy are to make it to the HVU without being detected by the USVs. They are hostile toward the HVU and the USVs, and do not cluster tightly but to join together outside a range of four nm. The PYTHAGORAS desires are listed in descending order of desire:

- Toward next waypoint (HVU),
- Toward nearest enemy (USV(s)),
- Away from nearest enemy if farther than two nm,

- Away from Closest unit Member if closer than one nm,
- Toward closest unit member if farther than four nm,
- Maintain last course,
- Select Random Direction.

To affect tactically challenging threat profiles, the simulation model makes use of a "highest desire" movement method among these options. The first two each have the highest desire, the third, slightly less, and the fourth, fifth, and sixth are all equal. The last two are carried over from the enemy characteristics in the ISR scenarios and the non-threatening enemies in the FP scenario. USV movement desire is exactly the same as for the Interceptor scenario.

D. METHODOLOGY

No experiment is complete unless there is output of value for analysis. The value is a function of the factors and the factor levels explored in the experiment (Chapter III) as well as the measures of effectiveness (MOEs) that are collected. The following MOEs appear to be most relevant, even though PYTHAGORAS is able to implement a variety of MOEs. The ISR scenarios explore the proportion of enemies detected. The FP scenario also examines the proportion of enemies detected. Since there are two types of enemies, there are two distinct MOEs for each type of enemy—the overall proportion of enemies detected and the proportion of threatening enemies that are detected. The final MOE to be evaluated is the number of threatening enemies that reach the HVU. Each MOE is evaluated individually against the factors for the respective scenario, and analyzed using regression methods. The results yield significant factors and interactions for each particular MOE. Further validation of the important factors confirms the results.

1. MOEs Implemented

a. Proportion of Enemy Detections

The numbers of each type of agent are known, since they are inputs to PYTHAGORAS at the beginning of each run. The output from PYTHAGORAS returns the number of detected enemies at the end of each run, yielding a proportion of enemies detected. The proportion of detections is essential to the ISR scenarios as well as the FP scenarios. For example, it is tactically important to know conditions in which sending out a USV would enable detection of only a small proportion of enemies. It is a waste of an asset if the proportion of detections is so low as not to enhance the mission. It is tactically important to specify the condition under which the HVU deploys the USV to interdict contacts. This study helps define those conditions. It is anticipated that as the number of USVs increase, the proportion of detections will initially increases but eventually levels off.

Force Protection is most critical at close ranges to the HVU. Knowledge of the probability of detection, as well as the current number of detections, could be used to develop an estimate of the proportion of unidentified enemies in the area. This type of information is of great value to tactical decision makers.

b. Proportion of Detections against Threatening Enemies

This MOE is calculated similarly to MOE (a), the proportion of detections of enemies that are threatening out of the total number of enemies. The real world actual number of enemies is unknown, therefore we don't know the probability of detection give the number of enemies. The benefits of this study are that we know the values of the all the factors so we can generate estimated probabilities of detection given the number of enemies for specific conditions.

c. Number of Threatening Enemies that Reach the HVU

Since the threatening enemies are designed to move toward the HVU, this study must show how many of these threatening enemies meet their goal. This MOE should give the decision-makers the information necessary to decide what USV options to exercise when planning a FP mission. This MOE is important in determining an effective numbers and employment of USVs for Force Protection missions.

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III. DESIGN OF EXPERIMENTS

A. LATIN HYPERCUBE DESIGN

Correct design of experiments enables efficient analysis of many factors at multiple levels. A design point represents the combination of one particular level for each factor in the simulation model. In general, choosing the values for the design points can be challenging, particularly when the number of factors is large, such as in this study. For example, observing 11 factors at three discrete levels would require 3^{11}, or 177,147 design points, to be run at least ten times each for randomness, for a total of approximately 1.8 million runs. Observing 11 factors at ten discrete levels would require 10^{11} or 100 billion design points to be run at least 10 times each for randomness, for a total of one trillion runs. In contrast, the designs used to explore the three scenarios in this thesis require less than 12,000 runs combined, yet allow for up to 33 discrete levels for each factor.

This base design for the study is a Nearly Orthogonal Latin Hypercubes (NOLH), which takes at most eleven factors and varies each factor across up to 33 different levels. Using a Microsoft Excel spreadsheet developed by Professor Susan Sanchez (Sanchez, 2004) based on Cioppa's (2002) designs, it takes the minimum and maximum value of each factor as inputs, and specifies combinations of integer values within the factor ranges as outputs. The resultant matrix is a set of design points that are generated so that the columns are virtually orthogonal to each other, defined as a correlation less than $|0.03|$, simplifying the process of adding and removing terms to a regression model. When all factors are independent, an individual factor has the same effect on the response variable whether or not other factors are included in the regression model.

The NOLH design is devised so the design space is covered fully. The factor levels are varied to maximize the coverage. Good space-filling permits complex analyses to be computed (Sanchez and Lucas, 2002). This study appends together four NOLH matrices, in order to get better space-filling and sufficiently reduced correlation. The middle run for each of the four matrices is the exact same design point (a function of the calculations to generate the values in the columns), so there are a total of 129 distinct design points run 30 times each for a total of 3,870 runs for each scenario. This provides structure so that the data can be compressed for each design point and for analysis as 129 independent responses.

The runs were conducted on a cluster of machines at the MITRE organization in Woodbridge, VA. Cleaning the data for analysis exposed errors in the compilation of the data files. Omitting these four associated design points yielded a correlation matrix producing a maximum correlation of |0.06|. Even though this is not below |0.03|, it is still sufficiently low for us to consider the factors nearly orthogonal. These replications help determine which of the varied factors are important for specific MOEs. Since the composition of the ISR and FP scenarios are slightly different, the design matrices are not exactly the same. However, each look at parallel factors. The design matrices are explained in detail in the following two sections.

1. Explanation of Variable Factors for ISR Scenarios

Ten factors are varied in PYTHAGORAS units for the ISR scenario. The factors are shown in Table 1, along with their minimum and maximum tactical values for the simulation experiments. In the remainder of this section, each factor is also explained in its PYTHAGORAS terms.

Table 1. ISR Scenarios NOLH Design, 10 Factors, 33 Design Points

Factor	Minimum Value	Maximum Value
USV Speed	2 knots	40 knots
Neutral Speed	2 knots	40 knots
Enemy Speed	2 knots	40 knots
Sea State	1	3
Number of USV(s)	1	24
Number of Contacts	1	250
% Enemies	10%	25%
USV(s) Permitted Range from HVU	1 nm	20 nm
Camera Range	1 nm	10 nm
Length of Simulation	30	500

The speed of each type of agent ranges from 1-20 pixels per time step, which converts to 2-40 knots. Each time step is 72 seconds long. The maximum speed of each USV is based on that of the RHIB, the base structure for the USV. The maximum speed of a RHIB is 40 knots (Navy Fact File, 2004). The smallest time step feasible to permit the conversion to 40 knots in PYTHAGORAS is 72 seconds. Two knots is the minimum at which each time step is not so long that resolution of the scenario is lost. If the range were one knot, the time step would need to be twice as long, significantly decreasing the fidelity of the scenario since detections can take place in less than two minutes. Both the neutral and enemy contacts are given the same range for the respective speeds.

The next factor varied is the sea state, accomplished in PYTHAGORAS by the changing the movement factor of the terrain. The movement factor is a number between zero and one. In order to implement the NOLH design, this factor is scaled by 10 to conform to spreadsheet design points given in integer value. The range of the factor in PYTHAGORAS is 0.5-1.0 (5-10 in the design matrix). The actual range of sea states is states 1-3. Above sea state three, a RHIB is highly unstable, its sensors are rendered less effective, and the hostile and neutral agents suffer similarly in their ability to maneuver. Looking at operations in the heightened sea states is an opportunity for further research. An overview of sea state classification and translation to PYTHAGORAS appears in Table 2.

Table 2. Sea State Definition for Pythagoras (from Definition of Sea State)

Pythagoras Movement Factor	Sea State	Wave Height (Ft)
0.9-1.0	1	0.5-1
0.7-0.8	2	1.5-2.5
0.5-0.6	3	3-4

In the scenario, an HVU is assigned a Squadron of USVs, which consists of six detachments of four USVs each, totaling 24 USVs per HVU (Ricci, 2002). At one extreme, it is desired to know the outcome when USVs are outnumbered by contacts, and in fact more enemy contacts than USVs. Otherwise, the HVU would be most likely to be able to handle the few contacts. To explore this broad range of alternatives, the number of contacts varies from 1 to 250, where the enemy agents make up 10-25% of all potential contacts. These two factors determine how many neutral and enemy agents are in the scenario.

The optical sensor has a maximum range which defines how far away the agent possessing the sensor can detect a contact. By changing the maximum range of the optical sensor, the time available for the PYTHAGORAS agent to "kill" the contact varies as well; it varies over the interval 1-10 nm, or 25-250 pixels. As the sensor range increases, the number of detections should increase as well.

The permitted range of the USVs from the HVU varies to assess how close the USV should be stationed with respect to the HVU. The range of the camera sensor varies throughout the simulation. This range determines how close the USV must be to the contact in order to get an accurate identification of the contact at hand. The sensor range varies from 1nm to 20nm.

The final design factor under consideration is the time on station, which determines availability for each USV to complete the mission. The projected time on station for the USV prototype is six hours. Utilizing the 72 second time step, the length of the simulation runs for 36 minutes up to 10 hours. If the analysis reveals a high correlation between the MOEs and the endurance, it would be beneficial to be able to lengthen the time a USV can remain on station.

2. Explanation of Variable Factors for FP Scenario

All of the factors varied in the ISR scenarios are also implemented in the FP scenario with the exception of time on station. Scenario-FP has an extra factor, threatening enemies, that the ISR scenarios do not. This necessitates an extra speed factor for the design as well as and additional MOE (percentage of threatening enemies out of the total number of enemies) for the analysis. For the purpose of preserving the NOLH matrix, the time on station factor is removed and kept constant at 10 hours for every run, and the threatening enemy speed and percentage of enemies that are threatening factors are added to obtain the FP design matrix. The speed factor remains between 2-40 knots as it is for all other agents in the ISR scenarios, and the same justification applies. The overall number of enemies, threatening and non-threatening, is 10-25% of the total number of contacts, which varies from 1 to 500. The threat constitutes between 10-90% of the total number of enemies so that involving both few and many threatening contacts are examined. The factors of the optical sensor range and the distance permitted from the HVU are the same as for the ISR scenarios. These eleven factors and the real world ranges of each factor for the Force Protection scenario are shown in Table 3.

Table 3. FP Scenario NOLH Design, 11 Factors, 33 Design Points

Factor	Minimum Value	Maximum Value
USV(s) speed	2 knots	40 knots
Neutral Speed	2 knots	40 knots
Threatening Enemy Speed	2 knots	40 knots
Non-threatening Enemy Speed	2 knots	40 knots
Sea State	1	3
Number of USV(s)	1	24
Number of Contacts	1	500
% Enemies	10%	25%
USV(s) Permitted Range from HVU	1 nm	20 nm
Camera Range	1 nm	10 nm
% Hostile Enemies	0%	100%

B. TACTICAL INTERPRETATION

As mentioned in the previous section, the research and experimentation is done so that it can be applied to the needs of the Fleet. To accomplish this, factors that can be controlled by the HVU, and the noise factors that cannot, are varied in the simulation experiments. Currently, the prototype for the USV has limitations, such as the range it can travel from the HVU and the sensor ranges. If the analysis in the next section proves a need for the USV to hold properties that are beyond the current capabilities, these capabilities should be implemented to achieve optimal functionality.

There are also factors such as the number of contacts and their speeds, and the sea state in the 1600 sq-nm area of ocean looked at in the scope of this thesis that are uncontrollable by the HVU. The controllable factors are the number of USVs and the speed of the USVs. The ultimate desire is to be able to observe an approximate number of contacts in the tactical scenario at a given sea state and know how many USVs should be employed to investigate. Ideally, the results in this thesis will provide useful information to the Fleet for tactical operations.

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IV. EXPERIMENTATION RESULTS, COMPARISONS, AND INSIGHTS

A. ANALYSIS APPROACH

There are several tools available to analyze simulation output data. Multiple linear regression is the first analytical tool. If the regression is not sufficient, other means may be employed for classifying the factors in terms of the MOE. Using regression, we look at the factors varied in the Design of Experiments (DOE), the predictor (regressor) variables, and each of the MOE's as a response to the predictors. The process seeks to identify factors, quadratic effects, and interactions that are significant in explaining variation in the MOEs.

For this study, the overall regression model is considered statistically significant if the p-value is less than 0.05. Individual terms in the model (main effects for a factor, quadratic effects, or interaction effects) are determined to be statistically significant if the p-value is less than 0.05. The smaller the p-value is, the stronger is the evidence that a relationship exists between the term(s) and the MOE.

One metric for determining whether a regression model is a "good" model is the R-squared value. R-squared is the proportion of the variance in the response that is explained by the terms included in the model. A full model includes all of the factors, the factors squared, and the two-way factor interactions as explanatory terms. This involves 65 terms for the ISR scenarios and 77 terms for Scenario-FP. When trying to determine what terms to include, a high R-squared is desirable, indicating the response can be closely predicted; having a minimal number of predictors is also desirable so that the actual variance of the response is at a minimum (Montgomery, 2001). Also, the cost of controlling more factors is usually directly related to the number of factors—another reason to keep the model simple.

There are several ways to look at a full model and determine which factors should be eliminated. This can be done by hand or by utilizing software to do the process. This analysis uses JMP™ software, which has a stepwise regression procedure. The forward regression option starts with no predictors in the model and adds a term if it has a small p-value. Backwards elimination starts with all predictors and sequentially removes them if the p-value is large. The mixed (or stepwise) option does both backwards elimination and forward selection simultaneously. Usually, entering and exiting criteria are set to avoid cycling so it is harder to remove a predictor after it has been added to the model (Montgomery, 2001). We use the mixed option of the stepwise regression offered by the software to do the analyses. This yields models with fewer terms than the associated full models while still achieving high R-squared values.

The model suggested by the stepwise regression procedure can be modified manually, using inference tests of the significance of regression and the significance of the individual coefficients. Further details are available in any statistical text (e.g., Montgomery, 2001), but we summarize the tests here. The significance of regression test has the following null and alternative hypotheses:

$$H_0 : \beta_1 = \beta_2 = ... = \beta_k = 0$$
$$H_a : \beta_j \neq 0 \text{ for at least one } j$$

where k is the last term in the model and j is any term from 1 to k. A rejection of H_0 indicates that there is at least one predictor that has a significant contribution. The method for determining a rejection is if the p-value is less than a significance level α, usually α=0.05. This p-value is found in the ANOVA table summarizing the model.

The other type of test for significance is on the individual coefficients in the regression. The null and alternative hypotheses for this test are below:

$$H_0 : \beta_j = 0$$
$$H_a : \beta_j \neq 0$$

where β_j is the coefficient for a specific potential predictor. A rejection of the null hypothesis for this test means the associated term should remain in the model; if there is sufficient evidence to reject the null hypothesis, then the term is be removed. The method for determining whether or not to reject the null hypotheses also involves a p-value, reflected in the Prob<|t| column in the table of coefficients for the model. Again, a typical criterion is to reject the null hypothesis if the p-value is less than 0.05.

If linear regression is not significant or does not provide a good fit, partitioning or regression trees can help determine important factors. This process explores which factors can be split, and at which factor level the split should occur. A candidate factor is one that has the largest sum of squares value. The output of the regression trees includes the mean and standard deviation of the response variable, given the conditions at the levels where the factors split.

