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Effectiveness of unmanned surface vehicles in anti-submarine warfare with the goal of protecting a high value unit

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THESIS

EFFECTIVENESS OF UNMANNED SURFACE VEHICLES IN ANTI-SUBMARINE WARFARE WITH THE GOAL OF PROTECTING A HIGH VALUE UNIT

by

Salim Unlu

June 2015

Thesis Advisor:	Thomas W. Lucas
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Littoral anti-submarine warfare (ASW) operations generally focus on deterring and eliminating enemy diesel-electric submarines from transit routes and protecting High Value Units (HVUs), such as amphibious warfare ships and logistics ships. In view of the ASW challenges in the littorals, it is critical to establish and maintain a highly effective ASW capability. The ASW techniques that we use today are mostly effective, but it is important to explore new technologies and techniques—such as potential unmanned surface vehicle (USV) solutions. This study uses an agent-based simulation platform known as Map Aware Non-Uniform Automata (MANA) to model the ASW effectiveness of USVs with the goal of protecting a HVU. The effectiveness of an ASW screen formation is measured by the proportion of successful classifications. The results are analyzed using comparison methods, stepwise linear regression, and regression trees. It is found from nearly 390,000 simulated ASW missions that when helicopters are replaced with USVs, which have the same sensor type and capability, they can provide the same classification effectiveness in an ASW screen formation. The analysis also shows that the most significant characteristic of USVs is the classification range of their dipping sonar.

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EFFECTIVENESS OF UNMANNED SURFACE VEHICLES IN ANTI-SUBMARINE WARFARE WITH THE GOAL OF PROTECTING A HIGH VALUE UNIT

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ABSTRACT

Littoral anti-submarine warfare (ASW) operations generally focus on deterring and eliminating enemy diesel-electric submarines from transit routes and protecting high value units (HVUs), such as amphibious warfare ships and logistics ships. In view of the ASW challenges in the littorals, it is critical to establish and maintain a highly effective ASW capability. The ASW techniques that we use today are mostly effective, but it is important to explore new technologies and techniques—such as potential unmanned surface vehicle (USV) solutions. This study uses an agent-based simulation platform known as Map Aware Non-Uniform Automata (MANA) to model the ASW effectiveness of USVs with the goal of protecting a HVU. The effectiveness of an ASW screen formation is measured by the proportion of successful classifications. The results are analyzed using comparison methods, stepwise linear regression, and regression trees. It is found from nearly 390,000 simulated ASW missions that when helicopters are replaced with USVs, which have the same sensor type and capability, USVs can provide the same classification effectiveness in an ASW screen formation. The analysis also shows that the most significant characteristic of USVs is the classification range of their dipping sonar.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAW	Anti-Air Warfare
ASuW	Anti-Surface Warfare
ASW	Anti-Submarine Warfare
ASW USV	Anti-Submarine Warfare Unmanned Surface Vehicle
DOE	Design of Experiment
FFGH	Guided-Missile Aviation Frigate
FP	Force Protection
HVU	High Value Unit
ISR	Information Surveillance and Reconnaissance
LCS	Littoral Combat Ship
MANA	Map Aware Non-Uniform Automata
MANA-V	Map Aware Non-Uniform Automata-Vector
MIW	Mine Warfare
MOE	Measure of Effectiveness
NOLH	Nearly Orthogonal Latin Hypercube
SEED	Simulation Experiments & Efficient Design
SLOC	Sea Lines of Communication
SOA	Speed of Advance
SSK	Diesel Electric Submarine
TDZ	Torpedo Danger Zone
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle
UUV	Unmanned Underwater Vehicle

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THESIS DISCLAIMER

The reader is cautioned that the computer programs presented in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logical errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

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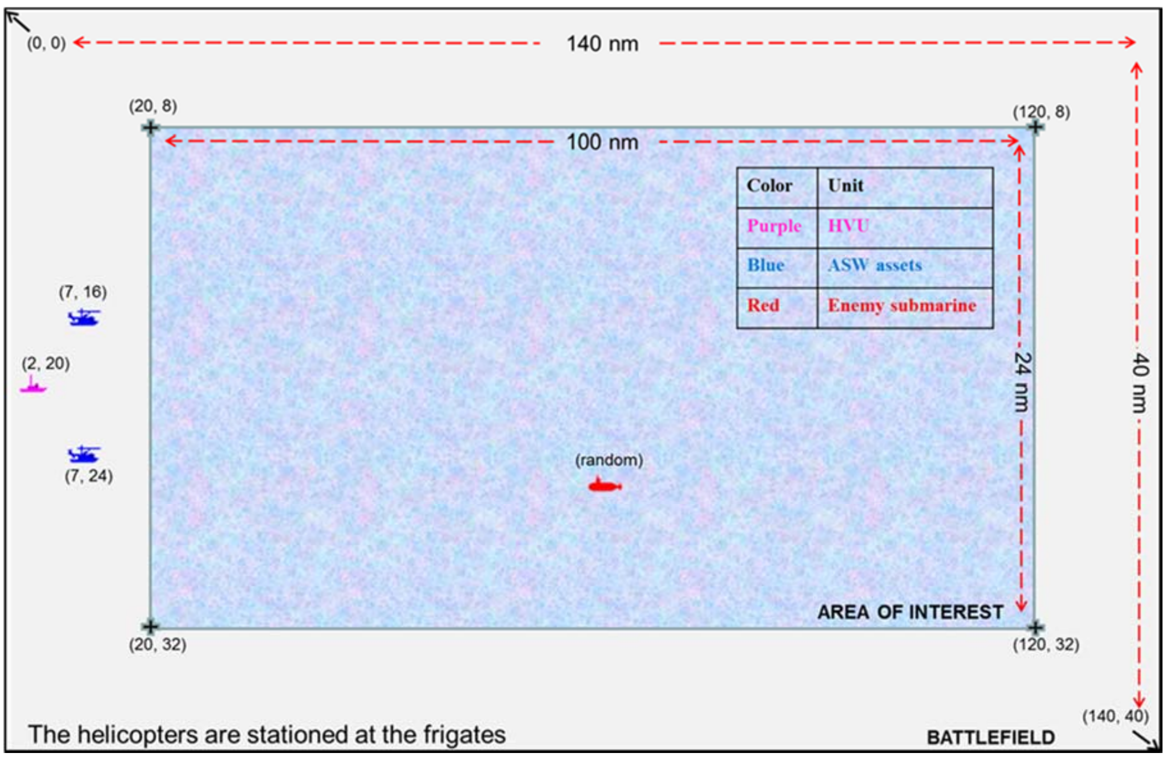
EXECUTIVE SUMMARY

The Turkish naval fleet conducts operations in its littoral waters to ensure free access to international waters and to deter any threat to the sea lines of communications (SLOCs). Thus, antisubmarine warfare (ASW) operations in Turkish littoral waters generally focus on deterring and eliminating enemy diesel-electric submarines from transit routes and protecting naval assets and high value units (HVUs), such as amphibious and logistics ships. These operations enable naval forces to conduct more successful force protection and sealift operations and keep the SLOCs open and secure.

Diesel-electric submarines are very quiet and stealthy—and pose a great threat to Turkey's and allied forces' SLOCs. With the increasing emphasis on littoral ASW, we should investigate complementary abilities to address and eliminate diesel-electric submarines with conventional forces. Technological enhancements bring us new capabilities to fight against stealthy underwater threats. Unmanned surface vehicles (USVs) have the potential to enhance the current littoral ASW capabilities. USVs have been used in naval operations since World War II, but recently these vehicles are gaining more interest from modern navies with their increased operational capabilities.

Effective employment and the correct tactical use of USVs may offer a great force multiplier. This can bring operational success, reduced risk and casualties to manned platforms, and improved operational effectiveness. Based on the discussion above, this thesis examines the effectiveness of unmanned surface vehicles in anti-submarine warfare with the goal of protecting a high value unit.

This study uses an agent-based simulation platform known as Map Aware Non-Uniform Automata (MANA) to model the ASW effectiveness of USVs while considering their advantage of long on-station time and disadvantage of low speed (as compared to helicopters). A generic scenario is created to allow us to experiment with potential USV capabilities in ASW missions. The modeling first focuses on building an existing ASW screening scenario in MANA. In this scenario, two frigates with hull-mounted active sonars are positioned on the inner ASW screen and two ASW helicopters with active dipping sonars are positioned on the outer ASW screen to protect an HVU from submarine attacks. This baseline scenario provides a standardized benchmark on current ASW performance. The battlefield characteristics and the overall representation of the baseline scenario are shown in the figure below. In the first alternative scenario, USVs are included in our model instead of helicopters. In doing so, USVs maintain a protective ASW barrier in front of the surface group. This model provides us some insights about USVs as to whether they can improve the effectiveness of ASW capabilities. Also, the model explores the overall effectiveness of ASW screening when USVs are employed with ASW helicopters. The same conditions are also explored for three frigate scenarios.



The battlefield characteristics and the overall representation of the baseline scenario (not drawn to scale).

After modeling the scenarios in MANA, over 390,000 simulated ASW screening missions are executed. In designing our experiment, we apply a nearly orthogonal Latin hypercube (NOLH) design which provides good space-filling and statistical properties. We use the experimental design to vary controllable and uncontrollable factors and examine how they affect the ability to detect and classify a diesel-electric submarine attempting to attack an HVU.

A comparison analysis is conducted among the scenarios with different numbers and varieties of platforms employed in an ASW screen formation. With side-by-side box plots and one-way analysis of the means by scenarios, it was found that when the helicopters are replaced with USVs, which have the same sensor type and capability, USVs can provide the same classification effectiveness in an ASW screen formation. The operating range of the USVs is considerably shorter than the operating range of the helicopters because of the autonomy requirements of USVs. Therefore, USVs are employed in the intermediate screen while the helicopters are employed on the outer screen. This gives the helicopters a great advantage against USVs because the helicopters can extend the reach of the frigates to the farthest point in the ASW screen and provide an early detection and classification of the diesel-electric submarine.

The proportion of successful classification is used to measure the effectiveness of ASW screen formation in a regression model. Based on this measure of effectiveness (MOE), the most significant characteristic of USVs is the classification range of their dipping sonar. In ASW, the classification range may depend on underwater conditions, background noise in the ocean, and sonar capability. The sonar parameters are mostly controllable because the selection of the sonar type and capability can be determined during the design process. But, the effectiveness of sonar is limited by environmental conditions. On the other hand, the speed is viewed as an insignificant characteristic of USVs in the model over the ranges explored. With this in mind, it is important that USVs self-deploy to the intermediate screen ahead of the HVU with sufficient time and endurance to satisfy their station-keeping requirements.

Many decision and noise factors have a highly significant effect on the outcome in our protective ASW scenario. The sonar parameters of the frigates are especially significant in the model. The frigate sonar classification range has the greatest influence on ASW mission success. The number of frigates is another significant factor that affects the outcome. Employing one more frigate in the screening formation, along with its assets, significantly increases the probability of detecting hostile submarines. Among the noise factors, the stealthiness of the diesel-electric submarine plays an important role in the model, as expected, since it is a well-known crucial factor in littoral ASW operations.