The goals of the both types of analyses include determining relatively simple models that relate the MOEs to their significant factors. This enables the analyst to make predictions of the MOE at particular combinations of factor values, and to relate the factors to the MOE for decision makers.

B. ANALYSES

1. Scenario-W Analysis

Scenario-W analysis begins by constructing a formulation that considered only the terms associated with the factors controllable by the HVU. Stepwise regression assists in determining which of these controllable factors are significant. This function is in JMP™, evaluating all potential terms at the significance levels for exiting and entering the model at 0.10 and 0.05, respectively. Initially, we consider a model that contains only terms involving the factors that are controllable by the HVU to see if situational awareness is required to accurately predict the MOE. These terms are: speed of the USV, number of USVs, permissive range from the HVU (also known as the combat radius), camera range, and the simulation run-time, representing the available time on station. Two-way interactions and quadratic effects are also included. Stepwise regression on these terms returns a model that explains 64.06% of the variance. The main effects included are the number and speed of the USV(s), the camera range and the simulation time. No interaction terms are included, but the quadratic effects of the number of USVs and the camera range are significant. The regression is significant since the p-value is less than 0.001 for the null hypothesis. As depicted in Figure 5, the actual versus predicted values do not have a tight cohesion, or a strong fit, for these data points. An indicator for seeking a better model is the residual plot, Figure 6, which shows that the variance is not constant. The variance seems to increase up to predictions of 0.4, then become stable. However, there is a wide gap for the residuals at predictions between 0.7 and 0.8. With less than two-thirds of the MOE variation explained by this model, a better explanation may be achievable. While the initial model may be of some use to decision makers, adding terms involving uncontrollable factors may improve the fit and residual plots and provide additional insight.

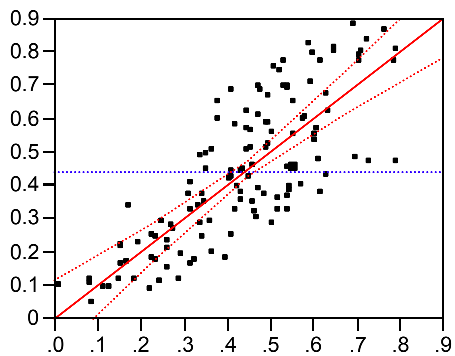

Figure 5. Actual vs. Predicted Responses for Significant Controllable Factors Model (Scenario-W)

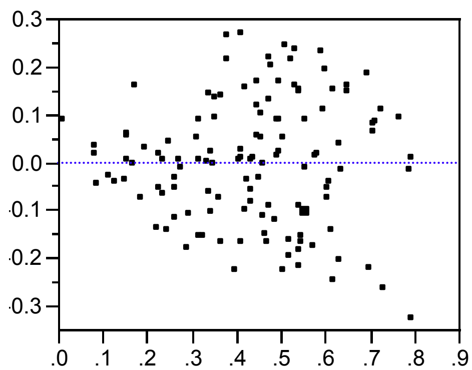

Figure 6. Residual vs. Predicted Responses for Significant Controllable Factors Model (Scenario-W)

A new model is generated after including all 65 possible terms: the main effects, two-way interactions and quadratic effects. Figure 7 shows the actual simulation values versus the predicted values for this "full" model. The data points are clustered much more tightly, which shows a good fit of the data to the model. The regression is significant and the explanation of the variance has increased to 93.71% from 64.06%. The residual plot, shown in Figure 8, also shows that there are no model defects.

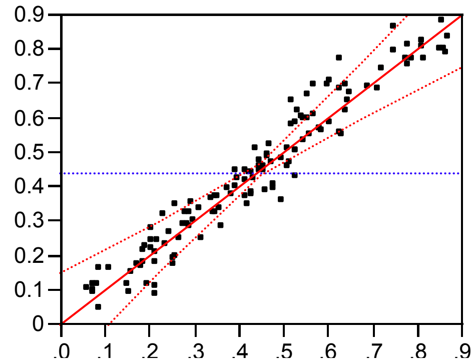

Figure 7. Actual vs. Predicted Responses for Full Model (Scenario-W)

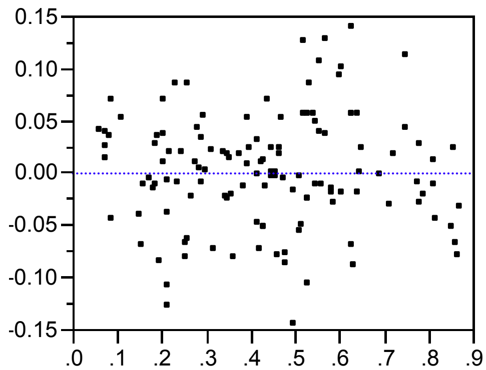

Figure 8. Residual vs. Predicted Responses for Full Model (Scenario-W)

Even though having 93.71% of the variance explained by these 65 terms is great, a decision-maker will find it much easier to examine a model with fewer terms. Using the stepwise function as before, the stepped model has only a slightly lower R-squared value (92.22%) but the number of terms drops to 22—a considerable improvement from the initial 65. Figure 9 shows the actual versus predicted values. Compared to Figure 7, the stepped model is still a good fit. Looking at the residual plot (Figure 10), there still does not seem to be a severe model defect since the residual plot is approximately a horizontal band and there are no outliers in the data.

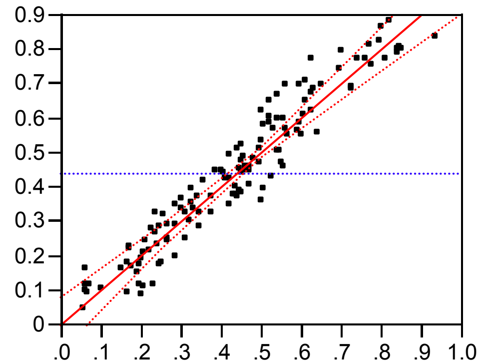

Figure 9. Actual vs. Predicted Responses for Stepped Model (Scenario-W)

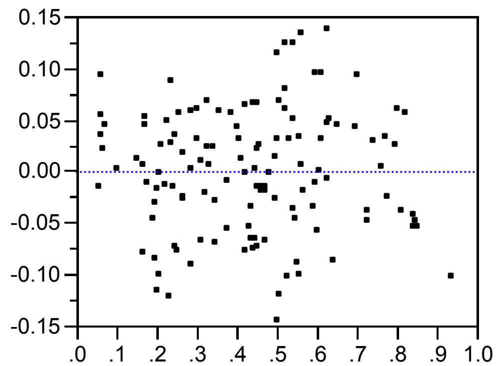

Figure 10. Residual vs. Predicted Responses for Stepped Model (Scenario-W)

The criteria we used for the stepwise procedure made it more difficult for terms to leave the model once they have entered, so it may be possible to remove some terms manually without greatly reducing the amount of explained variance. We removed terms where the test on individual regression coefficients is not rejected (p-value greater than 0.05). This third (and final) model uses only 11 terms, yet explains 88.99% of the variance of the proportion of enemies that are accurately identified. The regression is still significant. Figure 11 shows the actual vs. predicted plot for this final model for the Waypoint scenario. The residual plot in Figure 12 shows that the model still has no major defects. A few points (circled in Figure 12), were looked at as possible outliers, but all were within three standard deviations of the predicted value.

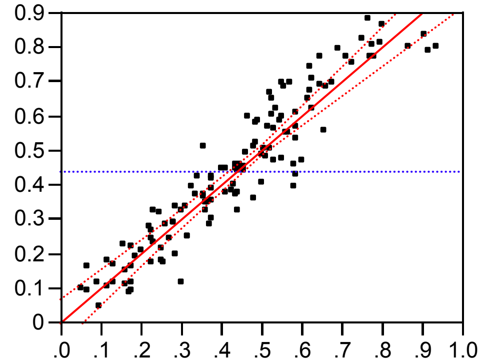

Figure 11. Actual vs. Predicted Responses for Final Model (Scenario-W)

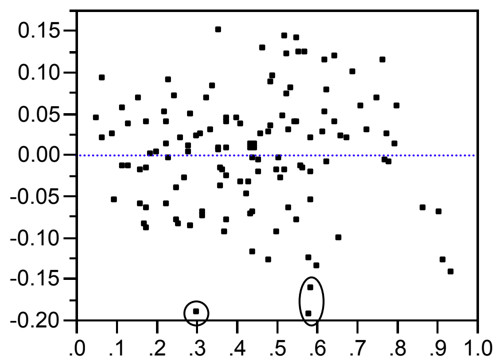

Figure 12. Residual vs. Predicted Responses for Final Model (Scenario-W)

The terms in the final model are shown in the Table 4 below, along with the coefficients, their standard errors, and their p-values. All of the significant controllable factors from the initial model are in the final model.

Table 4. Coefficients in the Final Model (Scenario-W)

Term	Coefficient	Std Error	P-value
Intercept	-0.108938	0.03293658	0.0013
Speed: USV(s) (knots)	0.00214313	0.0005882	0.0004
Speed: Enemy (knots)	0.00853616	0.00059336	0.0000
Number USV(s)	0.00988934	0.00096962	0.0000
Camera Range (nm)	0.0255352	0.00247689	0.0000
Simulation Length (minutes)	0.00070397	0.00003916	0.0000
(Speed: USV(s) -21.104)*(Number USV(s)-12.528)	0.00022515	0.0000923	0.0163
(Speed: Enemy -20.832)*(Simulation Length -317.338)	0.00001972	0.00000361	0.0000
(Speed: USV(s) -21.104)*(Speed: USV(s) -21.104)	-0.0001938	0.00006154	0.0021
(Number USV(s)-12.528)*(Number USV(s)-12.528)	-0.0009239	0.00017693	0.0000
(Camera Range -5.46848)*(Camera Range -5.46848)	-0.0068333	0.00108399	0.0000
(Simulation Length -317.338)*(Simulation Length -317.338)	-0.0000014	2.96E-07	0.0000

Table 4 shows that there are two significant interactions in the model. Taking a look at each interaction through either the contour plots or the prediction profiler reveals how the combination of the two factors affects the proportion of the enemies detected in the simulation. Figure 13 shows a matrix of the interactions included in the final model. Each sub-graph shows the impact on the predicted MOE of changing the row factor from its lowest to highest level for two cases: when the column factor is fixed at its lowest value, and when the column factor is fixed at its highest value. A quadratic effect in the model is shown by a curved line. When there are no interactions between the row and column factors the lines are dashed instead of being solid and always parallel. There are two lines because changing the value of one of the factors from its low value to its high value changes the MOE.

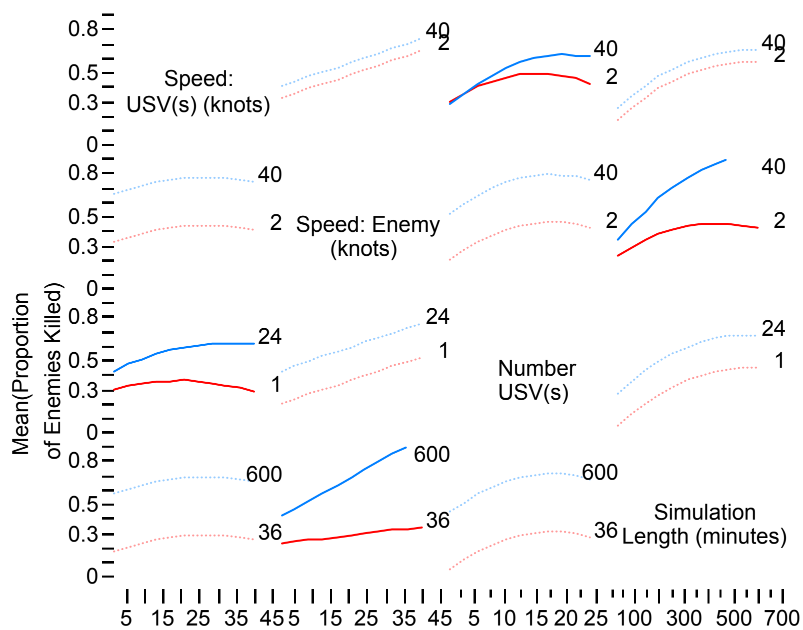

Figure 13. Matrix of Interaction Terms in Final Model (Scenario-W)

The first interaction to consider is that between USV speed and the number of USVs. The interaction matrix shows that the mean proportion of enemies detected increases as the number of USV increases when the enemy's speed is high. Figure 14 shows a contour plot of these two factors, which verifies the reaction of the response variable. The proportion of enemies that are identified increases as the speed of the enemy increases and as the number of USVs increases. Further clarification on the tactical meaning is processed through the prediction profiler in JMP™.

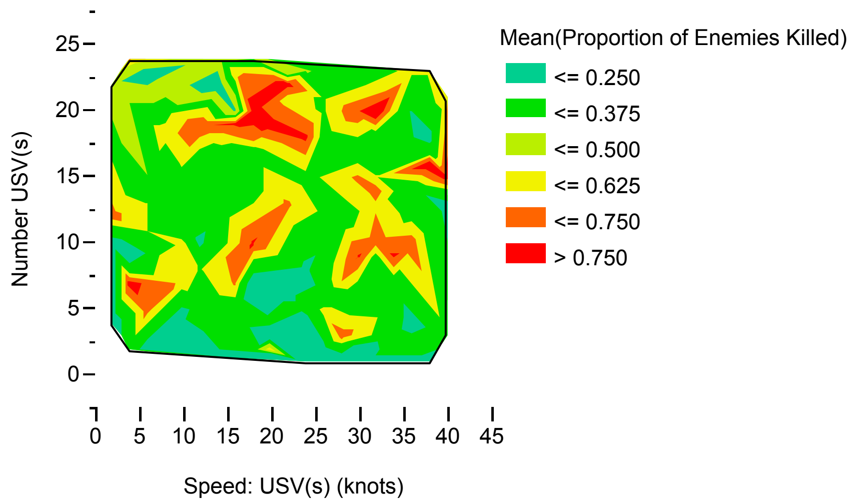

Figure 14. Contour Plot of USV Speed vs. the Number of USVs (Scenario-W)

JMP™ also has a Prediction Profiler that (like the Interaction Matrix graph) enables review of the predicted regression model instead of the original simulation output data. The vertical dotted lines correspond to the levels of the five factors. The horizontal dotted line corresponds to the predicted proportion of enemies killed. The solid line for a particular sub-graph shows the impact of changing that factor from its lowest to its highest level, while the other factors are held constant at the levels by the dashed vertical lines and numerical value below the plot. Figure 15 shows the base case in the profiler and, based on the regression model, generates a 95% confidence interval (CI) of the mean proportion of enemy agents detected. Curved lines in the profiler display the quadratic effects of the factors that appear as squared terms in the model.

The profiler also displays the relationship between each factor and the predicted value of the MOE. If the term returns a flat line, this denotes a strictly linear relationship and the term only appears as a linear effect in the model. If the profiler shows curvature, then the term is modeled with a quadratic effect. Some quadratic terms in this model have diminishing return, and others (in fact) show diminishing performance. For instance, in the Waypoint scenario, the value where the number of USVs does not increase the proportion of detections is at 17.7 in the base case. The interaction between the USV speed and the number of USVs was already explored through the prediction profiler.

When increasing both the USV speed and number of USVs until the MOE begins to decrease, while keeping the other factors at their base case levels (Figure 16), the point estimate of the prediction increases from 0.5652 to 0.6125 and the interval remains approximately the same width. Decreasing the USV speed to its minimum value and keeping the other variables constant (Figure 17) reduces the proportion of detections to 0.4599, but the interval widens. Figure 17 also shows that no more than 15.5 USVs are required when they are moving at slower speeds. When the USVs operate at maximum speed, at most 20.3 USVs are required. Overall, this interaction suggests that 18.6, rounded up to the next nearest whole number, 19, USVs are required when the USV speed is at its optimal value of 26.7 knots.

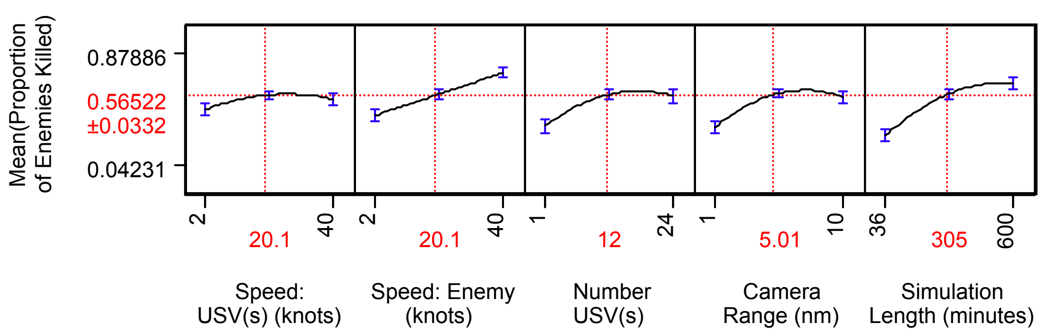

Figure 15. Base Case of Final Model, 95% CI (0.5320,0.5984) (Scenario-W)

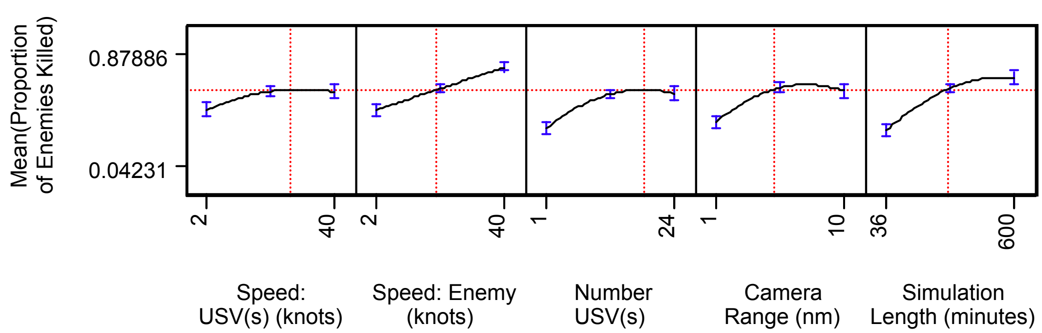

Figure 16. USV Speed and Number of USVs Interaction: Diminishing Returns (Scenario-W)

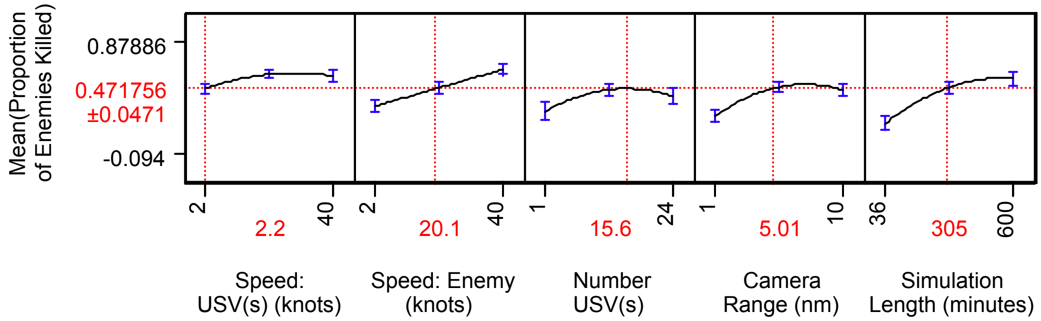

Figure 17. USV Speed and Number of USVs Interaction: Low USV Speed (Scenario-W)

The enemy's speed, in conjunction with the length of the simulation, has a different effect on the proportion of detections made by the USVs. Both factors must be near the upper boundary of the range for the proportion to be greater than 0.750. This can be seen by looking at the matrix of interactions in Figure 18. The matrix shows a divergence in the proportion of detections when either factor is at its maximum value. The contour plot in Figure 18 also shows this increasing relationship. Utilizing the profiler (Figure 19), the analysis of the enemy speed and USV endurance interaction shows that when the enemy speed is near its minimum value, the optimal time on station for the USV is 437 minutes. The proportion of detections decreases (slightly) with a longer time on station. The profile plot in Figure 20 shows that when the speed of the enemy is near its maximum, a longer time on station increases the proportion of detections, although there are diminishing returns for the simulation length. If the simulation was permitted to run for longer periods of time, there may be a turning point where there is a maximum return before the performance measure would decrease. This cannot be said with certainty, as the range of values examined does not demonstrate the outcome.

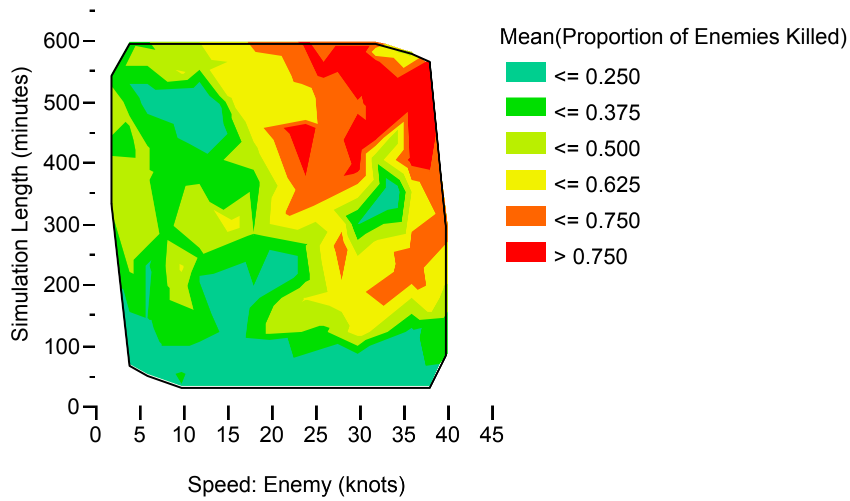

Figure 18. Contour Plot for Enemy Speed vs. Simulation Length (Scenario-W)

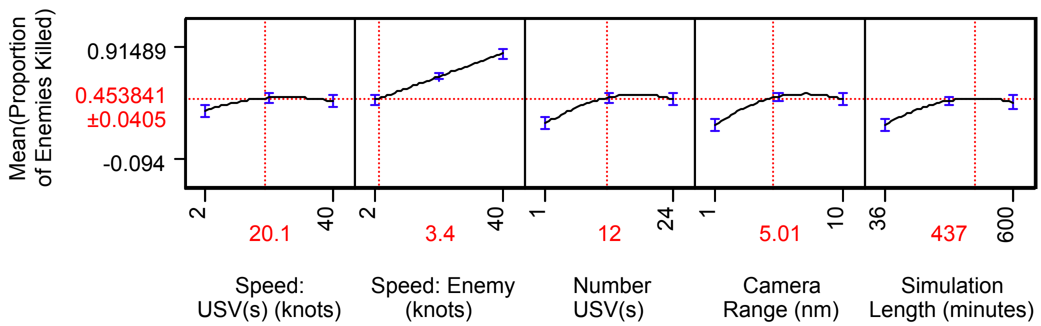

Figure 19. Enemy Speed and Simulation Length Interaction: Low Enemy Speed, Diminishing Return of Simulation Length (Scenario-W)

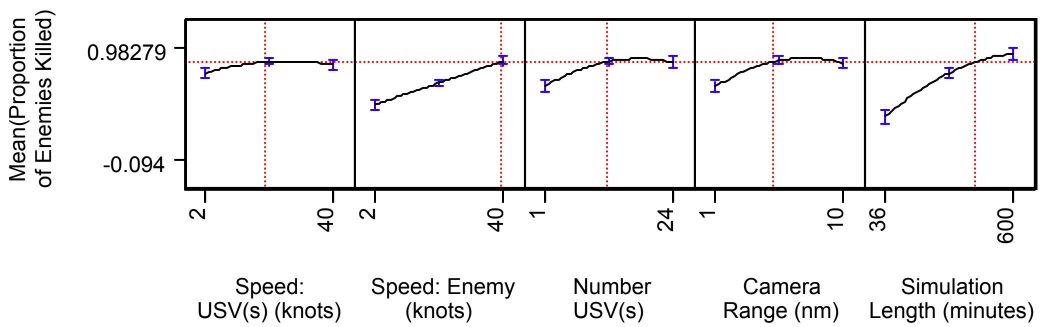

Figure 20. Enemy Speed and Simulation Length Interaction: High Enemy Speed, Increasing MOE in Simulation Length Range (Scenario-W)

There are four quadratic terms in the final regression model. The profiler depicts an individual “optimal” point for each quadratic effect compared to the base case. Because they are interactions, the terms cannot be combined to identify global optima. For the USV speed, the value is 29.0 knots; more than 18.1 USVs decreases the proportion of detections; and, the maximum needed camera range for the base case is 7.41 nm. Time on station does not span the diminishing return point for the base case. Figure 21 shows the prediction profiler with the combination of each of these points and the enemy speed at its base case value. The 95% CI of the proportion of detections is (0.7095, 0.7721).

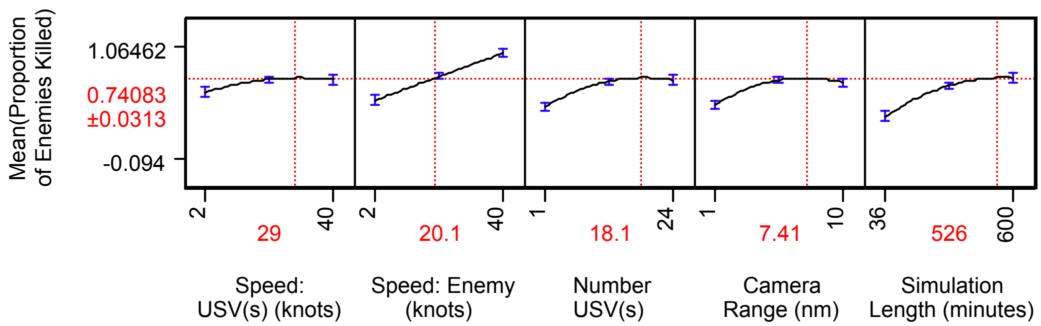

Figure 21. Quadratic Effects Against Base Case (Scenario-W)

2. Scenario-I Analysis

As with the analysis of the Waypoint scenario, we begin by constructing a model which only contains terms associated with factors the HVU can control—including the main effects, the two-way interactions, and the quadratic effects. Figure 22 shows that the model has a good fit, that the regression is statistically significant, and that 83.99% of the variance is explained by 11 significant factors that are controllable by the HVU. However, the residual plot (Figure 23) shows several outliers, so the model with these terms is inadequate and requires an alternative. Since the range of the MOE is bounded, all points in the residual plot must fall within a diagonal band.

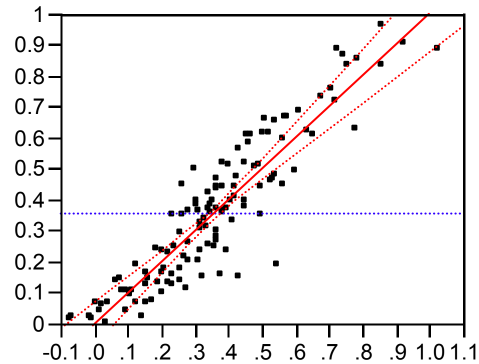

Figure 22. Actual vs. Predicted Responses for Significant Controllable Factors Model (Scenario-I)

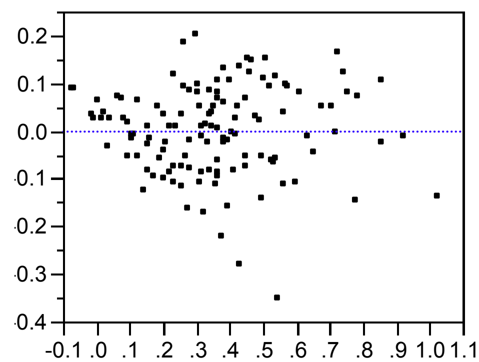

Figure 23. Residual vs. Predicted Responses for Significant Controllable Factors Model (Scenario-I)

Considering all 65 factors, the full model explains 93.81% of the variance of the mean proportion of enemy detections. The regression is significant and the residual plot shows neither non-constant variance nor outliers. Since 65 terms are too many for decision-making purposes, we again use the stepwise regression technique. The stepped model has a good fit (Figure 24) and the residual plot (Figure 25) shows that the model is adequate with no major defects.

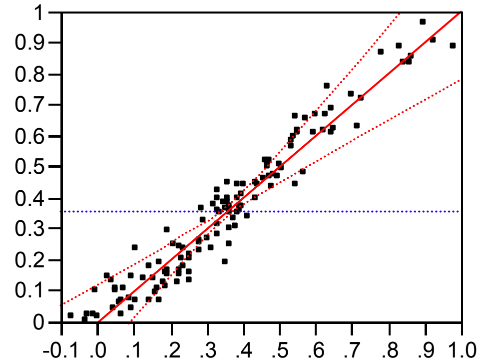

Figure 24. Actual vs. Predicted Responses for Stepped Model (Scenario-I)

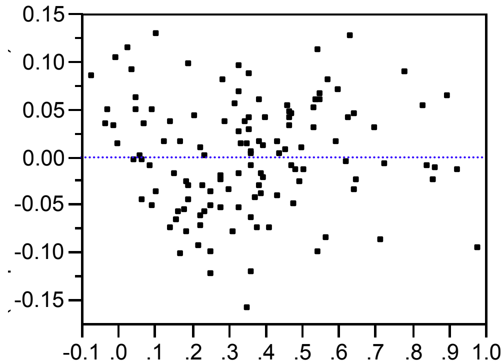

Figure 25. Residual vs. Predicted Responses for Stepped Model (Scenario-I)

Even though the plot shows a good fit, this is a complicated model with 30 factors. As in the analysis of the Waypoint scenario, we manually simplified the model by removing the terms that had a p-value between 0.05 and 0.10. The final model has only 12 terms and still explains a considerable amount, 85.27%, of the variance of the mean proportion of enemies killed. Figure 26 shows the model has a good fit. Although the residual plot (Figure 27) shows some slight departures from the desired horizontal band, its cloud-like shape (with the highest scatter near a prediction of 0.5) is characteristic of having a response variable that is a proportion between 0 and 1 (Montgomery, 2001).

Another comment on the residual plot of the final model is that there seems to be a linear boundary of the points in Figure 27. This is also a function of the actual response variable being restricted to the interval [0,1]. For example, if the model prediction is 0.0 then the residual must be positive; if the model prediction is 0.1 then the residual cannot be less than -0.1, etc. Fortunately, regression can still be used to identify important terms as it is known to be a good, unbiased predictor of the mean response even if the variance is not constant.

A pattern in the residual plot would indicate invalid prediction intervals for individual responses. Since we are only looking at identifying important terms and not predicting individual responses, this slight variation in the look of the residual plot can be overridden. The final model only contains one more factor than the model with significant controllable factors and increases the amount of variability that is explained by 1.28%. The added term is the quadratic effect of the number of USVs. Table 5 displays the coefficients that are included in the final model for Scenario-I.