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I owe my deepest gratitude to my thesis advisor Professor Thomas W. Lucas for his guidance and useful critiques. Without his help and guidance, I would not be able to perform this study and complete this thesis. There are no words to describe him. He is always there to help us with a golden heart.

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I. INTRODUCTION

“Peace at home, peace in the world.”

– Mustafa Kemal Ataturk

Since the end of the Cold War, the threat environment has shifted from open seas to the brown waters, with a greater emphasis on expeditionary operations, power projection, and force protection in littoral waters. One of the greatest military challenges of today is modern diesel-electric submarines operating in noisy and cluttered littoral environments. Diesel-electric submarines are very quiet and stealthy—and pose a great threat to Turkey’s and allied forces’ sea lines of communications (SLOCs). With the increasing emphasis on littoral antisubmarine warfare (ASW), we should investigate complementary abilities to address and eliminate diesel-electric submarines with conventional forces.

Technological enhancements bring us new capabilities to fight against stealthy underwater threats. Unmanned surface vehicles (USVs; see Figure 1) have the potential to enhance the current littoral ASW capabilities and reduce the risk to manned platforms [1]. USVs have been used in naval operations since World War II, but recently these vehicles are gaining more interest from modern navies with their increased operational capabilities [2].

Figure 1. Unmanned surface vehicle (image from Textron Systems, http://www.textronsystems.com).

A. OVERVIEW

Over the past two decades, the littoral waters have gained great importance. In December 1991, as the world watched in great surprise, the fall of the Soviet Union put an end to the Cold War. The post–Cold War era has had a great effect on both political and military activities. This era raised the possibility of unpredictable regional wars, tensions, and conflicts, especially in the Middle East, Southwest Asia, Northern Africa, Western Pacific, and Eastern Europe. Today, it seems that in the case of possible conventional combat, naval activities will likely take place in littoral waters [3].

These naval activities include force protection, surveillance, littoral ASW, mine-hunting, mine-clearing, and support for amphibious operations. In the littoral battlespace, naval forces may encounter some threats from potential enemies that are different from those in open seas in the form of quiet diesel-electric submarines (see Figure 2).

Figure 2. A diesel-electric submarine (image from Jane's Fighting Ships, https://janes.ihs.com).

This unique platform is considered the deadliest threat in littoral waters because it can shut down its diesel engines and run on a battery charge when submerged, resulting in almost zero noise, and sail undetected for a long period of time. Moreover, high noise and poor sound propagation conditions in the littoral waters give the diesel submarine an even greater advantage. It can stay extremely quiet and submerged for up to one week. Many countries around the world operate modern diesel-electric submarines because they are relatively inexpensive and have greater effectiveness in littoral waters. Some common classes of modern diesel-electric submarines include Type 209, Type 212, Kilo-class, Dolphin-class, Scorpene, and Soryu [4]. Modern diesel-electric submarines can be used for many purposes, such as threatening vital shipping lanes and attacking high value units (HVUs) [5].

The main role of the Turkish Navy is to provide security for shipping lanes and protect Turkey's rights and interests in its littoral waters, namely in the Aegean, Eastern Mediterranean, and the Black Sea (see Figure 3) [6].

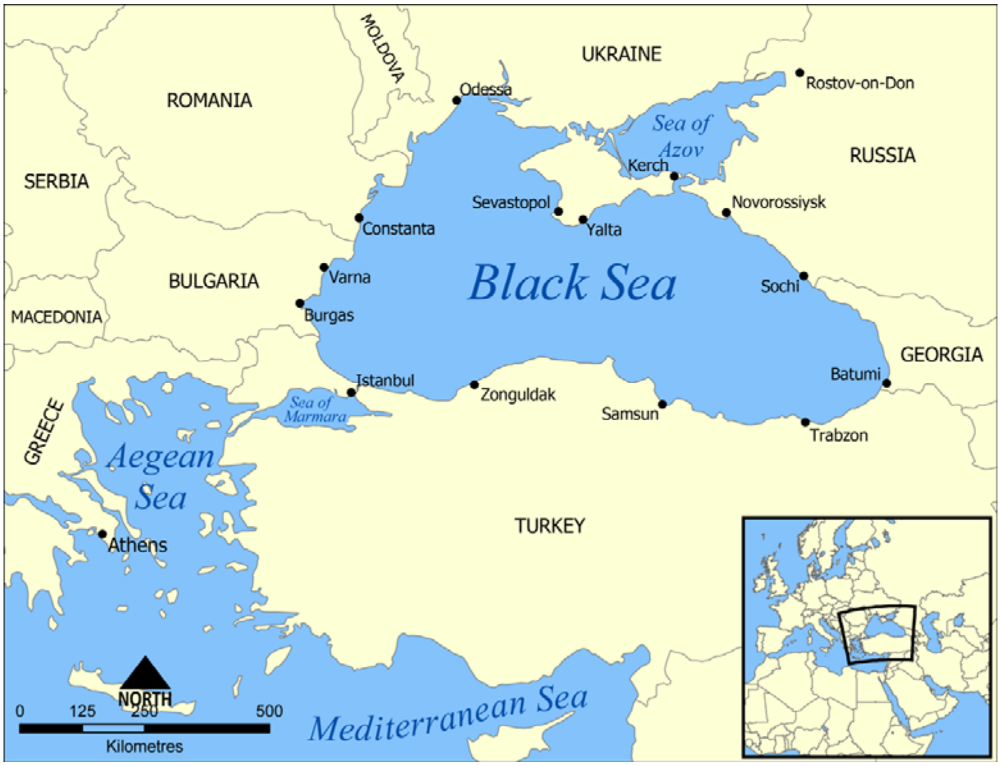

Figure 3. Turkey's surrounding seas: The Black Sea, the Aegean Sea, and the Mediterranean Sea (image from The Encyclopedia of Earth, http://www.eoeearth.org).

The Turkish naval fleet conducts operations in its littoral waters to ensure free access to international waters and to deter any threat to SLOCs. Thus, ASW operations in Turkish littoral waters generally focus on deterring and eliminating enemy diesel-electric submarines from transit routes and protecting naval assets and high value units (HVUs), such as amphibious and logistics ships. These operations enable naval forces to conduct more successful force protection and sealift operations and keep the SLOCs open and secure.

Detecting a diesel-electric submarine is challenging and requires a variety of different platforms and sensors. Each platform has its own ASW capabilities and can be employed in various anti-submarine operations. To improve ASW effectiveness, these platforms and their sensors support each other [5]. Due to the operational challenges and importance of littoral waters, it is critical to establish and maintain a highly effective ASW capability [7]. Convoy or HVU protection usually focuses on defensive ASW and requires a detailed organization of escorting assets. In order to protect HVUs against possible submarine attacks, the Navy can employ surface warships, aircraft, helicopters, and unmanned underwater and surface vehicles (UUVs and USVs) equipped with active or passive sonar. These ASW assets are deployed to patrol certain areas relative to the HVU's position [8]. Each type of operation requires a certain number of ASW units, manpower, time, and money.

The ASW techniques that we use today are mostly effective, but it is important to develop complementary skills, improve today's technology, and explore new systems, such as unmanned solutions. This can increase the effectiveness of ASW capabilities in deterring and eliminating enemy submarines and protecting friendly forces. Given today's increasing diesel-electric submarine threat from our enemies, it is important that the Navy has the capability of operating USVs in naval operations. Employing USVs in ASW operations has the potential to improve the efforts of existing ASW assets. Effective employment and the correct tactical use of USVs may offer a great force multiplier. This can bring us operational success, reduced risk and casualties to manned platforms, and improved operational effectiveness [1].

Based on the discussion above, this thesis examines the effectiveness of unmanned surface vehicles in anti-submarine warfare with the goal of protecting an HVU.

B. RESEARCH QUESTIONS

The research is guided by the following questions:

1. Can USVs give the same effectiveness as ASW helicopters against diesel-electric submarines ahead of naval convoys or HVUs?
2. What are the main advantages and disadvantages of employing USVs in an ASW screen formation?
3. Which characteristics of USVs are the most significant in ASW?
4. How do changes in decision parameters affect the probability of classifying a diesel-electric submarine?
5. What strengths and drawbacks does the simulation software Map Aware Non-Uniform Automata (MANA) have for modelling ASW scenarios?

C. SCOPE AND METHODOLOGY

This thesis explores how USVs can complement and extend existing ASW effectiveness in detecting and classifying diesel-electric submarines. This study also addresses many controllable and uncontrollable factors related to ASW to see which factors have the greatest effect on an ASW screen's classification rate. Results will help decision-makers understand how USVs can be employed in an ASW screen formation.

This thesis uses an agent-based simulation platform called MANA to model the ASW effectiveness of USVs while considering their advantage of long on-station time and disadvantage of low speed (relative to helicopters). Agent-based simulation is a technique in which we virtually construct multiple autonomous entities that make their own decisions and behave stochastically in their local environments [9].

The modeling first focuses on building an existing ASW screening scenario in MANA. In this scenario, two frigates with hull-mounted active sonars are positioned on the inner ASW screen and two ASW helicopters with active dipping sonars are positioned on the outer ASW screen to protect an HVU from submarine attacks. This baseline scenario provides us a standardized benchmark. In the first alternative scenario, USVs are included in our model instead of helicopters. In doing so, USVs will maintain a protective ASW barrier in front of the surface group. This model provides us some insights about USVs as to whether they can improve the effectiveness of ASW capabilities. Also, we explore the overall effectiveness of ASW screening when USVs are employed with ASW helicopters. The same conditions are also explored for three frigate scenarios.

After modeling the scenarios in MANA, nearly 390,000 simulated ASW missions are executed. In designing our experiment, we apply a nearly orthogonal Latin hypercube (NOLH) design which provides good space-filling and statistical properties [10]. We use the experimental design to vary controllable and uncontrollable factors and examine how they affect the ability to detect and classify a diesel-electric submarine attempting to attack an HVU.

D. LITERATURE REVIEW

A literature review is conducted to examine previous studies and documents about USV employment in naval operations. These studies and documents do not cover the scope of this thesis, but the methodologies and insights utilized in these studies are important to review before moving on to the model development phase.

In her master's thesis, Steele (2004) studies the performance of a USV with respect to its current capabilities in information, surveillance, and reconnaissance (ISR) and force protection (FP) missions [11]. She uses an agent-based simulation platform called PYTHAGORAS to build her mission scenarios. Steele's study explores alternative configurations of a prototype USV and its operational use. The results of the study provide some useful operational and tactical insights—ultimately, she recommends that the U.S. Navy use USVs in maritime missions.