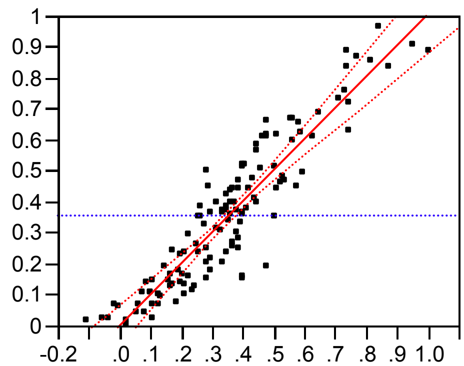

Figure 26. Actual vs. Predicted Responses for Final Model (Scenario-I)

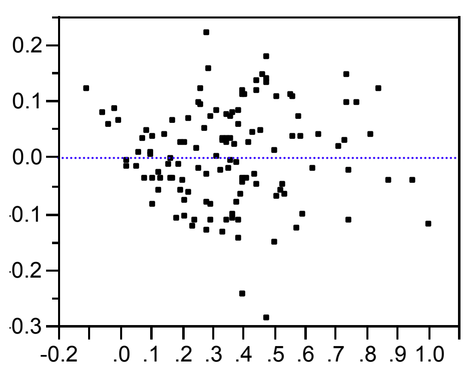

Figure 27. Residual vs. Predicted Responses for Final Model (Scenario-I)

Table 5. Coefficients in the Final Model (Scenario-I)

Term	Coefficient	Std Error	P-value
Intercept	-0.2881184	0.03972294	0.0000
Speed: USV(s) (knots)	0.01227101	0.00074078	0.0000
Number USV(s)	0.00978382	0.0012213	0.0000
Range from HVU (nm)	0.00639677	0.00147981	0.0000
Camera Range (nm)	0.01912085	0.00311894	0.0000
Simulation Length (minutes)	0.00061956	0.00004935	0.0000
(Speed: USV(s) -21.104)*(Camera Range -5.46848)	0.00118821	0.00027425	0.0000
(Speed: USV(s)-21.104)*(Simulation Length -317.338)	0.00001146	0.00000456	0.0135
(Range from HVU-10.3578)*(Simulation Length -317.338)	0.00002573	0.00000911	0.0056
(Camera Range -5.46848)*(Simulation Length -317.338)	0.00004923	0.00002039	0.0174
(Number USV(s) -12.528)*(Number USV(s) -12.528)	-0.0006928	0.00022288	0.0024
(Range from HVU -10.3578)*(Range from HVU -10.3578)	-0.0008192	3.00E-04	0.0074
(Simulation Length -317.338)*(Simulation Length -317.338)	-0.0000014	3.63E-07	0.0002

The final model includes four interactions terms. The relationships between the crossed terms are shown graphically in Figure 28. Each interaction is examined more closely by using the contour plots and the profiler as in the Waypoint scenario analysis.

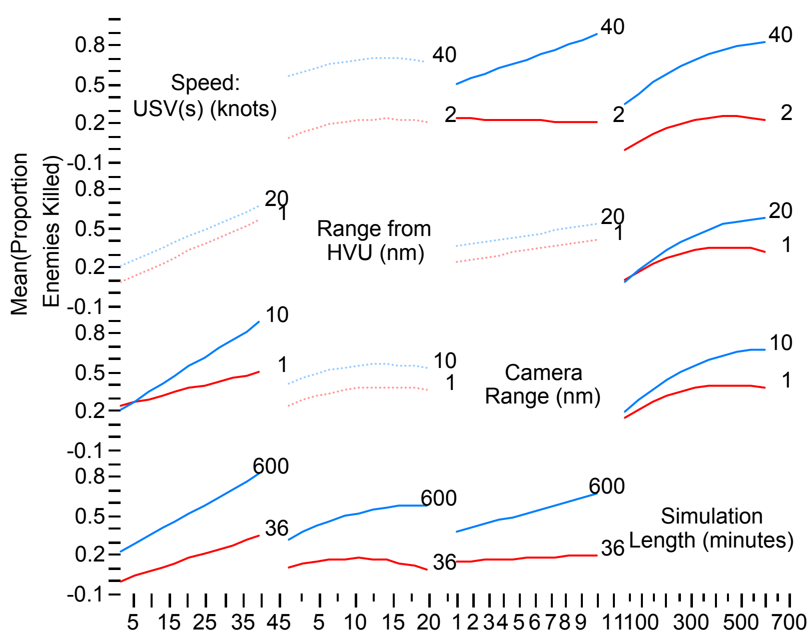

Figure 28. Matrix of Interaction Terms in Final Model (Scenario-I)

The significant interactions are those between the USV speed and camera range; USV speed and USV time on station; combat radius (permissive range from HVU); and USV time on station; and camera range and time on station. From the interaction matrix, there is an obvious change in the slope of the response in the first interaction, USV speed and camera range. Figure 29 demonstrates strong positive main effects: as either factor increases, so does the proportion of enemies detected. When a sensor has a longer range, it is logical that it would result in more detections.

Figure 29 shows that the camera range does not matter at low speeds, but increasing the camera range is very beneficial at high speeds. In reality, this is not to be expected, unfortunately. With increases in speed, platform stability decreases and so do sensor ranges. A moderate increase in the speed has a small impact on the proportion of detections at low ranges, but a much larger impact at high ranges. Figure 29 also shows that both factors need to be at the higher ends of their ranges in order for the proportion of detections to increase.

There is a minimum speed at which the USVs should travel, in a range of 10-20 knots. If the speed is too slow, then not even an increase in the camera range would raise the proportion of detections. This makes tactical sense.

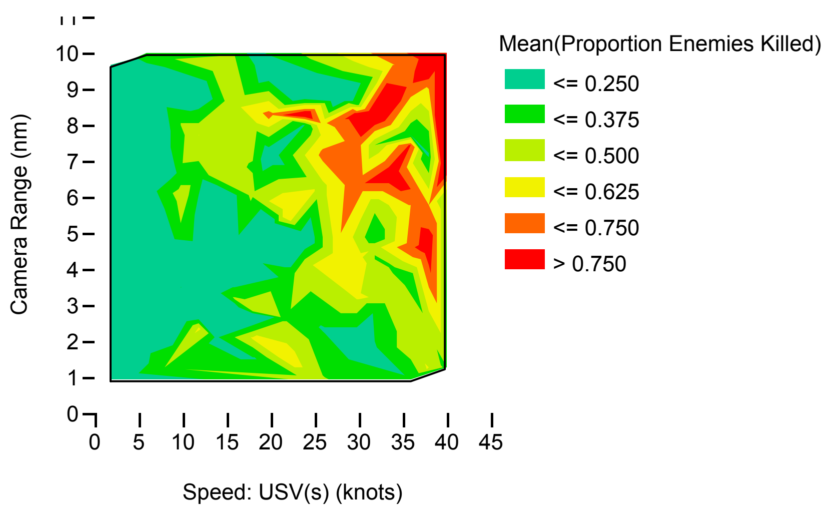

Figure 29. Contour Plot of USV Speed vs. Camera Range (Scenario-I)

The interaction between the USV speed and the simulation length does not show as drastic changes in the slopes as in Figure 28, but Figure 30 does show how the increasing relationship between the two factors jointly increases the proportion of enemies detected in the scenario. This relationship is intuitive since the longer the time available for a sensor to seek contacts, the greater the number of detections that can occur.

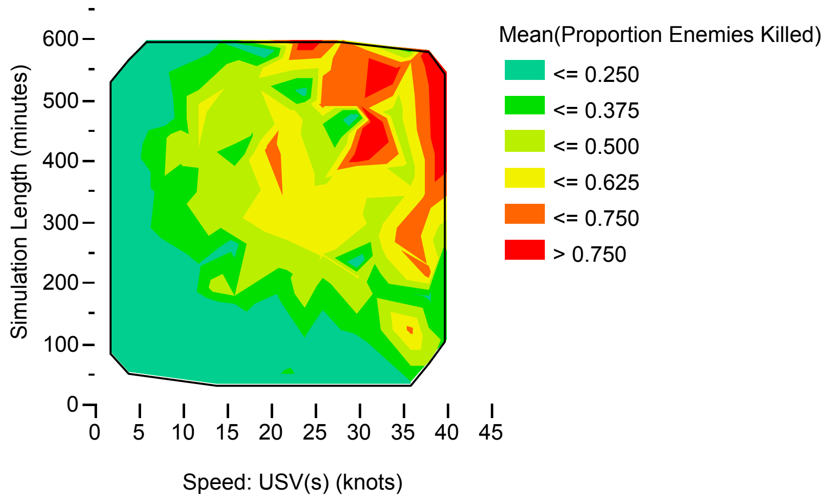

Figure 30. Contour Plot of USV Speed vs. Simulation Length (Scenario-I)

Figure 31 displays the relationship of the proportion of detected enemy agents with the interaction of the camera speed and the simulation length. This relationship is similar to the previous two. It takes high levels of both factors to achieve a high proportion of detections. The contour plot shows that long times on station with a short camera ranges result in lower proportions of detections than short endurances and high camera ranges. The USVs should be deployed for longer time periods only if the camera range can be increased as well. If the time on station is longer with a short camera range, the proportion of detections is less than if a USV with the same camera range were deployed for a short period of time.

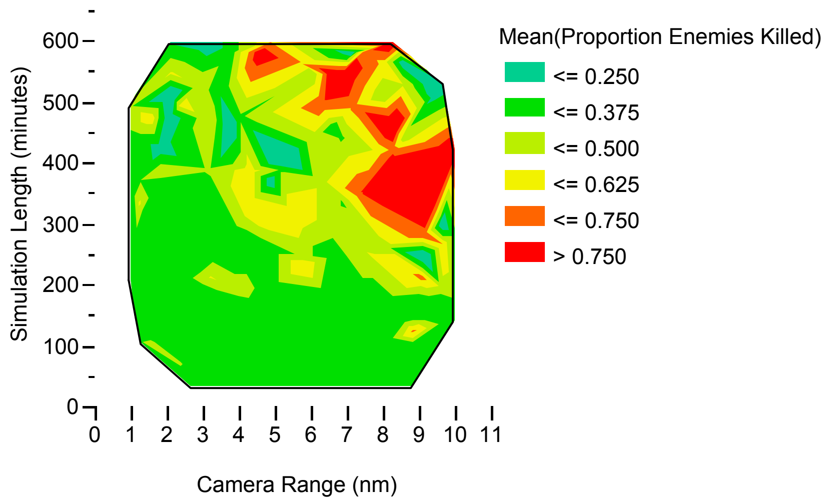

Figure 31. Contour Plot of Camera Range vs. Simulation Length (Scenario-I)

The last interaction term in the final model of the Interceptor scenario is the combination of USV combat radius and the time on station. The contour plot (Figure 32) shows some interesting effects of the relation of the factors. As the USVs are permitted to range further from the HVU, the proportion of detections increases, which is intuitive. As the area that is being searched increases, the USVs are able to approach more contacts, providing a larger proportion of enemies that are attainable. When the simulation length and the range are both at their maximum values, the proportion of detections is greater than 0.750, which is good. What is interesting is that the proportion of detections does not seem to depend on the simulation length when the range is at its lower limit but it does when the range is at its upper limit.

The prediction profiler (Figure 33) shows that a short time on station requires a combat radius from the HVU of 9.5 nm. With longer time on station, the combat radius at the point of maximum return is 18.7 nm. This indicates an increasing relationship between the MOE and this interaction. A combat radius of less than 2.0 nm, however, returns a maximum for time on station at 455 minutes (Figure 34).

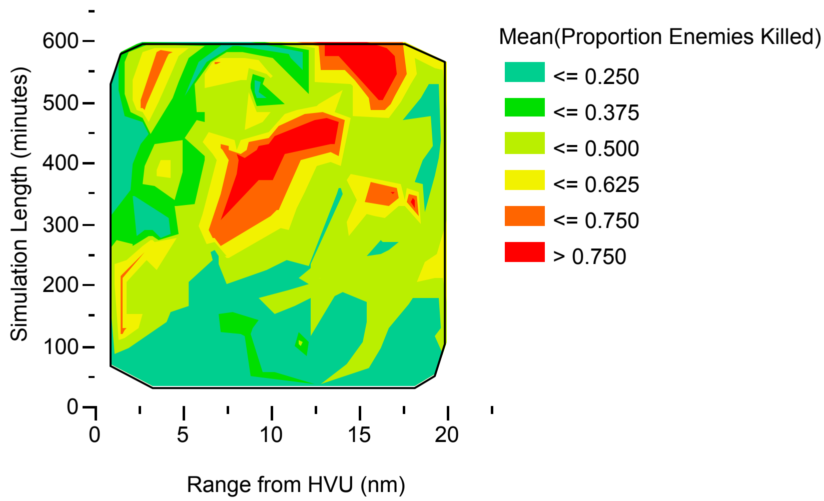

Figure 32. Contour Plot of Permissive Range vs. Simulation Length (Scenario-I)

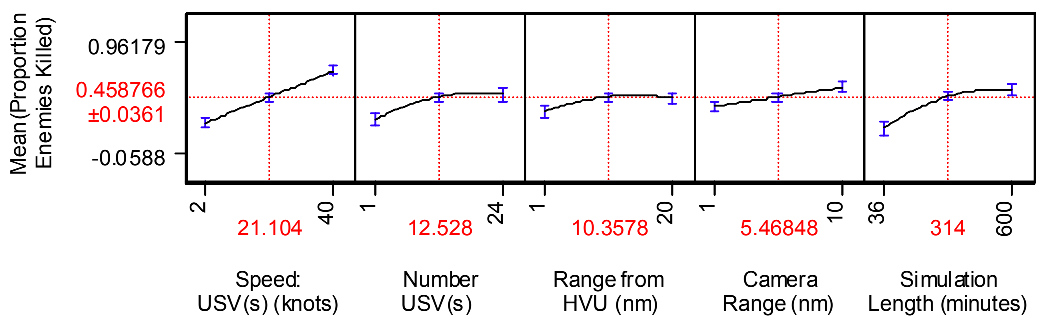

Figure 33. Base Case Final Model 95% CI (0.4226, 0.4948) (Scenario-I)

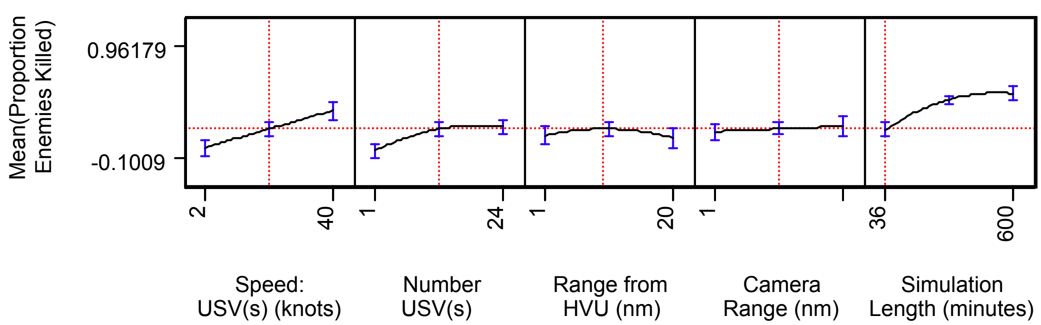

Figure 34. Short Time on Station: Maximum Return of Permissive Range (Scenario-I)

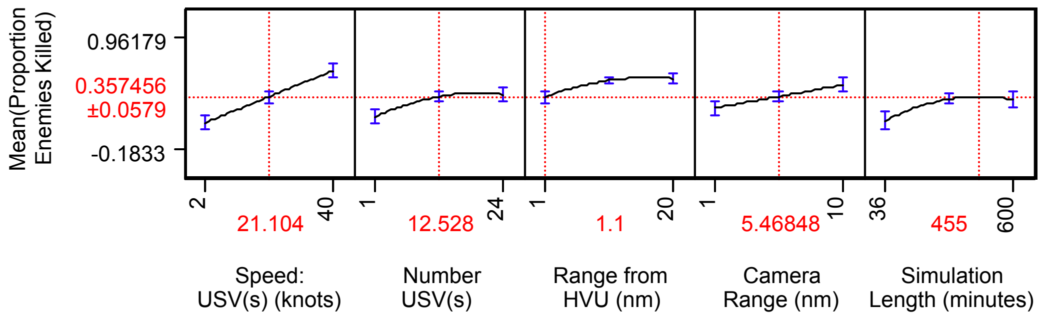

Figure 35. Short Permissive Range: Maximum Return of Time on Station (Scenario-I)

Using the prediction profiler to look at the quadratic effects of the number of USV, combat radius, and simulation length, the point of maximum return for each of these factors can be individually compared to the base case. Figure 36 demonstrates the points with USV speed and camera range kept at the base case values. The point of maximum return occurs with 19.5 USVs, a combat radius of 15.4 nm, and time on station of 535 minutes. The 95% CI for these points and the other factors at their base case is (0.5615, 6497).