In his thesis, Abbott (2008) examines the effective use of an employed LCS squadron to provide analytic support for the LCS program office [12]. He builds three different scenarios in MANA based on the current mission packages for LCS: Anti-Surface Warfare (ASuW), Anti-Submarine Warfare (ASW), and Mine Warfare (MIW). This study touches on USVs in one of these scenarios. In the ASW scenario, a USV is employed to act similarly to an ASW helicopter. It is assumed that the USV has a dipping sonar capable of finding a submerged submarine. In this model, once a USV detects a submarine, it helps to localize the submarine and passes this information to an LCS for prosecution. With respect to the ASW scenario, the results show that sensor systems play a significant role.

In 2013 the Research And Development (RAND) Corporation published *U.S. Navy Employment Options for Unmanned Surface Vehicles (USVs)* with the sponsorship of the Office of the Chief of Naval Operations, Assessment Division (OPNAV N81) [13]. This report researches the prospective suitability of USVs for U.S. Navy missions and functions. Firstly, it introduces the current and emerging USV marketplaces to understand the capabilities of platforms for U.S. Navy demands. Secondly, it develops concepts of employment to find out how USVs could be used in naval missions and functions. It then analyzes these concepts of employment to specify highly suitable missions and functions. The report identifies 62 potential missions and functions for USV employment and conducts a suitability analysis for these missions and functions based on pre-defined criteria. The results of this analysis show that among the 62 missions and functions, 27 of them are considered as highly suitable missions and functions for USV employment. Mostly, ASW missions fall in the category of less suitable missions and functions, but unarmed ASW area sanitization—a mission to detect and classify adversary submarines—is deemed a highly suitable mission in the emerging USV market. Unarmed ASW area sanitization focuses on ensuring that no enemy submarine is operating on transit routes or providing early warning when an enemy submarine is detected and classified. In this mission, USVs are deployed to an operating area ahead of an HVU with sufficient time to search for enemy submarines before the HVU arrives. USVs may conduct this mission overtly or covertly. While overt ASW operations dictate the use of active sonar, covert operations would use passive sonar for better concealment. Employing multi-mission manned platforms for this mission is expensive, both monetarily and in terms of valuable resources. Reducing the risk to manned platforms and freeing them for other missions are the main advantages of using USVs for this mission.

E. THESIS OUTLINE

Chapter II summarizes basic concepts of ASW, informs the reader about USVs currently employed by the U.S. Navy, and discusses the agent-based modeling and simulation modeling software MANA. Chapter III explains model development and describes each scenario used in this thesis. Modeling assumptions and limitations are covered as well as agent descriptions. Chapter IV discusses the exploration of the model. At the beginning of this chapter, we describe the design of experiment (DOE) techniques that are used to investigate the simulation. Then, we explain all the controllable and uncontrollable factors that could potentially affect the outcome. After the discussion of the model exploration, the model output is analyzed using several statistical techniques, such as least squares regression and partition trees. Following this, factor significance is examined. Chapter V concludes with a summary of the thesis and provides some recommendations and useful insights for decision-makers. It also includes some ideas and recommendations for further research.

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II. BACKGROUND

"The maritime should be considered as Turkey's major national ideal and we have to achieve it in less time."

– Mustafa Kemal Ataturk

This chapter provides a basic operational and theoretical background on USVs and ASW to help guide the development of the models and discussions in this thesis. Since this study analyzes an ASW scenario, it is important to have some basic information about the concepts and components of ASW. We then provide an overview of technological developments of anti-submarine warfare unmanned surface vehicles (ASW USVs) and introduce the major missions of USVs in littoral ASW operations. We also provide some background on agent-based modeling and MANA software.

A. ANTI-SUBMARINE WARFARE

The main purpose of ASW is to prevent our enemies from using their submarines effectively [14]. ASW is a branch of underwater warfare that employs a mix of naval platforms such as surface warships, helicopters, maritime patrol aircraft, and submarines to detect, track, damage, or destroy enemy submarines. In the near future, we will have the capability of operating a variety of unmanned vehicles in ASW operations. These various ASW platforms have different system and sensor capabilities.

In order to understand the proposed model, it is important to understand the nature of ASW. We briefly describe littoral ASW concepts, processes, platforms, and the acoustic environment.

1. Littoral ASW Concept

In littoral waters the diesel-electric submarine remains one of the most effective ways to threaten operational capability. Curt Lundgren addresses the submarine threat in his article "Stealth in the Shallows: Sweden's Littoral Submariners" published in *Jane's Navy International*:

> In the Royal Swedish Navy's experience, the conditions make it very difficult to detect and prosecute a submarine. Put simply, the Baltic is an ASW officer's nightmare and a submariner's heaven. … For an aggressor, submarines operating in the littoral environment are very bad news, and the resources and time required to find and prosecute a submarine threat are likely to be disproportionately high. … The well-designed and proficiently crewed submarine remains a highly stealthy platform in the littoral environment. [15]

Adversaries may conduct underwater operations on transit routes to threaten merchant convoys and/or HVUs. With the purpose of enabling joint or naval forces to conduct more successful operations, littoral ASW has to focus on denying submarine threats access to our areas of interest and preparing more secure spaces for friendly forces. In regional maritime conflicts, it is important to establish a clear battlespace and transit HVUs through the littoral waters [16].

In the near future the environment in the littoral waters will be more complex and chaotic due to higher density traffic and a more cluttered environment. Denying and eliminating stealthy submarines will be more difficult [17]. Because the littoral environment is very complex and noisy, traditional ASW tactics and systems optimized for the open ocean do not work effectively in littoral waters. High noise and poor sound propagation in the littoral waters negatively affect the effectiveness of the underwater acoustic sensors that are developed for open-ocean ASW [16]. While considering the special conditions in the littoral waters, there are requirements for complementary capabilities. A new technology insertion is a desirable approach to achieve and improve current and near-term ASW capabilities [16].

While the aim of littoral ASW operations is to detect, classify, localize, and neutralize adversary submarines, there will be a need to employ more capable ASW platforms, proficient operators, and reliable sensor systems [14]. Modern navies employ a variety of platforms, such as surface ships, maritime patrol aircraft, and helicopters for littoral ASW operations and coordinate these efforts at sea to complement ASW capabilities [16].

2. ASW Process

Since the purpose of ASW is to eliminate the submarine threat, the ASW process consists of several phases. In general, this process can be simplified into five consecutive phases: detection, classification, localization, tracking, and kill [18]. In a typical scenario, ASW assets are used to detect and classify a submarine target, hold the contact, and carry out an accurate attack (i.e., throw weapons or depth charges), and, if necessary, regain contact and re-attack [19]. In this research, the effectiveness of an ASW screen formation is measured by the proportion of successful classifications. Therefore, we touch only on the detection and classification phases. These initial phases must be successful before one can localize, track, and attack a submarine.

Although successful ASW requires all of these phases, the crucial and challenging phases are the initial detection and then classification of a submerged submarine hiding in the water. Once a submarine is classified, the HVU may move to avoid its weapon range. So, the success of an ASW operation is not only measured by the destruction of the enemy's submarines [20]. Indeed, protecting the HVU is the primary ASW objective.

a. Detection

Detection means the observation of an underwater contact, which may be a submarine [18]. There are several sensors designed to detect a submarine. We divide these sensors into two basic categories: acoustic sensors and non-acoustic sensors. While acoustic sensors pick up underwater acoustic signals and transfer them into sound, non-acoustic sensors use various techniques. Acoustic and non-acoustic sensors include active and passive sonars, radar, magnetic anomaly detection (MAD), electronic support measure (ESM) devices, and sonobuoys deployed from maritime patrol aircraft (MPA). Visual sighting can also be a way of detecting a submarine.

b. Classification

For any sonar contact, the first requirement is to come to a judgement about the contact. This judgment is called classification [18]. Classification can be a complicated phase of the ASW process, but it is very important to categorize whether a contact is related to a submarine or not. Contacts are classified as *submarine*, *non-submarine*, or *doubtful*. Non-submarine contacts include underwater objects such as sunken ships, sea creatures, downed aircraft, or lost cargo. If these underwater objects are incorrectly classified as submarines, it causes a waste of time and effort [18]. If a submarine is wrongly classified as non-submarine, the misclassification could threaten and damage HVUs or ASW forces.

In tactical situations, a diesel-electric submarine operates underwater. So, it is important to be able to detect it there. Since overall sonar performance is degraded in the littorals, this platform gains extra stealth [21]. In practice, passive sonar is not effective in noisy littoral environments against diesel-electric submarines. Active sonar is the best available means to detect and classify this silent threat before it can launch a torpedo.

3. ASW Platforms

This section discusses types of ASW platforms as well as the combination of their properties and employment methods. A variety of platforms, including surface warships, rotary-wing and fixed-wing aircraft, submarines, and unmanned vehicles are used to localize and eliminate enemy submarines.

There are some common capabilities that affect the success of ASW. The range or reach of units is an important factor in ASW as well as in ASuW and AAW. Other important factors are the speed and endurance of the units [14]. When an ASW commander makes his operations plans, he considers these factors and knows exactly the strengths and the weaknesses of the various ASW platforms.

Depending on the given task, specific platforms will be assigned to form the ASW task force. Most often, two or more escort ships and their organic helicopters are expected to accompany the HVU if threatened by a diesel-electric submarine,

a. Surface Ships

Surface warships have many warfare capabilities other than ASW. The most important function of surface warships is their command, control, and communication capabilities. Because the payload is proportional to the size of the platform, surface warships can carry a large number and variety of sensors and weapons—including other ASW platforms such as helicopters and USVs.

In the littoral environment, most surface warships use their hull-mounted active sonars. Although surface warships such as destroyers, frigates, and littoral combat ships (LCSs) have a speed advantage against diesel-electric submarines, they cannot use this advantage effectively in ASW as speed degrades overall sonar performance [14].

b. ASW Helicopters

Helicopters are widely used in ASW operations to detect and eliminate diesel-electric submarines hiding under temperature inversions in the water. Helicopters can be deployed from surface warships and extend the ships' ASW capability. An ASW helicopter can operate without detection because its movements cannot be seen by the submarine. It can hover above the surface, lower its dipping sonar (variable depth sonar), and operate the sonar at a wide variety of depths (see Figure 4). In this manner they cover a considerable area in a short time, providing ASW helicopters a great advantage. This advantage is generally considered as a characteristic unique to helicopters in ASW. These factors provide a significant capability for ASW helicopters as a screening unit ahead of a HVU or naval convoy [18].

Figure 4. Aerial view of an SH-60F Seahawk helicopter lowering a dipping sonar into the Pacific Ocean (image from Wikimedia Commons http://commons.wikimedia.org).

4. The Acoustic Environment

The underwater environment is different from the surface environment. Sound travels unevenly through water because water is not homogenous. Both passive and active sonar performance are significantly affected by the underwater environment. The measurements of temperature, pressure, and salinity all change at different layers of the water. The velocity and direction of sound depends on all of these factors. The changing acoustic conditions as a function of depth create a considerable bending effect on sound waves [18].

Temperature is the most significant variable that affects the propagation of sound through water. Typically, there are three layers at sea based on temperature: mixed layer (surface layer), thermocline, and deep water. The mixed layer is the first layer, where the temperature is almost constant with depth. The second layer is the thermocline, where temperature changes more rapidly with depth. The last one is the deep layer, where temperature decreases very slowly with depth [18]. The thermocline layer is the one that we are interested in. When sound travels into the thermocline, it tends to bend and creates *shadow zones* above and below the angle of the sound (see Figure 5). In practice, submarines know where the thermocline is located and use this knowledge to hide from surface ships. Submarines pass across the thermocline layer into and out of the mixed layer periodically to listen for targets. This factor gives diesel-electric submarines a great concealment capability.

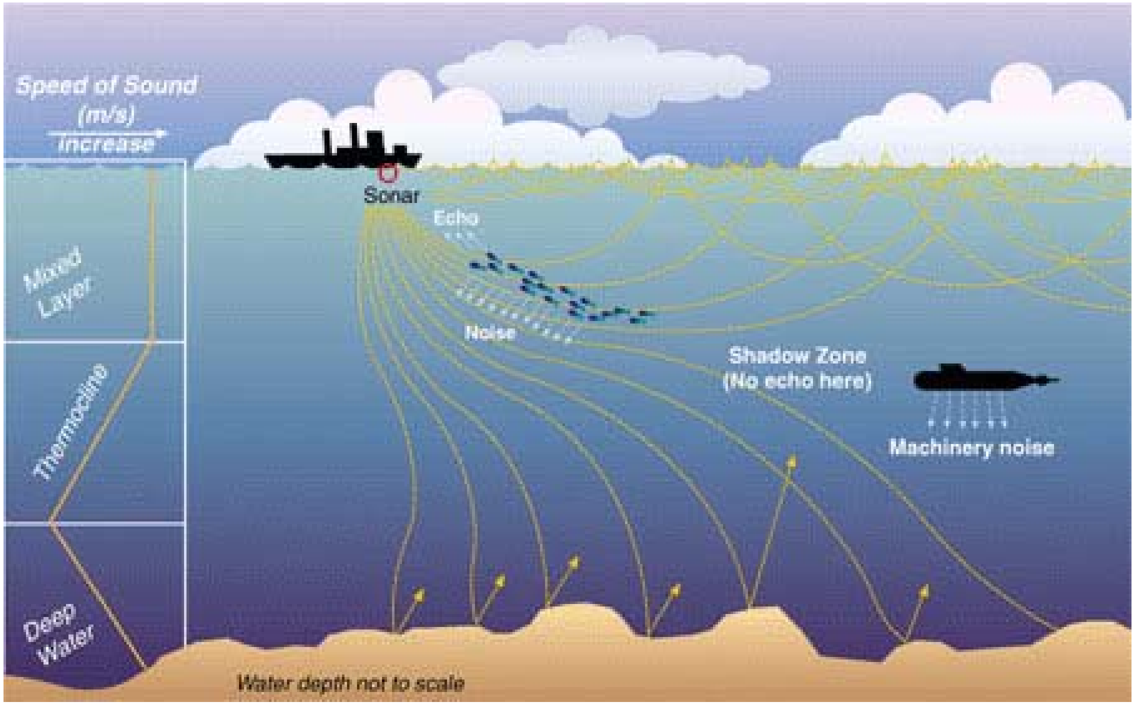


Figure 5. Thermocline layer effect (image from http://weather.kopn.org).

B. UNMANNED SURFACE VEHICLES

Unmanned vehicles have inspired great interest and contributed considerably to military operations over the past two decades. This trend is likely to continue into the near future. Employing unmanned systems in military operations will enhance warfare capabilities [22]. In recent years unmanned aerial vehicles (UAVs) and unmanned underwater vehicles (UUVs) have benefited from significant research and development efforts. USVs have received relatively less focus than the other types of unmanned vehicles.

1. Overview

According to the U.S. Navy's littoral anti-submarine warfare concept, "the accelerating rate of technological innovation gives increasing advantages to the navies that most quickly introduce appropriate new technologies into their fleets" [16]. According to a report of the Naval War College Global War Game in 2001, "USVs were key contributors in establishing situational awareness in the littorals and have shown the potential to provide critical access to high risk areas" [23]. In the case of possible conflicts against stealthier enemies, especially in littoral waters, putting manned platforms at risk is no longer a reasonable course of action. USVs are expected to be a critical complementary element of modern navies in the future.

USVs have some significant characteristics that can complement and enhance current warfare capabilities: reliability, maneuverability, long endurance, and high payload capacity. These primary features nominate the USV as a complementary element in multiple missions [24]. Today, modern navies are looking for ways to use these risk-reducing platforms in naval missions, especially in littoral waters.

In 2007, the U.S. Navy published "The Navy Unmanned Surface Vehicle (USV) Master Plan" [1]. This master plan examines the capabilities, classes, and potential naval missions for USVs. Seven high-priority USV missions are identified in the master plan. These missions, in priority order, are [1]

- Mine Countermeasures
- Anti-Submarine Warfare
- Maritime Security
- Surface Warfare
- Special Operations Forces Support
- Electronic Warfare
- Maritime Interdiction Operations Support

According to open online sources, the U.S. Navy currently has four classes of USVs. These are *Fleet Class I*, *Semi-Submersible Snorkeling Vessel*, *Harbor Class*, and *Small Class* [25]. Their primary missions are antisubmarine, mine countermeasures, and surface warfare missions for the littorals.

2. Development of the Anti-Submarine Warfare Unmanned Surface Vehicle

In recent years, advances in defense technologies have offered a variety of payloads and systems for USV applications. Potential payloads for USV systems include towed array sonars, dipping sonars, and acoustic sensors. A compact dipping sonar system is now optimized for the USV. Therefore, a USV can take advantage of the same sensor capability as ASW helicopters.

General Dynamics Robotic Systems (GDRS) developed an 11 meter "Fleet" class Anti-Submarine Warfare Unmanned Surface Vehicle (ASW USV) for use on the LCS and delivered the first one to the U.S. Navy in 2008. The ASW USV is autonomous and capable of operating in an extended-duration with a high-payload capacity. It has high speed capability (35+knots), thus it can expand the reach of surface warships. Characteristics of this ASW USV are shown in Table 1.

Table 1. Principal characteristics of anti-submarine warfare unmanned surface vehicle (ASW USV).

Characteristic		**Characteristic**	
Length	40 ft	**Payload**	5000 lb
Beam	11.2 ft	**Max Speed**	35+ kt
Max Weight	21,120 lb	**Endurance**	24+ hr

3. USV Employment for Antisubmarine Warfare

Today's ASW techniques are effective in most cases, but employing USVs is likely to increase the effectiveness of ASW. Employing USVs in littoral ASW operations has potential to enhance the efforts of existing ASW assets. Effective employment and the correct tactical use of USVs offers a great force multiplier.

U.S. Navy USV Master Plan (2007) defines littoral ASW missions in three major categories (see Figure 6): "Hold at Risk," "Maritime Shield," and "Protected Passage" [1].

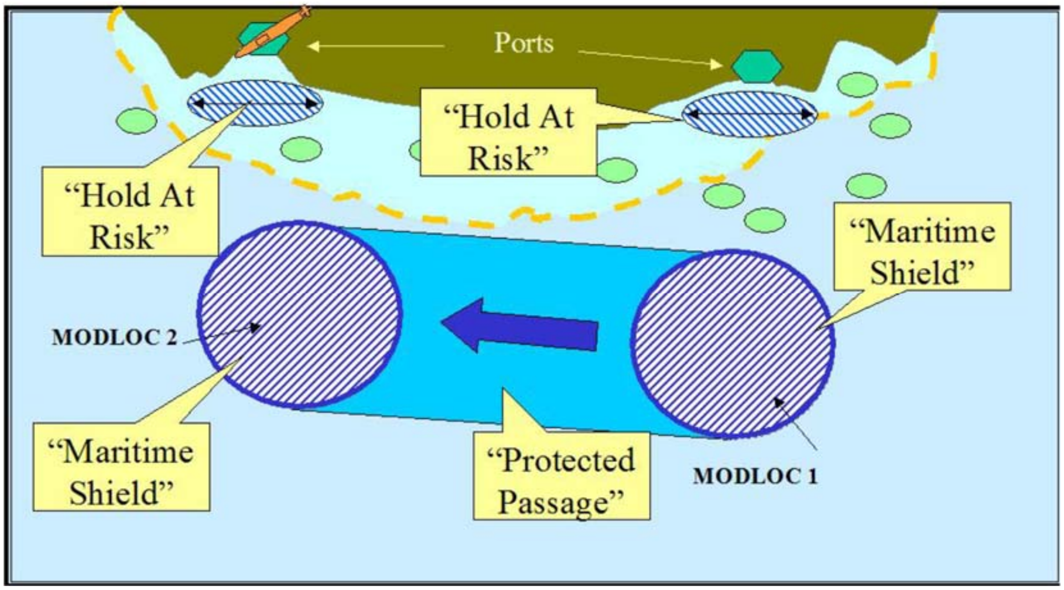


Figure 6. Littoral ASW missions in three major categories.

- In a *Hold at Risk* scenario, USVs monitor for submarines in the entrance of ports or chokepoints, but they are not the ideal candidate for this category due to their limited stealth.
- *Maritime Shield* missions focus on clearing a Carrier Strike Group (CSG) or Amphibious Ready Group (ARG) operating area from adversary submarines and keeping that area secure.
- In a *Protected Passage* scenario, USVs clear the battlespace of enemy submarines to enable secure routes for an Expeditionary Strike Group (ESG) or HVU.

In all the scenarios, USVs reduce the risk to manned platforms and serve as offboard sensors, thereby extending the reach of warships. A warship can launch a USV and serve as its mother ship.

C. AGENT-BASED MODELING

Agent-based modeling is a simulation modeling technique that has been used extensively in solving real-world problems, including military applications [26]. In agent-based modeling, we simulate multiple autonomous decision-making entities called *agents*. Each agent makes its own decisions on the basis of a set of user defined rules and behaves stochastically in its local environment [27]. Agents can determine their behaviors with their predefined personalities and be aware of events or other agents by using organic or inorganic sensors.

Agent-based models can perform non-linear behavior patterns, capture organizational dynamics, and provide valuable insights about real-world systems [26]. Military applications of agent-based simulations are widely used in the decision-making process. Agent-based simulations can capture the more chaotic and intangible aspects of military conflicts. These simulations assist decision-makers in testing war plans, reviewing or proposing force structures, providing detailed information on today's high technology products, deciding how to use sensors and weapons, and exploring potential changes in doctrine or tactics [28].

There are many simulation tools that are widely used for agent-based modeling. These tools include general computational mathematics systems such as MATLAB and Mathematica; general programming languages such as Python, Java, C++, and C; and other agent-based modeling platforms such as NetLogo, Swarm, Repast, AnyLogic, JANUS, MANA, and Pythagoras [29]. These tools are used in different fields of study and real-world applications. Figure 7 displays a screen shot of a USV scenario in Pythagoras [11].