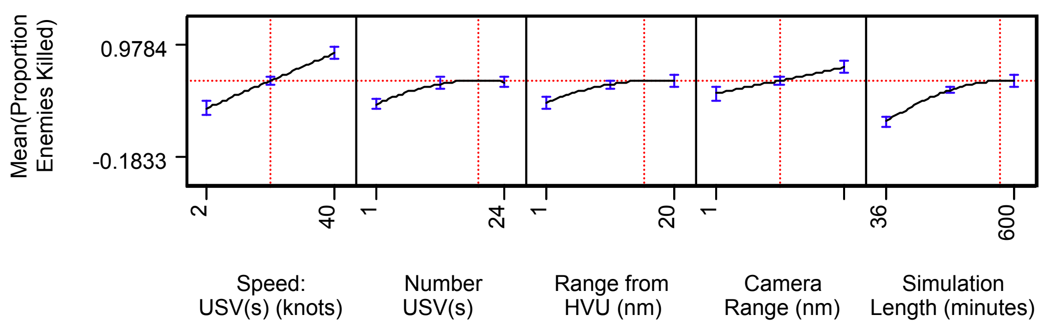

Figure 36. Quadratic Effects Against Base Case (Scenario-I)

3. Comparison between Scenario-W and Scenario-I

When looking at the two final regression models for each of the ISR scenarios, there are some factors that are significant in both and some that are only significant in one model. Table 6 decomposes the terms in each model. Terms that are horizontally aligned and in bold appear in both models. It is interesting that these terms are all controllable. We briefly compare and contrast the impact of these common terms.

Table 6. Side-by-side Comparison of the Factors in the Waypoint and Interceptor Regression Models

Waypoint Model	Interceptor Model
Speed: USV(s)	**Speed: USV(s)**
Speed: Enemy	
Number USV(s)	**Number USV(s)**
Number of Contacts	
	USV Range from HVU
Camera Range	**Camera Range**
Simulation Length	**Simulation Length**
Speed: USV(s)*Number USV(s)	
	Speed: USV(s)*Camera Range
	Speed: USV(s)*Simulation Length
Speed: Enemy*Simulation Length	
	Camera Range*Simulation Length
	USV Range from HVU*Simulation Length
Speed: USV(s) *Speed: USV(s)	
Number USV(s)*Number USV(s)	**Number USV(s)*Number USV(s)**
	USV Range from HVU*USV Range from HVU
Camera Range *Camera Range	
Simulation Length*Simulation Length	**Simulation Length*Simulation Length**

We first take a closer look at the factors that are common to both regression models. USV speed appears as a main effect with a positive coefficient in both models, although its coefficient in the Waypoint model is much smaller than that in the Interceptor model (0.0021 vs. 0.0123). This suggests that high USV speeds are less beneficial when the USVs travel predetermined paths. The negative coefficient for the quadratic effect of USV speed in the Waypoint model indicates that increasing the speed has diminishing returns, and may eventually be counterproductive, creating holes in coverage. Finally, USV speed appears in interactions in both models, although the interactions involve different (but controllable) factors. This suggests that any "optimal" USV speed would depend on other characteristics of USV deployment. Increasing the USV speed increases the proportion of detections experiment for the majority of cases examined.

The number of USVs appears with a positive main effect and a negative quadratic effect in each regression model. This translates to a diminishing return from increasing the number of USVs in each model. Since there is an interaction with the USV speed in Scenario-W, a range of the value to achieve maximum returns for the number of USV is between 16 and 19 USVs when the speed is at its minimum and maximum values, respectively. There is no interaction for Scenario-I; the value where the maximum return occurs is 20 USVs. According to our models, having larger numbers of USVs would decrease the proportion of detections; though over the factor ranges investigated these decreases are minimal (see Figures 17 and 36).

Finally, the last main effect that occurs in both regression models is the simulation length. The factor also appears as a quadratic term in each of the models. The maximum time on station before the performance of the MOE decreases is near the maximum in the range, 600 minutes for the Waypoint model and around 475 minutes in the Interceptor model. The simulation length appears as an interaction with the enemy speed in the Waypoint model and with the USV speed, camera range and permissive range in the Interceptor model. The interaction in the Waypoint model is positively related to the factors and the MOE.

When both factors are increased, the MOE increases even more than the main effects would suggest. The range of the simulation length based on the enemy speed is 420 – 600 minutes. Ten hours is the upper limit since it is the maximum value of the simulation length in this experiment. For Scenario-I, the best interval for time on station should be Scenario-I is 455 – 600 minutes. The intersection of these two ranges, 455 – 600 minutes, is the suggested range for the time on station for the USV.

As for the factors that are different, the enemy's speed is important in the Waypoint model as a main effect and an interaction, but does not appear in any way in the analysis of the Interceptor model. This implies that the knowledge of the enemy is more important in the Waypoint scenario than in the Interceptor scenario. However, not knowing the enemy's speed does not appear to change the operational tactics suggested by the Interceptor model.

Another difference is the permissive range from the HVU, which appears in several terms in the regression model for the Interceptor analysis but does not appear in the Waypoint model. Again, this is logical since the USVs remain on a predetermined path, which is constant throughout the experimentation, in the Waypoint scenario. A variation of the Waypoint scenario might be to specify a path for the USVs but allow them to leave this path if they detected an enemy, and then return once the enemy was killed. The results for the Interceptor model suggest that the permissible range might be important in this type of scenario. This is a potential area for future research.

The camera range shows up as a main effect in each regression model but only as a quadratic term in the Waypoint regression model. Again, intuition suggests that if the USVs are more restricted in their movement, then the maximum range of their sensor plays a more substantial role in the proportion of detections. The quadratic effect shows that after some distance, the performance measure decreases. Looking at Figure 17, there is a maximum return point; that distance is at 7.41 nm. There is an interaction between the camera range and the USV speed in the Interceptor regression model. For the lowest speed, the camera range has little impact on the proportion of detections. At high speeds, a longer camera range increases the proportion of detections.

Overall, there is a point where too many USVs can cause a decrease in the proportion of detections. USV speed in Scenario-W does not need to be maximized but it should be in a scenario that closely represents Scenario-I. In the Waypoint model, even though more enemies were detected using a high sensor range, there is a point that the camera range does not need to exceed. Conversely, the analysis of Scenario-I shows that as long as the camera range increases, so will detections. Finally, time on station in each model shows the USV endurance that is needed for each scenario given that the number of enemies started with does not change.

4. Scenario-FP Analysis

While the Force Protection scenario contains the same MOE as the ISR scenarios, with the threat agents included, two additional MOEs are considered. The two accompanying MOEs are the proportion of the threatening enemy agents that are detected and the number of the threatening enemy agents that reach the HVU before being detected. The description of the analysis is in that order.

Before any further analysis, it is once more necessary to translate PYTHAGORAS representations to tactical definitions. During the process of obtaining FP data, it turned out that threat density among contacts ranging from 10-90% was not achieved properly, in part because of the restriction of factor levels to integer values. Instead, the actual range turns out to be 0-100%. Overall, a total of 125 design points were used with 30 replications at each design point for a total of 3750 simulation runs. Because the final design matrix had correlations less than |0.08|, multicollinearity is not a concern in the model-building steps.

a. Proportion of Enemies Detected Analysis

In an attempt to have a similar approach to analysis as in the previous cases, we began by investigating the overall proportion of detections of both types of enemy agents, threatening and non-threatening. An initial look at the regression involving only the significant controllable factors, the quadratic terms and the two-way interactions is statistically significant (p-value<0.001) but explains only 19.39% of the variance in the MOE. Next, we used stepwise regression where all 77 terms (main effects, quadratic effects, and two-way interactions) were potential explanatory variables. The resulting model is significant (p-value<0.001), but the 10 terms explain only 31.99% of the variance. Figure 37 clearly shows a deviance of a "good" fit when compared to the Actual vs. Predicted plots from previous analyses. The residual plot (Figure 38) shows a weak fit, but does not reveal any patterns or outliers that would suggest ways the model could be improved.

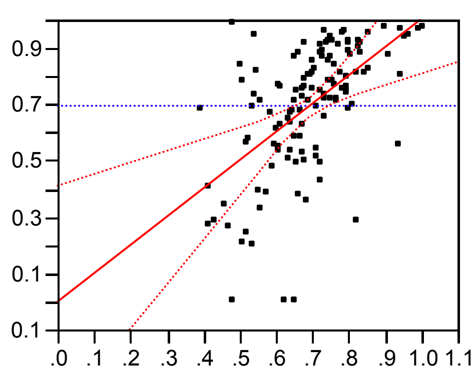

Figure 37. Actual vs. Predicted Responses for Stepped Model (Scenario-FP)

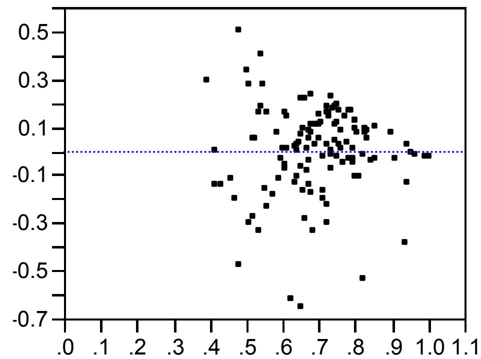

Figure 38. Residual vs. Predicted Responses for Stepped Model (Scenario-FP)

Since regression does not seem to predict well for the combination of these FP factors and the MOE, next we look at using a nonparametric partitioning approach, called regression trees. This methodology helps identify which factors can be split, and at what levels, in order to cluster the data into groups. Ideally, the points within a group will have similar MOE values, but the MOE values will differ widely across groups. Candidate factors have large sum-of-squares values. The first factor that can be split at a distinct level is the percentage of threatening enemies (Figure 39). This means that if the data points are split into two groups, one where the percentage of threatening enemies is less than 17 and the other where the percentage is greater than or equal to 17, the mean of the proportion of detections would be 0.4409 and 0.7227, respectively. The first split gives an R-squared value of 0.138 (13.8%) with only one term.

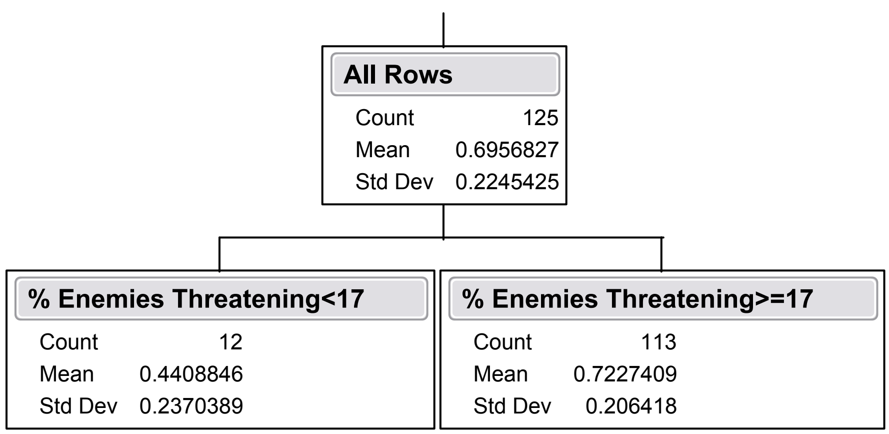

Figure 39. First Split of Regression Tree in the Overall Proportion of Enemy Detections (Scenario-FP)

Subsequent splits can continue until any stopping criterion is met. Multiple splits can be made on the same factor. After 5 factors are shown to explain the performance of the MOE, a total of 5 splits are required, the second and third illustrated in Figure 40. The second split occurs when the percentage of threatening enemies is greater than 17 and the new split occurs when the speed of the USV at 28 knots. A higher speed with a higher percentage of threatening enemies gives a mean of 0.7955 out of 42 observations. Likewise, an explanation can be stated for each successive split.

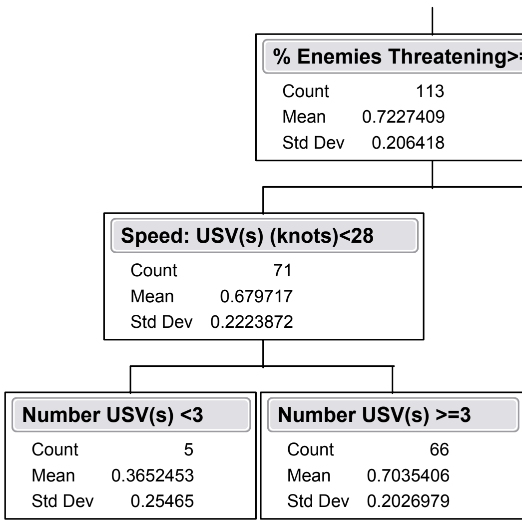

Figure 40. Second and Third Splits in a Regression Tree (Scenario-FP)

A summary of the splits appears in the Leaf Table (Table 7). An example of how to read the Leaf Table for the highest mean (0.8241 in the last row) follows: if the percentage of threatening enemies is greater than 17% and the USV speed is greater than 28 knots and the range from HVU is greater than 3.96 nm, then the mean overall proportion of detections of enemy agents is 0.8241. This leaf contains 37 out of the 125 total observations.

Table 7. Leaf Table: Overall Proportion of Enemy Contacts Detected (Scenario-FP)

Leaf	Mean	Count
% Enemies Threatening<17&Range from HVU (nm)>=12.28	0.27492	5
% Enemies Threatening<17&Range from HVU (nm)<12.28	0.55943	7
% Enemies Threatening>=17&Speed: USV(s) (knots)<28&Number USV(s) <3	0.36525	5
% Enemies Threatening>=17&Speed: USV(s) (knots)<28&Number USV(s) >=3	0.70354	66
% Enemies Threatening>=17&Speed: USV(s) (knots)>=28&Range from HVU (nm)<3.96	0.58318	5
% Enemies Threatening>=17&Speed: USV(s) (knots)>=28&Range from HVU (nm)>=3.96	0.82416	37

Another summary of the factors used is the Factor Contribution Chart (Figure 41) which displays the sum-of-squares value for the main effects of each factor. Table 7 and Figure 41 both summarize the performance of the partitions. The final R-squared value after 5 partitions is 0.358. Therefore, only looking at 5 main effects, 35.8% of the variance can be explained. The regression tree results are worth much more than the regressions that are not significant or regressions where less variance is explained with 5 additional terms.