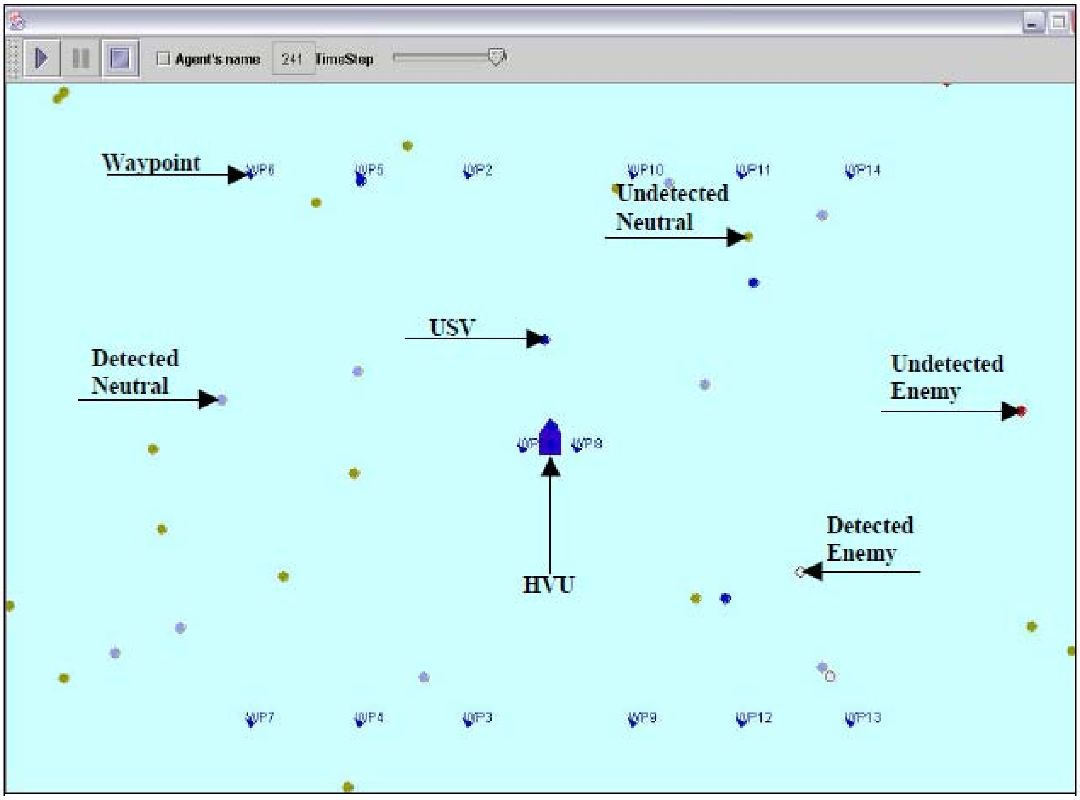


Figure 7. A screen shot of a USV scenario in Pythagoras, from [11].

D. MAP AWARE NON-UNIFORM AUTOMATA (MANA)

The simulation tool used in this thesis is MANA, which is developed by the Defence Technology Agency in New Zealand. MANA has been widely used for military and academic studies, including several master's theses at the Naval Postgraduate School. These studies include maritime protection of critical infrastructure assets [30], counter-piracy escort operations in the Gulf of Aden [31], unmanned aerial vehicle contributions for expeditionary operations [32], the effectiveness of unmanned aerial vehicles in helping secure a border [33], and the operational effectiveness of a small surface combat ship in an anti-surface warfare environment [34].

MANA is designed for modeling complex adaptive systems, such as combat situations. MANA builds time-stepped, mission-level, stochastic simulations. MANA contains entities representing military units which interact with their environment and the other entities and make their own decisions. Unlike physics-based models, MANA is very useful to simulate and analyze the effects of command and control, situational awareness, and sensor and weapon systems [35]. Figure 8 shows the startup screen of MANA.

Figure 8. The startup screen for MANA.

MANA modelers have the ability to edit battlefield characteristics and create a terrain map and background according to specific scenarios. Agents behave independently on the virtual battlefield based on their personalities, goals, sensors, weapons, and terrain type. However, they will not respond to the situations in the same way because the platform is stochastic and each agent uses its own information provided by personal sensors or communication links and stored in organic/inorganic SA maps. Agents can also have completely different personalities in different states and behave in that way by activating trigger states.

MANA Version 4 User Manual defines four basic parameters that affect an agent's behavior [36]:

- *Personality weightings* determine an agent's tendency to move towards or away from friendly, neutral, or enemy entities, or waypoints, or terrain.
- *Move constraints* are meta-personalities which modify an agent's basic personality weightings. This brings an agent a detailed behavior ability which is closer to the reality.
- *Intrinsic capabilities* are tangible or physical characteristics of an agent including its speed, sensors, weapons, targeting priorities, and fuel level.
- *Movement algorithm modifiers* affect an agent's speed and degree of autonomy when moving.

More information can be found in *MANA Version 4 User Manual* and *MANA-V (Map Aware Non-uniform Automata–Vector) Supplementary Manual*.

III. MODEL DEVELOPMENT

"We are entering an era in which unmanned vehicles of all kinds will take on greater importance in space, on land, in the air and at sea."

– George W. Bush

In this chapter, a brief description of ASW screen formation is given, as well as the scenarios used for this thesis. After addressing the scenarios, we discuss some key modeling assumptions and limitations. Finally, measures of effectiveness and model stop conditions are explained.

A. ANTI-SUBMARINE WARFARE SCREEN FORMATION

The purpose of defensive ASW operations is to protect a convoy of ships or HVUs within a group through high-threat areas. Because conventional submarines are serious threats to HVUs in the littoral waters, naval operations usually focus on defensive ASW. HVU protection requires detailed organization and a carefully set formation. A defensive ASW formation (see Figure 9) is generally used for preventing a submarine from reaching a position around an HVU from which it could launch a torpedo. It is necessary to use acoustic equipment effectively by employing highly maneuverable surface craft, such as destroyers and frigates, and helicopters at an effective distance from an HVU or a convoy of ships. This formation is generally called an *ASW screen formation*.

The screen size depends on the availability of screening vessels in the ASW task force. If a large force is available, two or three screens may be employed in the formation. One or two screens are normally used for small forces. There are three classes of ASW screens [37]:

- The *inner* ASW screen is a screen in which surface ships position around an HVU or convoy for the purpose of preventing a submarine from reaching the torpedo danger zone.

- The *intermediate* ASW screen is a second screen that is farther away from a formation of ships, has the potential to enhance detection and neutralization capabilities.
- The *outer* ASW screen is a sound screen well ahead of the formation of ships and HVU for the purpose of detecting the approach of a submarine and alerting the assets early.

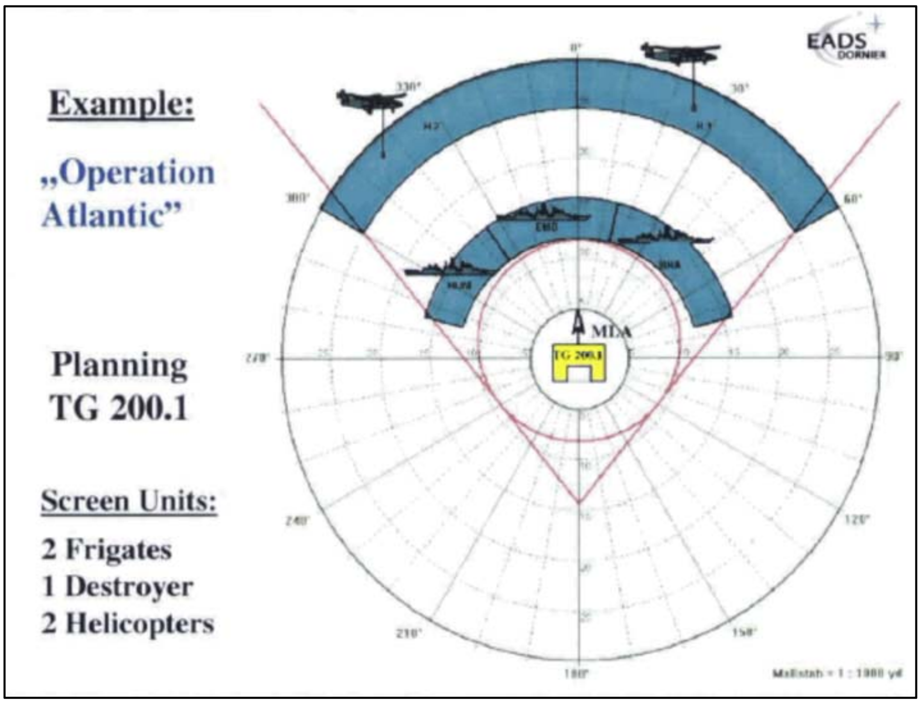


Figure 9. Possible ASW screen formation, from [38].

The inner ASW screen is the most important one among these three classes. The form of the inner ASW screen is shaped based on the number of available screening ships. The outer screen is the next most important one, and ASW helicopters are generally used for it. If screening vessels exceed the number required for the inner and outer ASW screens, the intermediate ASW screen may be employed.

B. SCENARIO DESCRIPTIONS

This thesis uses the combat simulating platform called MANA to model the scenarios. In this section, the battlefield features are briefly explained. Then, a generic

ASW scenario is created to increase to facilitate exploring USV capabilities and tactics. Next, we describe all of the scenarios.

1. The Battlefield

The battlefield is configured as 40 nautical miles (nm) wide by 140 nm long. On this battlefield, our area of interest is a 100 × 24 nm box in which MANA positions the enemy submarine randomly. The entire battlefield is plain terrain; thus, the terrain has no effect on the movements of the agents. In this model, the Cartesian coordinate system describes all positions in the battlefield. For all scenarios, the top left-hand corner of the battlespace is point (0, 0), and the bottom right-hand corner is point (140, 40). The battlefield characteristics are shown in Figure 10.

2. Generic Scenario

A Turkish naval task force (Blue) has been tasked to move from an area of operation to another. The aim of this task force is to transport logistics to friendly forces operating at sea. This task force consists of guided-missile aviation frigates (FFGH), ASW helicopters (SH-70B), and unmanned surface vehicles (USVs). Their main goal is to protect the HVU, a mid-size replenishment oiler (AOR). Helicopters and USVs are organic to the frigates. These assets can be deployed from the frigates and generally operate ahead of the task force.

Intelligence reports warn that an adversary (Red) diesel-electric submarine threatens the SLOCs. It is assumed that this enemy submarine is on Blue's transit routes, waiting for a favorable moment to engage the HVU with a torpedo. The submarine selects its target carefully; it almost never launches a torpedo blindly into the task force. It is assumed that an attack on ASW assets is never expected because the diesel-electric submarine desires the more strategic oiler and an attack on an escort will alert its primary target. That is, the submarine will not put its life at risk unless it can fire at the HVU.

An ASW screen is formed to detect and classify a submarine when a task force is transiting high-threat areas. The deployment tactic plays an important role on detection and classification of the submarine. The ASW assets try to detect and classify the submarine before it penetrates the screen, takes a planned approach, and launches a torpedo. Once the submarine is classified, normally, the ASW task force attempts to execute the localization, tracking, and kill phases. However, this scenario focuses solely on classifying the submarine before it enters the torpedo danger zone (TDZ) around the HVU. Classifying the enemy submarine can be interpreted as reducing the risk to the HVU. In this study, the ASW process after the classification phase is not simulated. The overall representation of the generic scenario is depicted in Figure 10.

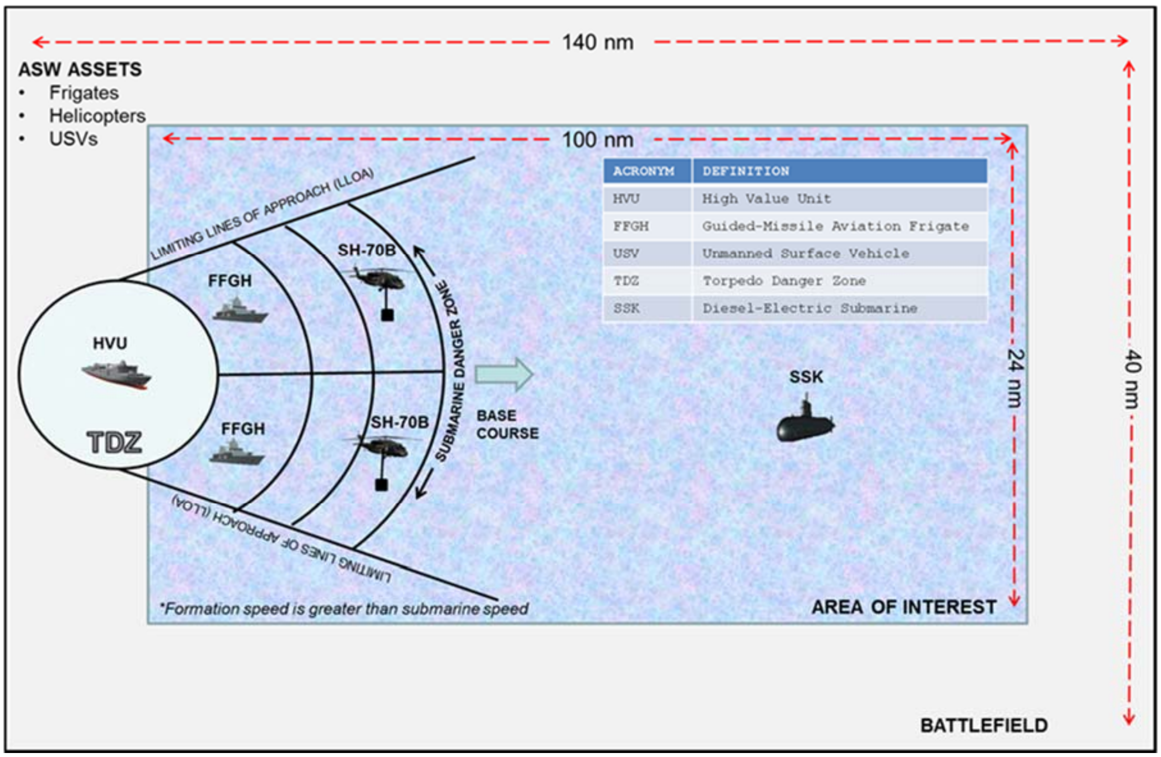


Figure 10. The battlefield characteristics and the overall representation of the generic scenario (not drawn to scale).

The baseline and advanced scenarios are modeled using MANA. The scenarios were built to explore the use of combinations of frigates, helicopters, and USVs to protect an HVU from a single enemy submarine. In the scenario setup, the number of available frigates ranges from two to three. The number of helicopters and USVs are dependent on the number of frigates, which serve as mother ships to helicopters and USVs. The overall scenario description is shown in Table 2. The modeling process is explained in simple language in the following sections.

Table 2. The overall scenario description.

Scenario	ASW Units		
Baseline Scenario	2 FFGH	2 HELO	-
Scenario Two	2 FFGH	-	2 USV
Scenario Three	2 FFGH	2 HELO	2 USV
Scenario Four	3 FFGH	3 HELO	-
Scenario Five	3 FFGH	-	3 USV
Scenario Six	3 FFGH	3 HELO	3 USV

3. Baseline Scenario

This scenario is created based on existing ASW screening settings. It provides us a standardized benchmark. There are four classes of agents in the battlespace: the HVU, frigates, ASW helicopters, and the enemy submarine. In the baseline scenario, the HVU is screened by two frigates and two organic ASW helicopters because it does not have an ASW capability, and it is vulnerable to submarine attacks. The frigates are equipped with hull-mounted sonars, and the ASW helicopters are equipped with dipping sonars. All equipped vessels are using their sonars in active mode. The submarine listens for sound in passive mode.

While the frigates are positioned on the inner ASW screen, the helicopters are positioned on the outer ASW screen. The initial locations of the units are defined using Cartesian coordinates. The ASW assets are initially located at the western edge of the battlefield outside the box. The coordinates of the battlefield, the area of interest, and the initial locations of the units are depicted in Figure 11.

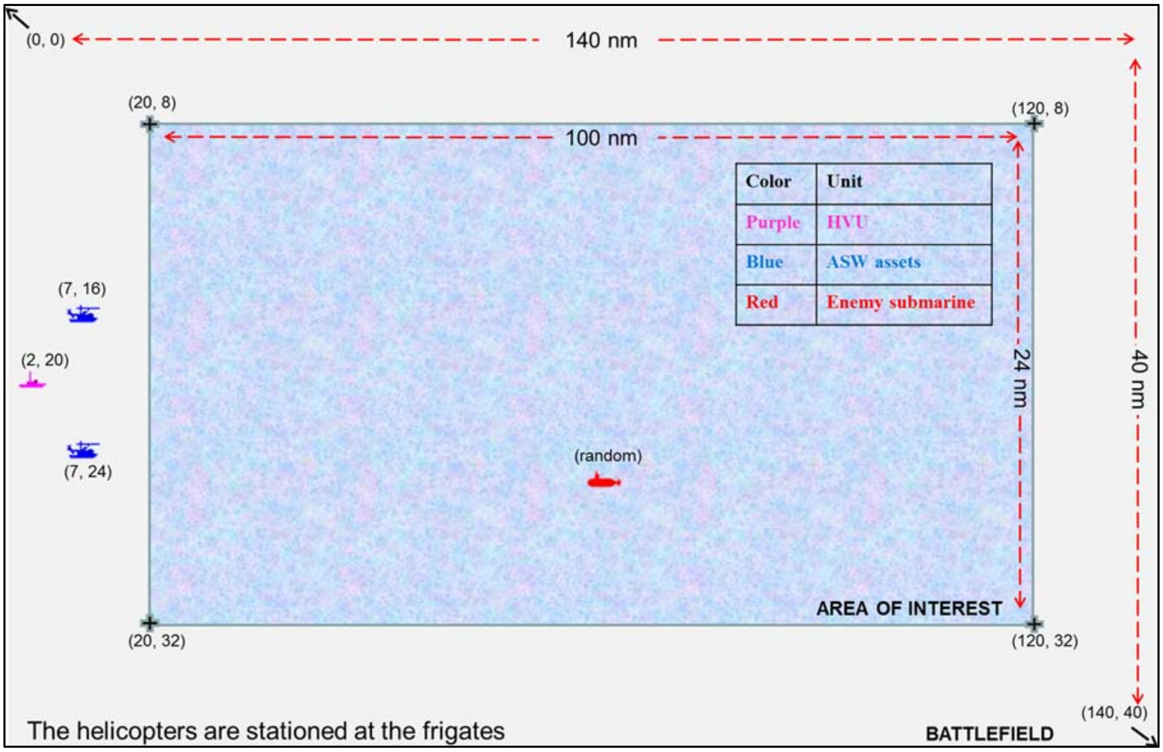


Figure 11. The coordinates of the battlefield, the area of interest, and the initial locations of the units for the baseline scenario (not drawn to scale).

The HVU begins at the point (2, 20) and proceeds as a moving reference point at 10 knots, which is the speed of advance (SOA). The frigates maintain this speed, and their movements depend on the HVU. The helicopters are initially stationed on the frigates. They launch from their mother ships and move to the first dip location once the simulation starts. Once there, they hover in place and lower their sonar transducers into the water.

MANA randomizes the initial positions of the agents within their defined homeboxes. Therefore, we can expect different outcomes each time the model is run. At initialization, the diesel-electric submarine is positioned randomly by MANA in the area of interest and thereafter moves randomly at 3 knots. When it becomes aware of the task force, it attempts to penetrate the ASW screen and increases its speed up to 10 knots.

4. Scenario Two

In this scenario, USVs are included in an intermediate screen instead of the outer screen ASW helicopters. In doing so, USVs will maintain a protective ASW barrier in front of the surface group. Referencing the coordinate system in Figure 11, the starting locations of the units are shown as follows:

- BlueHVU: (2,20)
- BlueEscort1: (7, 26)
- BlueEscort2: (7, 14)
- BlueUSV1: (19, 25)
- BlueUSV2: (19, 15)

USVs carry a dipping sonar similar to the one used by the helicopters. The USVs use a "Sprint & Drift" tactic ahead of the mother ship. They sprint ahead to their next dip location, and once there, they drift on the water and lower and operate their dipping sonar.

5. Scenario Three

In Scenario Three, we update the baseline scenario again. In this scenario, all of the available assets are deployed: two frigates, two ASW helicopters, and two USVs. All of the agents are using the same tactics previously discussed. While ASW helicopters are positioned on the outer ASW screen, USVs are positioned on the intermediate ASW screen. The HVU, frigates, and USVs are located at the same starting locations as in Scenario Two. Once the simulation starts, the helicopters are deployed ahead of the USVs.

6. Scenario Four

In this scenario, the HVU is screened by three frigates and three organic ASW helicopters. There is no difference between this scenario and the baseline scenario in terms of the deployment tactics and parameter setup, but the number and placement of the units change. The initial locations of the units are shown in Figure 12.