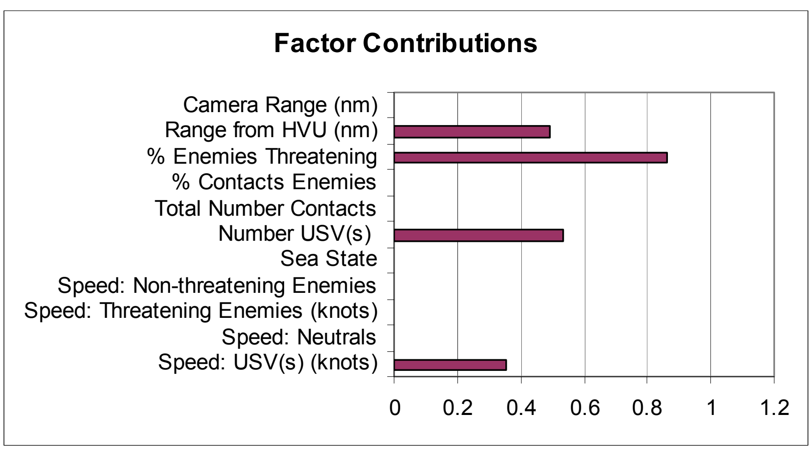

Figure 41. Contribution of Each Factor in the Overall Proportion of Enemies Regression Tree (Scenario-FP)

The most important factor in explaining the variance of the overall proportion of enemies is the threat density. This indicates that knowledge about the enemy is more important in the FP scenario than in the Waypoint and Interceptor scenarios. When the combat radius is split, it suggests that large ranges are good when there is a low percentage of threatening enemies, while low ranges are good when the percentage of threatening enemies is high. The split on the number of USVs implies that having more than three USVs does not seem to help much in this FP scenario for the overall proportion of enemies detected.

b. Proportion of Threatening Enemies Detected Analysis

We next explore the mean proportion of threatening enemies detected. As Figures 42 shows, the vast majority of design points had perfect detection (MOE = 1.0). A preliminary test for Significance of Regression quickly shows that regression is not an appropriate tool for modeling this MOE. Not one of the controllable factors is significant and including all 77 factors does not lead to a model that provides a good fit or one that can be used for prediction.

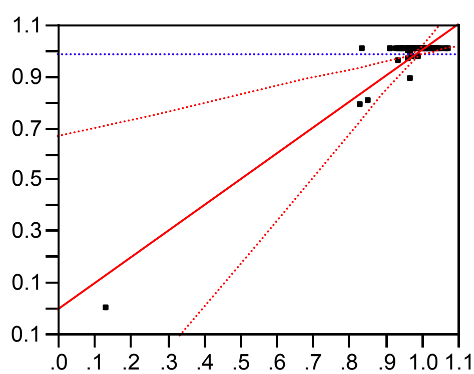

Figure 42. Actual vs. Predicted Responses for Full Model (Scenario-FP)

This MOE also requires the use of non-parametric methods for analysis. We once again see what insights can be gained by using regression trees. The process is the same as before, and summaries of the analysis are in Table 8 and Figure 44. Again, the first factor that is split is the percentage of enemies that are threatening. This split occurs at a level of 12%, and results in explaining 16.8% of the variance in the MOE. The second split is at the number of USV factor. When there are one or two USVs and more than 12% of the enemies are threatening, the proportion of threatening enemy detections is 0.9485. When more than 12% of the enemy contacts are threatening, having three or more USVs results in 0.9995 as the proportion of threatening enemies detected. The second split increases the R-squared value to 0.194. At the third partition, the R-squared value equals 0.215 and subsequent splits do not tangibly increase the value.

Table 8. Leaf Table: Proportion of Threatening Enemies (Scenario-FP)

Leaf	Mean	Count
% Enemies Threatening<12	0.8	5
% Enemies Threatening>=12&Number USV(s) <3&Speed: USV(s) (knots)<26	0.90524147	6
% Enemies Threatening>=12&Number USV(s) <3&Speed: USV(s) (knots)>=26	0.99175926	6
% Enemies Threatening>=12&Number USV(s) >=3	0.99950617	108

Essentially, the mean proportion of detections decreases when threat density is less than 12%. When more than 12% of the enemies are threatening, the proportion of detections depends on the number of USVs and the USV speed. The highest proportion of detections occurs with three or more USVs. If less than three USVs are available, detections are high if the speed of the USVs is greater than or equal to 26 knots. If the speed is less than 26 knots, then the mean proportion of detections is lower. Clearly, slightly lower detection probabilities may be less of a concern if the total number of threatening enemies is small. This leads to the discussion of the next MOE.

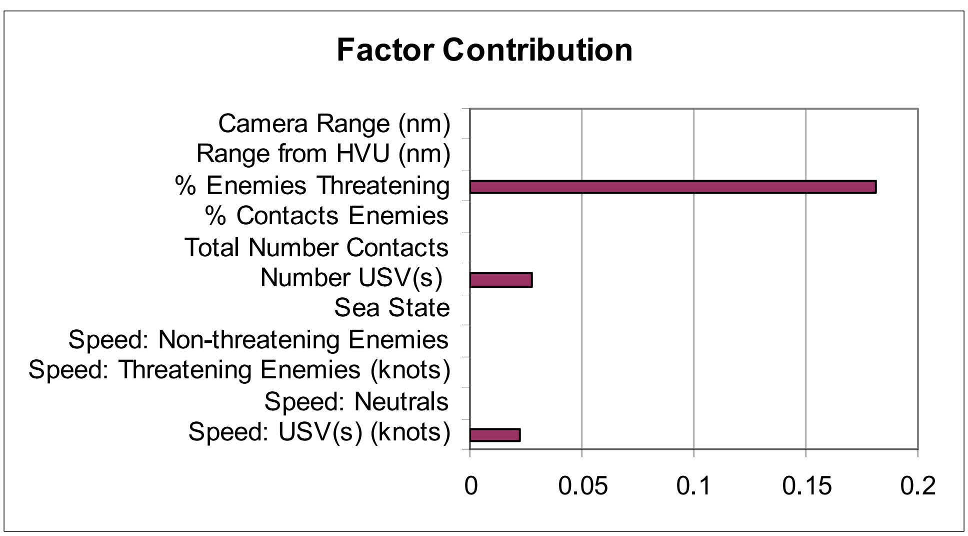

Figure 43. Contribution of Each Factor in Proportion of Threatening Enemies Regression Tree (Scenario-FP)

c. *Number of Threatening Enemies that Reach the HVU*

The controllable factors, USV speed, number of USVs, camera range and permissive range from HVU, are the first to be looked at for the regression against the number of threatening enemies that reach the HVU. A regression with the main effects of the controllable factors, interactions and quadratic effects (not shown) indicated a great deal of heteroscedacity. This suggests that a transformation of the response variable is appropriate. Since the MOE is a count which is characteristic of a Poisson distribution, a square-root transformation could make the residual plot of the regression less heteroscedastic. After transforming the MOE, the analysis continues with a stepwise procedure of the controllable factors. This yields a 0.4853 R-squared value with only the number of USVs, its quadratic effect, and the camera range in the model. The actual vs. predicted plot (Figure 44) does not show a tight fit even though it passes the test for significance of regression.

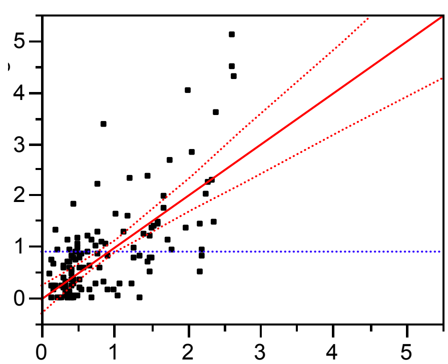

Figure 44. Actual vs. Predicted Responses for Significant Controllable Factors for Number of Threatening Enemies that Reach the HVU (Scenario-FP)

Therefore, the inclusion of all of the factors' main effects, two-way interactions and quadratic effects are regressed on the MOE. Initially, 95.28% of the variance is explained by the 77 factors, but as mentioned previously, a model with many fewer terms that can still explain a considerable amount of the variance is a better option to present to decision makers. Using stepwise regression followed by manual removal of some marginally significant terms yields the final model that explains 89.72% of the variance with only 12 terms. Figure 45 shows the fit of the final model via the actual value plotted against the predicted values, and Figure 46 plots the residuals against the predicted values. Once again, the line on the lower left of the plot is representative of the boundary that the number cannot be lower than zero, since it is a count. Of greater concern is the number of points where the model predicts a negative value, as well as the cluster of six points circled in the upper right-hand corner of Figure 46. These are related since the cluster has a strong influence on the regression model.

Further investigation showed that most of these points were associated with a small number of USVs, but after checking the original data we found no reasons for eliminating these points. The model fit could be improved if a dummy variable corresponding to USVs less than four were added as an explanatory term, but the problem of negative predictions remained. Because of this, we decided regression trees were a more appropriate analysis tool.

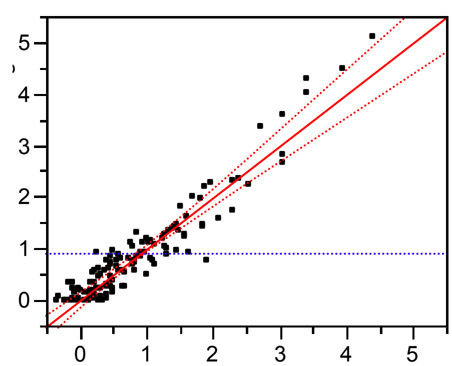

Figure 45. Actual vs. Predicted Responses for Final Model (Scenario-FP)

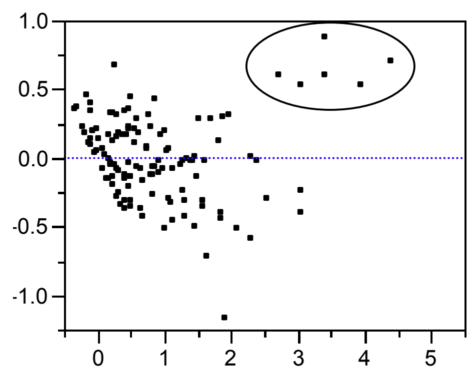

Figure 46. Residual vs. Predicted Responses for Final Model (Scenario-FP)

Consistent with the residual plot, the first split in the regression tree occurs at four USVs (Figure 47), with an R-squared value of 0.369. This single factor is explaining 36.9% of the variance. The subsequent splits are shown in the Leaf Table (Table 9). After making five partitions, we find that 68.1% of the variance is explained by only four factors. This is our final model since any more splits increase the R-Squared value by less than 1%. Table 9 shows that if the number of USV is greater than or equal to11, the mean number of threatening enemies that reach the HVU is 0.5310. If the number is bound between four and less than 11, and the total number of contacts is less than 345 of the possible 500, then the mean number is 1.2372. Fewer than four USVs alone produced a mean of 8.5044, but if the percentage of enemies that are threatening is examined, then the mean changes. If the percentage is less than 40%, then the mean is 2.5667: if the percentage of threatening enemies is greater than 40%, the mean increases greatly to 13.7 threatening enemies who reach the HVU. Figure 48 is a chart of the relative contributions of each factor that is varied throughout the simulation.

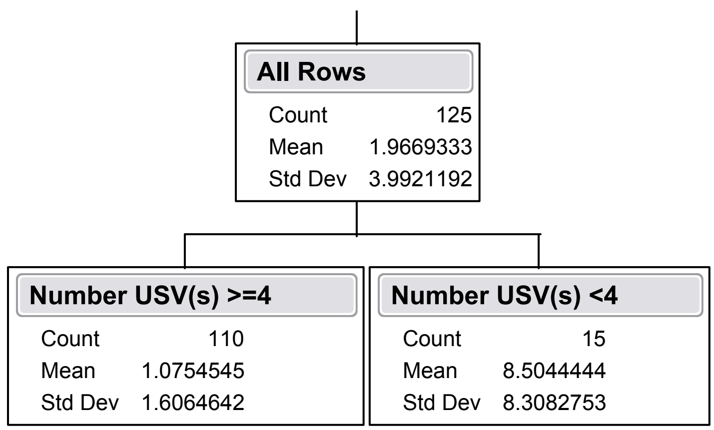

Figure 47. First Split for Number Threatening Enemies that Reach HVU (Scenario-FP)

Table 9. Leaf Table: Number of Threatening Enemies that Reach the HVU (Scenario-FP)

Leaf	Mean	Count
Number USV(s) >=4&Number USV(s) >=11	0.53102	72
Number USV(s) >=4&Number USV(s) <11&Total Number Contacts<345	1.23718	26
Number USV(s) >=4&Number USV(s) <11&Total Number Contacts>=345&Speed: Threatening Enemies (knots)<32	2.39444	6
Number USV(s) >=4&Number USV(s) <11&Total Number Contacts>=345&Speed: Threatening Enemies (knots)>=32	5.58889	6
Number USV(s) <4&% Enemies Threatening<40	2.56667	7
Number USV(s) <4&% Enemies Threatening>=40	13.7	8

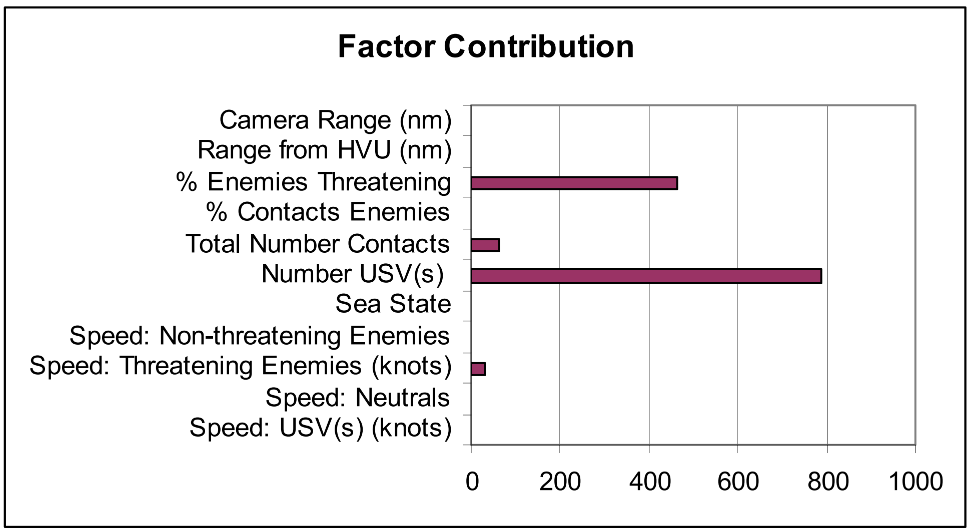

Figure 48. Factor Contribution Chart: Number of Threatening Enemies that Reach the HVU (Scenario-FP)

B. VERIFICATION AND VALIDATION

There are some analytical methods that can be used to check the validity of the results the simulation data gives. The probability of detection in the Waypoint scenario can be compared to the analytical probability of detection using the sweep width of the sensor. The Interceptor scenario has each USV independently and individually choosing which contact to search. By looking at the analytical computations, a comparison between the simulation results and the Random Search model can confirm or refute the simulation results. The computational formulas are from Naval Operations Analysis

(Wagner, et al., 1999). The Waypoint and Interceptor scenarios have much greater fidelity and resolution than the random search models. Even so, comparing the simulation results with the analytical computations yields some insight into the simulation models' validity under specific conditions.

First, consider comparisons for the Waypoint scenario. Sweep width (w) is the area under the static probability of detection (P_d) curve of the sensor. Since the USVs are moving, the new P_d is

$$P_d = \frac{w}{s} \tag{1}$$

where s is the space between the patrol routes. For the Waypoint scenario, s is held constant at 100 nm and w changes as the camera range factor varies. Equation (1) shows that when spacing is kept constant, the P_d increases as w increases. This occurs when the sensor range increases in the Waypoint (and other) scenarios, therefore, the P_d increases with the sensor range. Probabilities of detection for a few combinations of sweep width (camera range) and the space between patrols are shown in Table 10.

Table 10. Analytical Values for Scenario-W

	Sweep Width (Camera Range)	
	Min	Max
Space between patrols (constant at 100 nm)	0.02	0.155

A scatter plot of the camera range vs. the mean of simulated values at each range is provided in Figure 49. The plot looks at the mean of the MOE at each level of the camera range. Comparing these means to the analytical values (Table 10), there is obviously not much consistency between these values. Since there are abstractions to the scenario, stated in Chapter II, this is one reason that the simulated values do not match the analytical values. However, P_d increases relatively linearly as the range increases, which happens in the analytical equation. A property of the simulated data that is not characteristic of the analytical model is that the camera range has a quadratic effect in the regression equation for Scenario-W. This could be related to the fidelity with which we chose to model the patrol patterns.

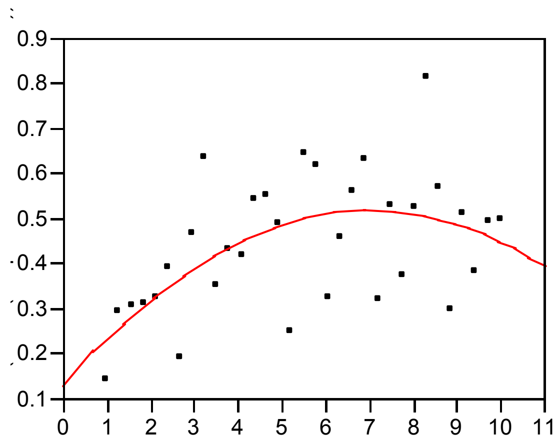

Figure 49. Scatter Plot of Camera Range vs. Mean Proportion of Enemies Detected (Scenario-W)

Next, we consider the Interceptor scenario. The random search formula gives a cumulative probability $F_d(t)$, the probability that at least one detection occurs in the time t. The range of the sensor (r), the velocity of the search vehicle (v), the size of the area to be searched (A), and the time that the search is being conducted (t) are the factors that determine the F_d. All of these contributors are varied in the simulation models except the area, which is kept at a constant 1600 sq-nm. Using the following equation,

$$F_d = 1 - e^{-2rvt/A}, \qquad (2)$$

cumulative probabilities can be determined for various factor combinations. As in the analytical case for the Waypoint scenario, we computed cumulative probabilities of detection for combinations of the minimum and maximum factor values.

Table 11. Analytical Values for Scenario-I

		Camera Range/Velocity(Speed)			
	F_d	Min/Min	Min/Max	Max/Min	Max/Max
Time	Min	0.086	0.834	0.593	1.0
	Max	0.777	1.0	.9999997	1.0

These analytical values can be qualitatively compared with contour plots of the simulation results. Only two factors can be looked at simultaneously, so a total of three contour plots are examined. The first is the camera range and speed contour plot (Figure 50). The simulation results appear to correspond to the P_d analytical values (looking across the values in Table 11), since increasing either factor increases the P_d and increasing both raises the proportion of detection even further. The simulation results also conform to the analytical results in that the lower right hand corner (high speed, low camera range) tends to yield higher detection probabilities than the upper left-hand corner (high camera range, low speed).

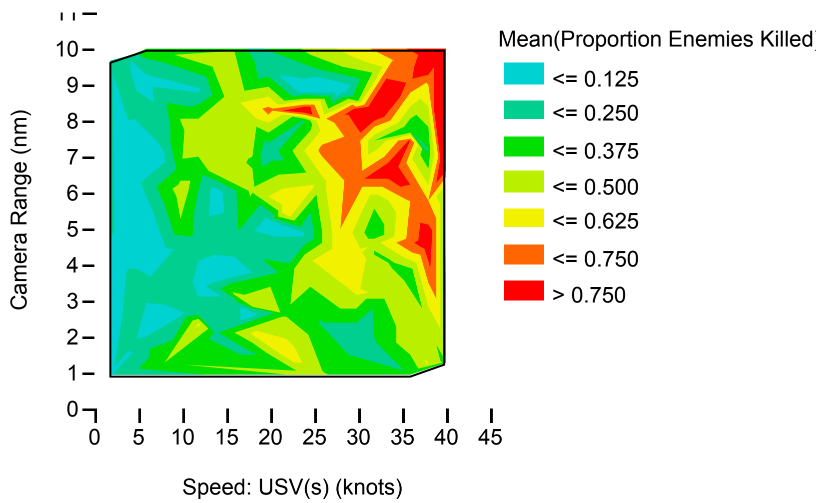

Figure 50. Contour Plot of Camera Range and USV Speed (Scenario-I)

The analytical values for Scenario-I show that the P_d increases as the period of time spent searching increases. Figures 51 and 52 both show this relationship between the values of the simulation length factor. Once again, increasing either the camera range or the USV speed increases the P_d. Figure 51 shows that the combination of high endurance and short camera range tend to yield higher detection probabilities than the low time, high camera range combination. These conform to the analytic results when the speed is low: when the speed is high, both combinations perform well.

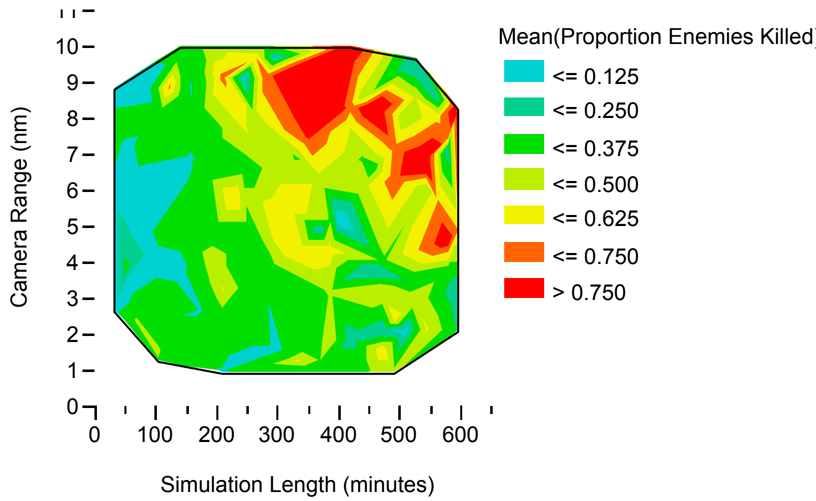

Figure 51. Contour Plot of Camera Range vs. Simulation Length (Scenario-I)

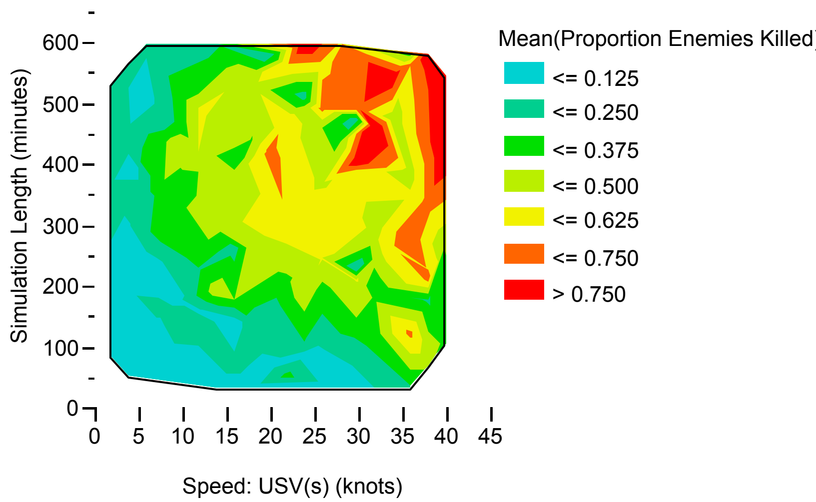

Figure 52. Contour Plot of USV Speed vs. Simulation Length (Scenario-I)

The analytical values are optimistic when compared to the simulation values because both analytical formulas are designed for static targets, and the targets are moving in each of the three scenarios in this thesis.

C. SCENARIO COMPARISONS AND INSIGHTS

We have examined and compared results for five situations involving three MOEs (proportion of enemy detections, proportion of threatening enemies detected, number of threatening enemies that reach the HVU) and three scenarios (Waypoint, Interceptor, and Force Protection). Although two different analysis approaches were used, we can compare the results across scenarios by looking at the common terms (Table 12). The shaded cells show where the final models do not contain the specific factor. One factor is significant in each of the five analyses—the number of USVs. USV speed is significant in all analyses except the FP-number that reach HVU. Camera range and simulation length are important in the two regression analyses discussed in the comparison of the two models. Finally, the percentage of threatening enemies is important in each of the FP analyses, which were the only analyses to consider this factor.

The good news for the planners and decision makers is that these are all controllable factors except the percentage of threatening enemies. This means that decisions to deploy the USV in one of the three proposed scenarios are subject to neither inaccurate information nor assumptions in the face of uncertainty. This is not to say that the models' other significant factors are trivial, but regardless whether tasking involves Interceptor or Force Protection missions, some important information is already known about the impact of the number of USVs, the USV speed, and the sensor range.

Table 12. Comparison of Model Terms

	Model-W	Model-I	Model-FP		
	Proportion of Enemies Detected	Proportion of Enemies Detected	Overall Proportion of Enemies Detected	Proportion of Threatening Enemies Detected	Number of Threatening Enemies that Reach the HVU
USV(s) speed	X	X	X	X	
Neutral Speed					
Threatening Enemy Speed					X
(Non-threatening) Enemy Speed	X				
Sea State					
Number of USV(s)	X	X	X	X	X
Number of Contacts	X				X
% Enemies					
USV(s) Permitted Range from HVU		X	X		
Camera Range	X	X			
% Threatening Enemies			X	X	X
Simulation Length	X	X			

For comparison purposes, we want to isolate the impact of the explanatory factors common to all (or most) of the analyses. Because the design matrix is nearly orthogonal, these contributions are essentially equal to the R-squared values for fitting reduced models. The three terms, number of USVs, USV speed, and camera range explain 27.20% of the variance in the proportion of detection for the Waypoint scenario and

16.14% of the variance for the Interceptor scenario. This leads us to say that if time permits, understanding the current operational scenario and accurately estimating any non-controllable factors may help the decision-maker choose appropriate settings for the controllable factors.

As previously mentioned throughout the analyses, a quadratic term with a negative coefficient means there are diminishing returns and perhaps even diminishing performance. The thesis varied the number of USVs from 1 to 24 and the largest number of USVs that would add to the mission without a decreasing effect is 20 USVs. This number of USVs is achievable for a Carrier Strike Group (CSG) or Expeditionary Strike Group (ESG) that is comprised of several ships.

Although not impossible, procuring a fleet of USVs is not an overnight process. A look at what outcome can be predicted by one and four USVs for each MOE would likely be more useful in the near future than looking at the big picture. To accomplish this, we set up a "current" case intended to reflect the current position where only one USV is available, a "near-term" case where there are four USVs available, and compare these to situations where the number of available USVs is not constrained.

For the Waypoint model, the settings for the other significant factors are USV and enemy speeds set at 20.1 knots, the number of contacts at 49 (a plausible number), the camera range at eight nautical miles (the range for the current configuration), and the time on station at four hours. With one USV the prediction interval is (0.2556, 0.3608), with four USVs the interval is (0.3495, 0.4303), and the interval is (0.5291, 0.6005) when the number of USVs is set to 17.4 (its apparent "best" value). Note that the interval is widest when there is one USV and narrowest when there are 17. This means that not only does the average detection probability improve as the number of USVs increases, but also that the results are slightly more consistent.

For the Interceptor model, the current case for comparison is to set the speeds to 20.1 knots, the combat radius is five nautical miles (the current capability), the camera range to eight nautical miles (the current configuration), and a time on station of four hours. With one USV the prediction interval is (0.1056, 0.2342), with four USVs the prediction interval is (0.1970, 0.2864), and the interval is (0.3705, 0.4511) with 19.9

USVs (its apparent "best" value). As before, the width of the interval decreases as the number of USVs increases, so adding USVs improves both the mean and the consistency of the MOE.

For regression trees, comparisons can be made using the leaf characteristics, as we now illustrate. In the proportion analyses, the first split occurs at three USVs for both MOEs, so the lower partition is used for one USV and the upper partition is used for four USVs. Here, if the threat density among all contacts is less than 17%, there is no dependence on the number of USVs and the mean overall proportion of detections is 0.4409 (computed from Table 7). If the percentage of threatening enemies is at least 17% and the USV speed is greater than 28 knots, there is no dependence on the number of USVs and the mean overall proportion of detections is 0.7955 (computed from Table 7). Increasing the number of USVs from one to four is beneficial when the percent of threatening enemies is at least 17% and the USV Speed is less than 28 knots; in this case, the mean overall proportion increases from 0.3652 to 0.7035.

For the proportion of threatening enemies detected, if there is less than 12%, the mean proportion of detections is 0.8000. When the proportion is greater than or equal to 12% the dependence on the number of USVs is seen. If a single USV is available and the percentage of threatening enemies is greater than 12%, then the mean is 0.9485 (the weighted average of the means in the 2nd and 3rd rows in Table 8). If four USVs are available and the percentage of Threatening Enemies is greater than 12%, then the mean of the proportion of detections is 0.9995.

For the third MOE (the number of threatening enemies that reach the HVU) a split occurs at four USVs (Table 9). Therefore, there is still a separate prediction for one and for four USVs. With one USV, the mean number of threatening enemies that reach the HVU is 8.5044. Having four USVs reduces the number of threatening enemies that reach the HVU to 1.075. If the number is greater than four and less than 11, the number increases to 2.1070 threatening enemies that reach the HVU.

V. CONCLUSIONS

The primary goal of this thesis is to come to the aid of the Navy and state whether and how the USV should be incorporated into maritime missions. This thesis cannot provide definitive answers, but it does present some useful and interesting initial findings. As pointed out previously, simulation is an abstraction from reality, and therefore the results should be viewed as insights rather than specific numerical values. For example, reported MOE values should be used in a relative comparison to the other values. Regardless, there is no other stochastic simulation of USV tactics known to have been conducted before this.

Three scenarios were constructed and analyzed: a Waypoint scenario and Interceptor scenario for intelligence, surveillance and reconnaissance scenarios, along with a Force Protection scenario. A design of experiments (DOE) approach was used to extract data from these scenarios for analysis purposes. The resulting models show the relationship between the proportion of detections or number of enemy agents that reach the high value unit (HVU) and the factors (10 for ISR scenarios and 11 for the FP scenario) that are varied throughout the design. The breadth of the thesis study is to expand the current limitations of the Spartan Scout to check for thresholds, relationships and where emphasis should be placed on the actual expansion of the significant capabilities.

The factors that are in the DOE are the speed of each type of agent, the sea state, the number of USVs, the total number of contacts and the percentage of contacts that are enemies, the range of the camera sensor, the distance that each USV is permitted to travel away from the HVU, and the USV time on station. Some characteristics are kept constant throughout the experiment, such as the probability of detections for all sensors and the probability of kill for the weapon. The sensors are also the same for each class of agent. Finally, factors that are not included but could be incorporated in future models include latency, temperature inversions, currents, and other meteorology and oceanography features.