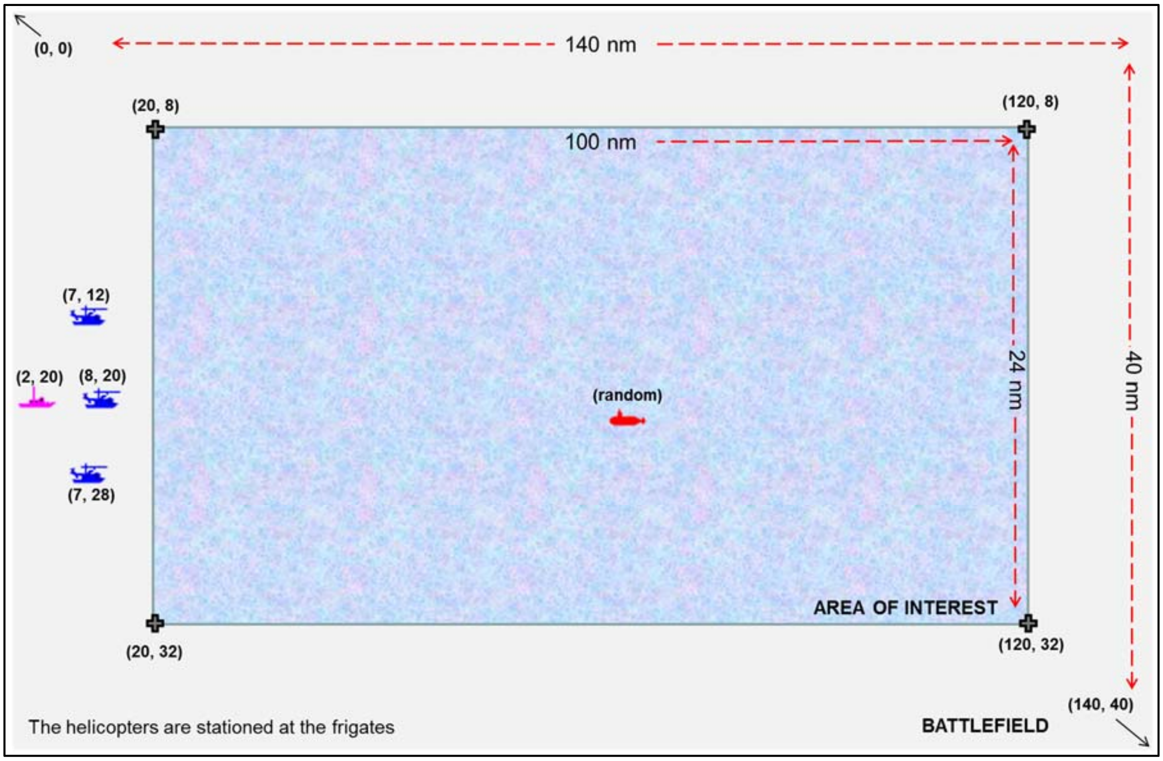


Figure 12. Scenario Four: The initial locations of the units (not drawn to scale).

7. Scenario Five

In Scenario Five, USVs are deployed again in our model instead of ASW helicopters. The deployment tactics and parameter setup are the same as before, but the initial locations and the sectors relative to the HVU are different. Referencing the coordinate system in Figure 12, the starting locations of the units are shown as follows:

- BlueHVU: (2,20)
- BlueEscort1: (7, 28)
- BlueEscort2: (7, 12)
- BlueEscort3: (8, 20)
- BlueUSV1: (18, 28)
- BlueUSV2: (18, 12)
- BlueUSV3: (18, 20)

8. Scenario Six

In Scenario Six, all of the available assets are deployed: three frigates, three ASW helicopters, and three USVs. All of these agents act in the same manner as in previous scenarios. The HVU, frigates, and USVs are located at the same starting locations as in Scenario Five. Once the simulation starts, the helicopters are deployed on the outer ASW screen ahead of the USVs in an intermediate screen.

C. AGENT DESCRIPTIONS

MANA agents have a variety of tangible characteristics, such as agent allegiance (friendly, enemy, or neutral), class parameters, threat levels, movement speed, and personal concealment rate.

The basic assessment of an agent's identity is that of allegiance. Allegiance determines the side of an agent. We define the allegiance of the HVU, frigates, helicopters, and USVs as *friendly,* and the allegiance of the diesel-electric submarine as *enemy*. There are no *neutral* agents in our scenarios. We also added stationary dummy agents that simulate random dipping locations for helicopters and USVs. Their allegiance is defined as enemy for modeling purposes as they "attract" the helicopter and USV agents. The numeric value *1* represents blue forces and *2* represents red forces.

Agent class parameters and agent threat levels help define the type of the enemy. Agent class is used to differentiate the target types for weapon engagement. Because we do not simulate the kill phase in this model, a dummy weapon model is used for stopping the simulation when the submarine is classified.

The threat level is used to differentiate the target types on the situational awareness maps of the agents, so the agent can react to that information according to user assigned personality weightings. Table 3 shows the overall tangible characteristics of the agents.

Table 3. The tangible characteristics of the agents.

Agent	Description	Allegiance	Agent Class	Threat
HVU	High Value Unit	1	1	3
Escort Ship	Guided-Missile Aviation Frigate (FFGH)	1	2	1
Helicopter	ASW Helicopter	1	3	1
USV	USV equipped with dipping sonar	1	3	1
Submarine	Conventional Diesel-Electric Submarine	2	4	3
Dipping Agent	Dummy Enemy Agent	2	94-99	2

1. Friendly Forces Behaviors

The movement behavior of an ASW unit is based on its personality weightings and next waypoint. In MANA, the personality weightings are set between -100 and 100 for adjusting the directivity of the agent. For more details, see the *MANA Version 4 User Manual* [36]. A positive weighting value attracts an agent while a negative value repulses it. The modeler can play with the weighting values to obtain the desired behavior.

a. HVU and Escort Ships

For defining the movement behavior of the HVU and the escort ships, their personality weightings towards the next waypoint are set to 100. Their movement toward the waypoint is slightly randomized by setting the random patrol bar to 10. This adds a small amount of random wiggle to their movement, as with real platforms. The HVU uses just the *Default State* settings because it does not change its behavior during the simulation. Figure 13 shows the personality weightings and trigger states of the HVU.

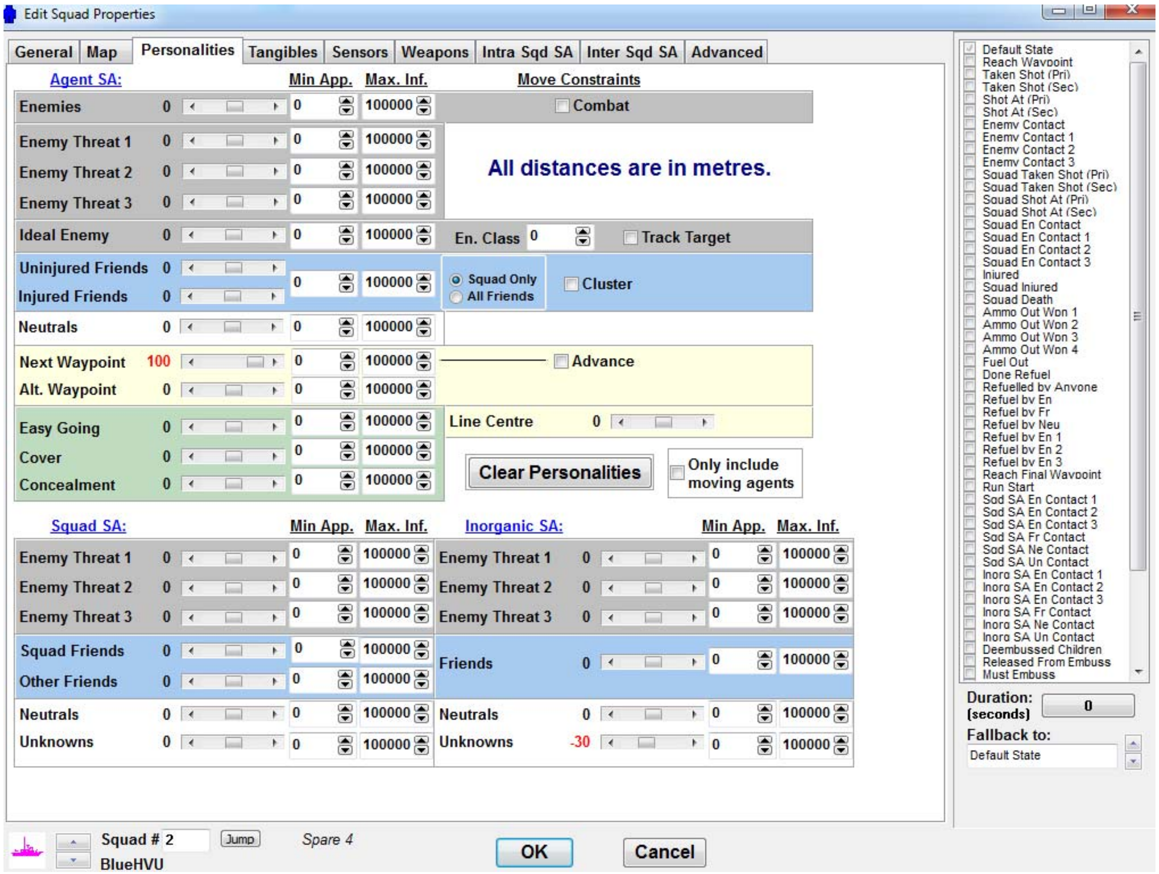


Figure 13. The personality weightings and trigger states of the HVU.

The escort ships have four states created to simulate helicopter operations. We did this by applying the embussing feature in MANA. The helicopters are carried by the escort ships until a release trigger point is reached. In the beginning of the simulation, the escort ships change their state from *Default State* to *Run Start*. In this state, they release their child squads, that is, their organic helicopters. After the duration time of the trigger state passes, the escort ships' states fall back to the *Must Embuss* state. In this state, the escort ships call their child squads back. After the child squads arrive at the escort ships, they station there during the *Embussed Children* state. This process is used to model the endurance of the helicopters. Table 4 shows the trigger states of the escort ships.

Table 4. The trigger states of the escort ships.

State	Embussing Behavior	Next State
Default	Nothing	Run Start
Run Start	Release Child Squads	Must Embuss
Must Embuss	Embuss Children	Embussed Children
Embussed Children	Nothing	Run Start

b. Helicopters and USVs

The helicopters and USVs have the same movement pattern. They first move to the nearest dipping location, which is semi-randomized in the area of interest. Dummy enemy agents are created to simulate dipping locations and randomized in their homeboxes. The homeboxes are set to a reasonable search pattern. The threat level of these agents is set to 2, and they attract the helicopters and USVs in their *Default State*. Once a helicopter or USV finds the nearest dummy agent, it fires at this agent, and then changes its state to *Taken Shot (Sec)*. In this state, a helicopter hovers over the water and lowers its dipping sonar for four minutes. Next, its state falls back to *Spare 1* during which it enables its dipping sonar. Then, it recovers its dipping sonar for four minutes and moves forward to find the next dummy agent. Table5 summarizes this process.

Table 5. The trigger states of the helicopters and USVs.