There are three types of factors that are varied in the DOE. First are the uncontrollable factors. These are the speeds of the non-friendly agents, the total number of contacts, percentage of contacts that are enemy contacts, and the sea state. Next are the factors that need to be configured into the design and tasking of the USV: the number available to deploy, the camera range, and the range that the USVs are permitted to travel away from the HVU. One last pair of factors is also controllable in the sense that a time-dependent situation will decide their values. These factors are the speed of the USV and the number to deploy in the given situation.

A. INSIGHTS FOR USV DESIGN AND DEPLOYMENT

The uncontrollable factors are beyond the control of friendly forces. If this group turned out to have the highest impact on the MOEs, it would imply that the USVs could not be deployed effectively without accurate knowledge or assumptions about the enemy position. Only the regression tree analysis of the FP simulation model produced results that contained uncontrollable factors as significant terms.

For the three FP MOEs (the proportion of all enemies detected, proportion of threatening enemies detected MOEs, and number of threatening enemies that reach the HVU), the only factors that were found significant were the percentage of threatening enemies and the threatening enemy speed. The threatening enemy speed was only found significant in the number of threatening enemies that reach the HVU MOE. Even though the level of these factors cannot be controlled, they should be considered when determining appropriate levels for the controllable factors mentioned previously.

The configuration factors should be implemented in USV design. Analysis shows that the optimal number of USVs operationally available per HVU is in the range of 16-20. This is a large number to procure per HVU, and may not even be feasible because of space limitations aboard the ships and the need for extra platforms to sustain this availability. However, a qualitative summary of the results indicates that a single USV is insufficient, that adding USVs improves performance in all three models up to a point, but that the performance eventually levels off and may even deteriorate slightly. The need for a relatively large number of USVs to cover a 1600 sq-nm area may indicate that other more complex methods for coordinating USV actions should be considered.

The other two design factors are the camera range and the tactical range from the HVU. These turn up as interactions in the Interceptor model with the endurance, and the camera range interacts with the USV speed. The main effect of the camera range, in the Waypoint and Interceptor models, has a positive coefficient which supports the general belief that more capability is better. However, the quadratic effect shows up in both models with a negative coefficient which means that there is a point where the performance will decrease.

Combat radius is only significant in the Interceptor model as a positive main effect and a negative quadratic effect. The lack of significance for the Waypoint model suggests that if USVs are solely tasked to follow preplanned mission profiles, the Navy should not spend money improving combat radius if it does not improve the operations. Experimentations show the same effect for either factor interacting with the endurance and leads to the conclusion that increasing the camera range does not require an increase in the combat radius. Neither of these factors was found to have significant interactions in the other regression analysis.

Soon, a decision-maker aboard CSG or ESG will have the ability to choose the number of USVs to deploy and the speed at which they operate. In this case, an observation of the situation at hand should be conducted. The regression models or regression tree analyses in Chapter IV can be used to generate point estimates of the desired MOEs. These, in turn, can assist the decision-maker's assessment of alternatives. Interval estimates (such as those illustrated with JMP^{TM}'s profiling tool) can be obtained via software after refitting the models to the experimental data (Steele, 2004).

Since currently only one prototype USV is operable, the probability of detecting enemies is not very high for any of the three models. For the near term, it is interesting to know the potential benefit of a slightly larger number of USVs. When all other factors are held at levels typical of the Spartan Scout's existing configuration, an increase to four USVs leads to a substantial improvement in all MOEs. Four was chosen because it was a relatively small number but appeared as a split in the regression tree analysis for the

Force Protection model. Increasing the number of USVs from one to four also narrowed the confidence intervals for the mean responses.

Overall, one surprising piece of information is that the sea state is not significant in the performance of any of the MOEs analyzed. This could be a function of how sea state was modeled: we included influence on USV maneuverability, but not the impact on degrading sensor performance. It is also interesting to note that the enemy speed appears in the Waypoint model as a significant main effect and an interaction, yet it was not present at all in the final Interceptor model.

As mentioned with the Interceptor model, an increase in either the camera range or the combat radius increases the proportion of detection without having to increase the other factor. Similar results might hold for other types of sensors. The results suggest recommending only increasing the capacity of one of these ranges. The decision of which range should be increased is dependent on the costs, the technological feasibility of improving one attribute rather than the other; and which makes logical sense.

Although sea state was not a significant factor, the actual camera range truly depends on the height of the waves. This relationship was not modeled due to the limitations of the PYTHAGORAS software. If the wave height is greater than the height of eye of the camera, or creates sufficient haze, an increased camera range would not have any effect. Therefore, we recommend increasing the combat radius of the USV from the HVU. Since the Spartan Scout is controlled by radio frequency this could be accomplished by broadcasting the radio frequency via an airborne relay, instead of the ship's mast.

B. AGENT-BASED SIMULATION EXPERIMENTS

Agent-based modeling is a tool that can be used by the military to represent individual entities that are a part of a larger group, but ultimately have the same orders. The individual entities are given the orders but are each able to look at the current environmental conditions and determine the best movement and action for the individual agent and is still within compliance of the original orders. The simulation provides ways to analyze situations where actual field experimentation is either impossible to do thousands of times or the risk to the personnel and cost of the equipment is too high to duplicate thousands of times. Utilizing agent-based simulation, military applications can be looked at without having to put military personnel at risk as well as saving potential equipment and monetary losses.

The above paragraph is a moot point when the level of fidelity and resolution cannot be reached. There are downfalls to using any time step simulation platform. One mentioned previously is the challenge of defining the length of a time step in the terms of the simulation model, while maintaining a preset distance representation and reasonable speeds. Such a restriction can cause the loss of resolution either in the distance a pixel represents or in representing what happens during the length of a single time step. In addition to the length of the time step, modeling the waypoints required the speed and waypoint distances to be synchronized appropriately. This too was a function of the time step. Discrete-event simulation, where the future events drive the time clock, would eliminate the need to monitor agents locations and actions only at predetermined times. Instead, the simulation would keep track of when the next event will occur, move the time clock to that point, and update the agents' states and positions appropriately.

Converting PYTHAGORAS to a discrete-event platform would not be a simple task, but if discrete-event models similar to the Waypoint, Interceptor, and Force Protection scenarios could be built, it would be interesting to compare results to those of this thesis. If expanded or new models of USV deployment are built in PYTHAGORAS or a similar time step modeling platform, we recommend thinking carefully about what the pixels represent, potential speeds that will be used and the desired resolution of the time step before developing the scenarios. In this thesis, we arbitrarily picked a distance to be represented by a pixel in the initial scenario-building process. Later on, there were very few options for choosing the time step representation that allowed the simulation models to work as desired without rescaling all of the distances.

Another recommendation is to make the agents change their behaviors and/or properties using some mechanism other than triggers activated by color changes, since the color changes also determine whether agents perceive other agents as friendlies, neutrals, or enemies. The most prominent illustration is in Scenario-FP.

PYTHAGORAS is set up so that the different agents in a class have speeds within a defined tolerance, but each individual USV does not change speed if even if it detects and begins chasing a threatening enemy. Adding the ability for the agents to change speeds when in pursuit of an enemy would make the model more like the tactical scenario of Force Protection.

Despite these caveats, the DOE approach was extremely valuable for exploring the scenarios and uncovering insights. Future studies should continue to examine many factors simultaneously. Using stepwise regression simplifies the process of determining which factors are not important, especially since the full models contain 65 or 77 factors. This automated procedure did not do all of the work and is not a substitute for human judgment: the results still needed manual tweaking to achieve a solid model with a simplified list of terms.

Regression trees are very useful when linear regression does not provide adequate models. This non-parametric analysis was able to give insights for the MOEs with only a few factors in a comprehensible manner. Other insights to draw from the thesis: although regression does a good job of making prediction equations, it cannot be done on all sets of data. Sometimes other means are necessary, such as regression trees, to find relationships between the factors varied in the DOE and the outcomes.

C. RECOMMENDATIONS FOR FUTURE WORK

An exploratory investigation inevitably leads to more questions. With simulation as the medium for generating data, simplifying assumptions must be made. This, in itself, is not a negative comment because the purpose of modeling is to extract the essential characteristics of a system. For this thesis, assumptions were made on certain aspects of the USV, its operations, and its environment. These are described in earlier chapters so the reader can understand what has and has not been included in the modeling. However, some of these could be looked at more in depth to see if relaxing assumptions provides a more accurate representation of real-world operations. Additionally, some other aspects of the FP scenario merit further research. Brief descriptions follow.

1. Analysis with METOC Factors Included

The meteorological factors omitted from the scenarios are the wind, current, tides, and sea temperatures. Based on the Joint Meteorology and Oceanography (METOC) Handbook and the USSOC Manual Number 525-6, factors other than wave height need to be analyzed in order to keep the crew and equipment as safe as possible. The analysis in this thesis only considers the wave height since we believed *a priori* that this would have the largest impact. Designing an experiment that includes a more detailed meteorological representation, as well as the factors used in the current analysis, could yield a more accurate sense of how the USV will behave in the open seas.

2. High Sea States

USVs are a very new technology, and this thesis is the first time PYTHAGORAS has been used for USV support. There currently is not a precise, or even ballpark, way to determine if the scenario is accurately defining the situation in high seas, due to lack of tactical data. This influenced our decision to set up scenarios only for the USV's "favorable" operating conditions (sea states 1, 2, and 3). Wave heights of 6-8 feet are "marginal" operating conditions for USVs. This range is above sea state 3, and the USV performance behavior is likely to be quite different when it is operating in marginal conditions rather than operating in favorable ones (Joint METOC Handbook, 2000).

As USVs are given more opportunity to be tested and utilized, data could be collected under high sea state operations. This type of information could, in turn, be used to build and perhaps even calibrate models for USV operations in high sea states. The approach described in this thesis provides a template for this type of analysis, and combining the results could very well give a good overall view of the conditions in which the USV can operate effectively.

3. Rescale Simulation Model

As mentioned previously, latency was not included due to the time step length. A change to the scale of the model, allowing the time step to be smaller, would permit the agents' behaviors between the current 72-second time steps to be drawn out of the simulation. To change the scale, the pixel definition and the scale of the speed have to be altered. The time step would have to be changed so that the fraction of a second needed for the host ship to record information from the USV is noticed. Changing this feature in the modeling might give more accurate answers to the questions presently posed in the current analysis, although at the cost of a larger computing effort.

Along with changing the actual scale of the models, it would be useful to have a closer look within the range of factors that are varied. For example, the number of contacts was extremely exaggerated so potential threshold values were not missed. Since there are thirty-three levels on a range of 1-500, different NOLH designs involving more factor levels could be used so that greater fidelity is seen through out the range. With 500 contacts in a 1600 sq-nm area, the maximum contact density is one contact per approximately three square nautical miles. Greater control over models would support higher contact densities in more focused area of operations.

4. The Effect of Threatening Enemies Reaching the HVU in the Force Protection scenario

Taking a look at how the USVs react when a hostile enemy reaches the HVU could be the next step into determining the purpose of the USV when a threat is imminent. One view is that the HVU would have much more on its hands than worrying about what the USVs are doing at this point since it is known that the personnel of the HVU are going to be in grave danger when a threatening contact is under the nose of the ship. However, there may still be a need for the USVs once the threatening contacts reach a certain radius within the HVU. This could be modeled in PYTHAGORAS, or some other agent-based platform, but the scenario should represent the attack on the HVU, the USVs reactions, and the aftermath. Such a scenario would probably involve a more detailed representation of the HVU, such as allowing the HVU to move.

D. SUMMARY

Preventing fatal incidents such as the April 2004 maritime interdiction operations occurrence is an advantage to implementation of the USV into Naval missions. In this thesis, multiple linear regression and regression trees are coupled with a DOE that analyzes up to 11 factors simultaneously. These illustrate how the USV can be introduced into the Fleet to effectively assist in ISR and FP activities. The results provide several operational and tactical insights, and form the basis for a recommendation to the US Navy to use the USV in an active role in maritime missions. They also provide guidance on the benefits of improving USV sensing and endurance capabilities, and reveal that simply maximizing numbers of USVs is not necessary for attaining high mission performance.

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LIST OF REFERENCES

Definition of Sea States. Available online at: http://www.oceandata.com/support/Sea%20State%20Table.htm. (Accessed on 6 April 2004)

Properties of the RHIB found on the Navy Fact File. Available online at: http://www.chinfo.navy.mil/navpalib/factfile/ships/ship-rhib.html. (Accessed on April 2004)

Bitinas, E., 2004: *Pythagoras Manual*. Not published.

Navy Newsstand, cited 2004: Two Sailors Killed in Arabian Gulf Oil Terminal Attacks. Story Number NNS040424-01, 24 April 2004. [http://www.news.navy.mil/search/display.asp? story_id=12977] (Accessed May 2004).

Cioppa, T. M., (2002): Efficient Nearly Orthogonal and Space-filling Experimental Designs for High-Dimensional Complex Models. Dissertation. Department of Operations Research, Naval Postgraduate School, pp. (Available online at: [http://library.nps.navy.mil/uhtbin/cgisirsi/Mon+May+17+14:24:58+PDT+2004/0/520/02sep_Cioppa_PhD.pdf] (Accessed May 2004)

Joint Meteorology and Oceanography (METOC) Handbook, 2000. 3d ed. Available online at: [https://www.metocwx.quantico.usmc.mil/metoc_resource_center/publications/jointpubs/JMH-2000.pdf] (Accessed May 2004). (2000).

Law, A. M. & W. D. Kelton, 1999: *Simulation Modeling and Analysis*. 3d ed. Tata McGraw-Hill, 760 pp.

Montgomery, D. C., et al., 2001: *Introduction to Linear Regression Analysis*. 3d ed. Wiley and Sons, 635 pp.

Quarderer, K.M., 2004: Personal Communication via email. 27 January 2004.

Quarderer, K.M., 2004: Daily Report 28 January 2004. 17 pp.

Ricci, V., and Yates, Benjamin S., 2002: *Spartan Scout Unmanned Surface Vehicle Concept of Operations (CONOPS).* Naval Undersea Warfare Center Division, Newport, Rhode Island.

Rich, N., 2003: Power Point Presentation received via email. 02DEC.ppt. 8 January 2004.

Rich, N., 2004: Personal Communication via email. 28 January 2004.

Sanchez, S. M., 2004: Spreadsheet for Generating Orthogonal and Nearly-orthogonal LH designs in Natural Levels. http://diana.gl.nps.navy.mil/SeedLab/NOLHdesigns.xls (Accessed June 2004).

Sanchez, S. M. and T. W. Lucas, 2002: Exploring the World of Agent-Based Simulations: Simple Models, Complex Analyses. *Proceedings of the 2002 Winter Simulation Conference,* 116-126.

Statement of Work, 2003: Maritime Tactics in Support of Unmanned Vehicles (UV's). Project Director: Mr. Peter Lorenz

Steele, M. J., 2004: Spreadsheet with USV Simulation Summary Output. http://diana.gl.nps.navy.mil/SeedLab/SteeleThesisData.xls (Accessed June 2004).

USSOC Manual Number 525-6, 1998. Available online at: http://www.specialoperations.com/Navy/Boat_Ops.htm. (Accessed May 2004).

(Eds.) Wagner, D. H., et al., 1999: *Naval Operations Analysis*. 3d ed. Naval Institute Press, 421 pp.

LIST OF ACRONYMS

CI	Confidence Interval
DOE	Design of Experiments
FP	Force Protection
GET	USS GETTYSBURG
HVU	High Value Unit
ISR	Intelligence, Surveillance, and Reconnaissance
MIO	Maritime Interdiction Operations
RF	Radio Frequency
RHIB	Rigid Hull Inflatable Boat
USV	Unmanned Surface Vehicles

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