State	Speed (knots)		Enable Sensor? (Yes/No)	Duration (seconds)	Next State
	Helicopter	USV			
Default	Flight Speed	Sprint Speed	No	Sprint Time	Taken Shot (Sec)
Taken Shot (Sec)	0	0	No	240	Spare 1
Spare 1	0	0	Yes	Dip Time	Spare 2
Spare 2	0	0	No	240	Default

2. Enemy Behaviors

The submarine behavior is a simple process. It has two states: *Default* and *Enemy Contact*. In the default state, it patrols in its homebox and tries to detect ASW units. A patrol zone is created by using the random patrol feature in MANA. This allows the submarine to travel on a straight path on random routes in the patrol zone. The random patrol settings of the submarine are shown in Figure 14.

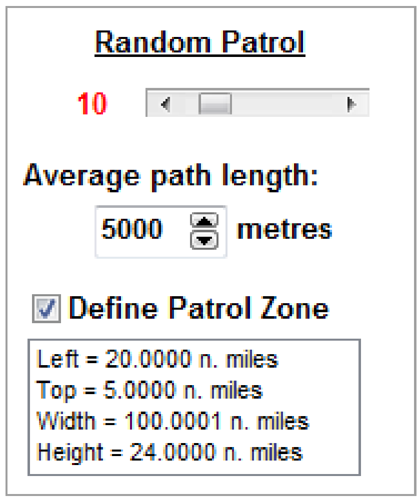


Figure 14. The random patrol settings of the submarine.

Once the submarine detects an ASW unit, it changes its state to *Enemy Contact.* It then moves through the center of the formation and attempts to reach the TDZ. The submarine moves forward in a submerged approach region and attempts to remain undetected to reach the TDZ. This movement is set with several changes in personality settings of the agent. The personality settings of the submarine in *Enemy Contact* state are shown in Figure 15.

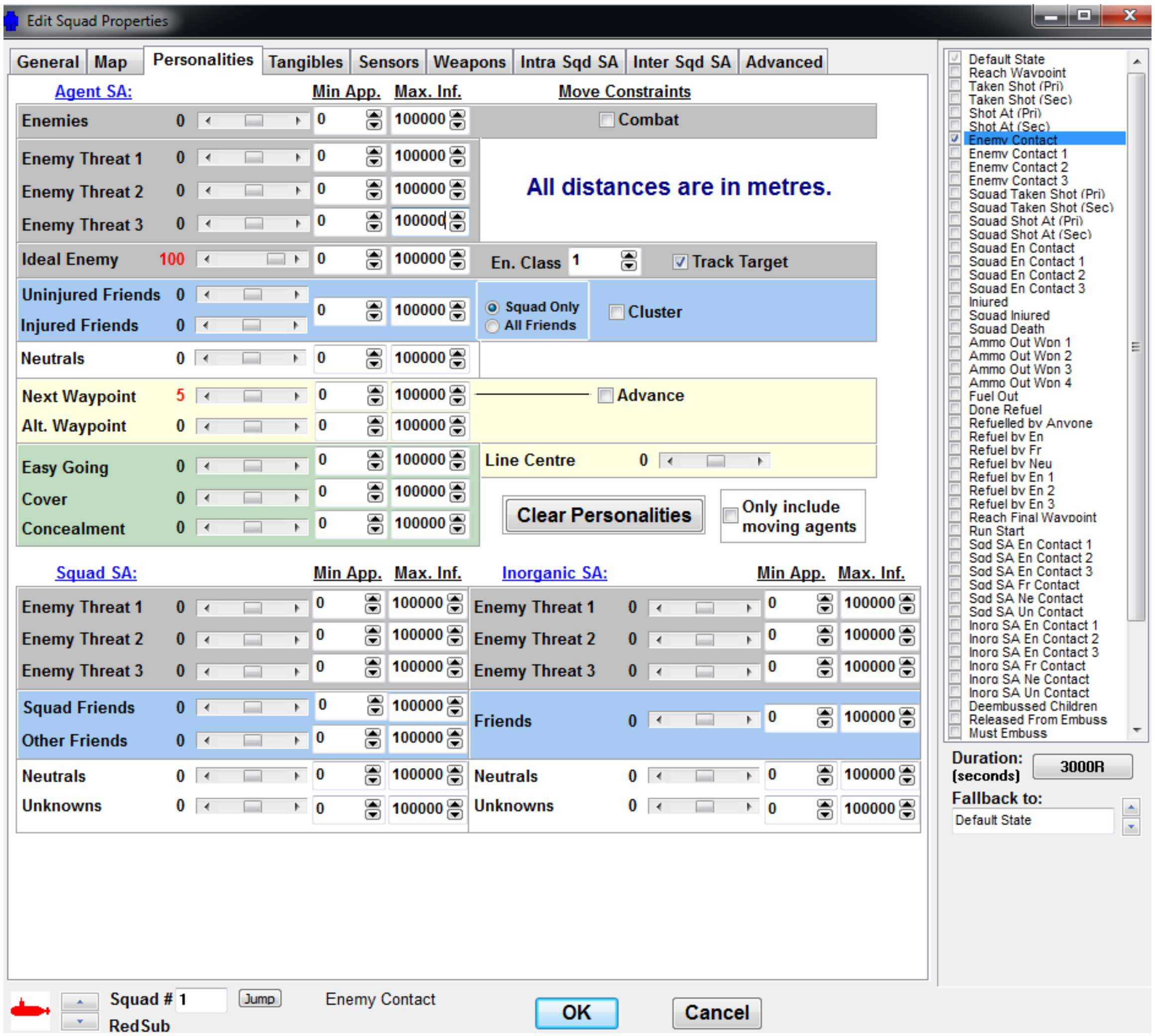


Figure 15. The personality settings of the submarine in enemy contact state.

3. Sensor Behaviors

In the model, sonar is the only detection sensor used by the agents since the submarine is submerged. The escort ships use their hull-mounted sonar while the helicopters and USVs use their dipping sonar in active mode to detect the submarine. The submarine uses its hull-mounted sonar in passive mode to detect the ASW assets. While an advanced (probabilistic) sensor model is used to model the active sonar of ASW units, a cookie-cutter sensor model (see Figure 16) is used to model the passive sonar of the submarine.

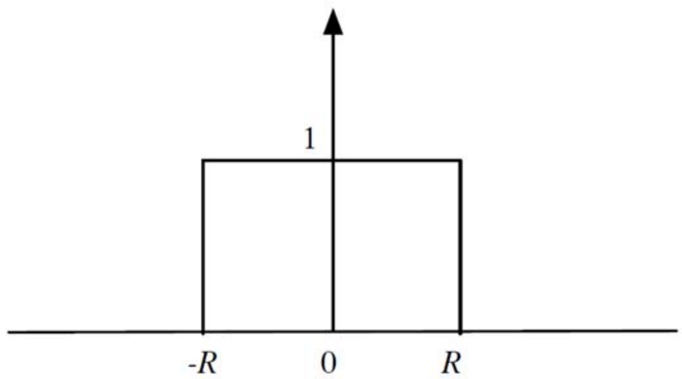


Figure 16. Cookie-cutter sensor.

Two different sensors are modeled as cookie-cutter sensors for the submarine's passive sonar. One sensor type is modeled for counter-detection of ASW units that operate active sonar. The other sensor type is modeled for detecting the HVU, which does not have any acoustic sensors. Because counter-detection of active sonars can be performed at greater ranges than the passive sonar's detection range of the HVU, the counter-detection range is fixed at 18,288 meters (20,000 yards) in this model while the detection range is fixed at 10,973 meters (12,000 yards). A cookie-cutter sensor detects all contacts within its maximum range. Once an ASW asset enters the detection range of the submarine, MANA records the detection and classification with the probability of 1.0. The sensor models are visualized in Figure 17.

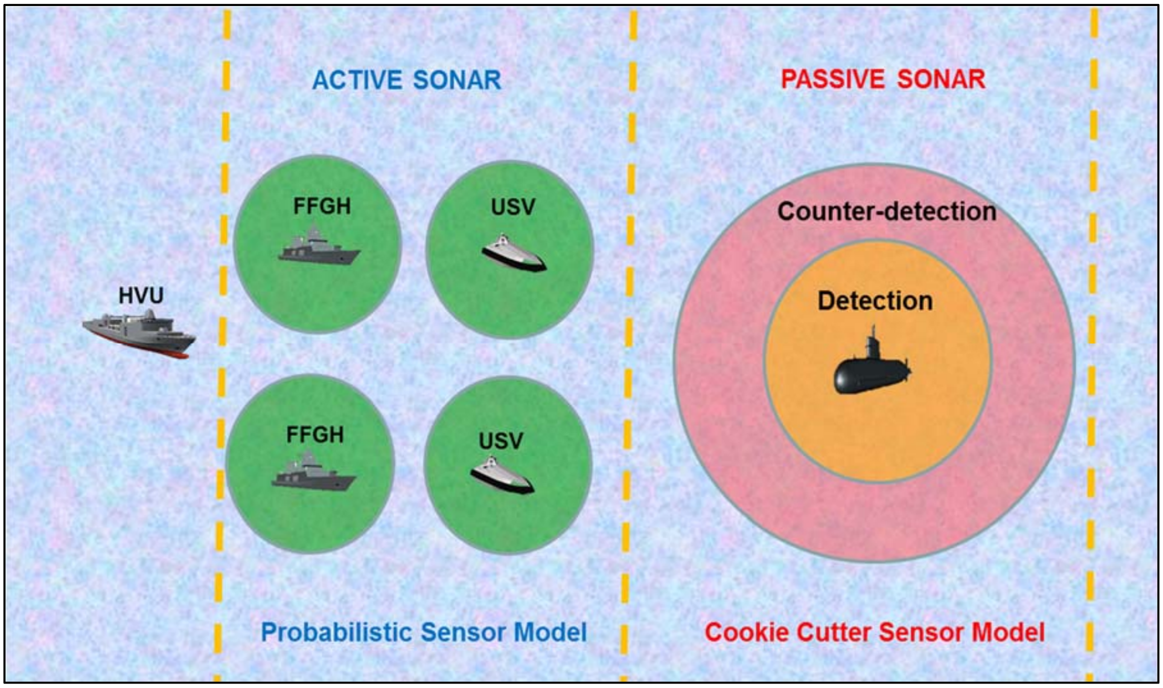


Figure 17. Sensor models.

In MANA, sensor models for the advanced sensor type are defined with a detection range-time table and the classification range-probability table [36]. The detection range-time table defines the average time between detections in seconds for the specified sensor detection range. Figure 18 shows an escort ship's sensor setup panel. In this panel, the detection range of the frigate is set to 10,973 meters (12,000 yards). If an underwater contact moves in the detection range of the sensor, the frigate will detect this contact on average every 300 seconds—with a random draw each time step. For every detection event, the submarine has a chance to hide in the water based on its personal concealment rate. Once a contact has been detected, the ASW unit has to categorize whether the contact is related to a submarine. Detection is a required event for the classification process to occur.

The classification range-probability table determines the probability of classifying the contact for the specified classification range once the detection event occurs. In Figure 18, the classification range is set to 7,315 meters (8,000 yards). This means that if the submarine is in this range, the escort ship has a chance to classify it. If the submarine is in the detection range, but out of the classification range, the detection may be successful, but the classification will not be.

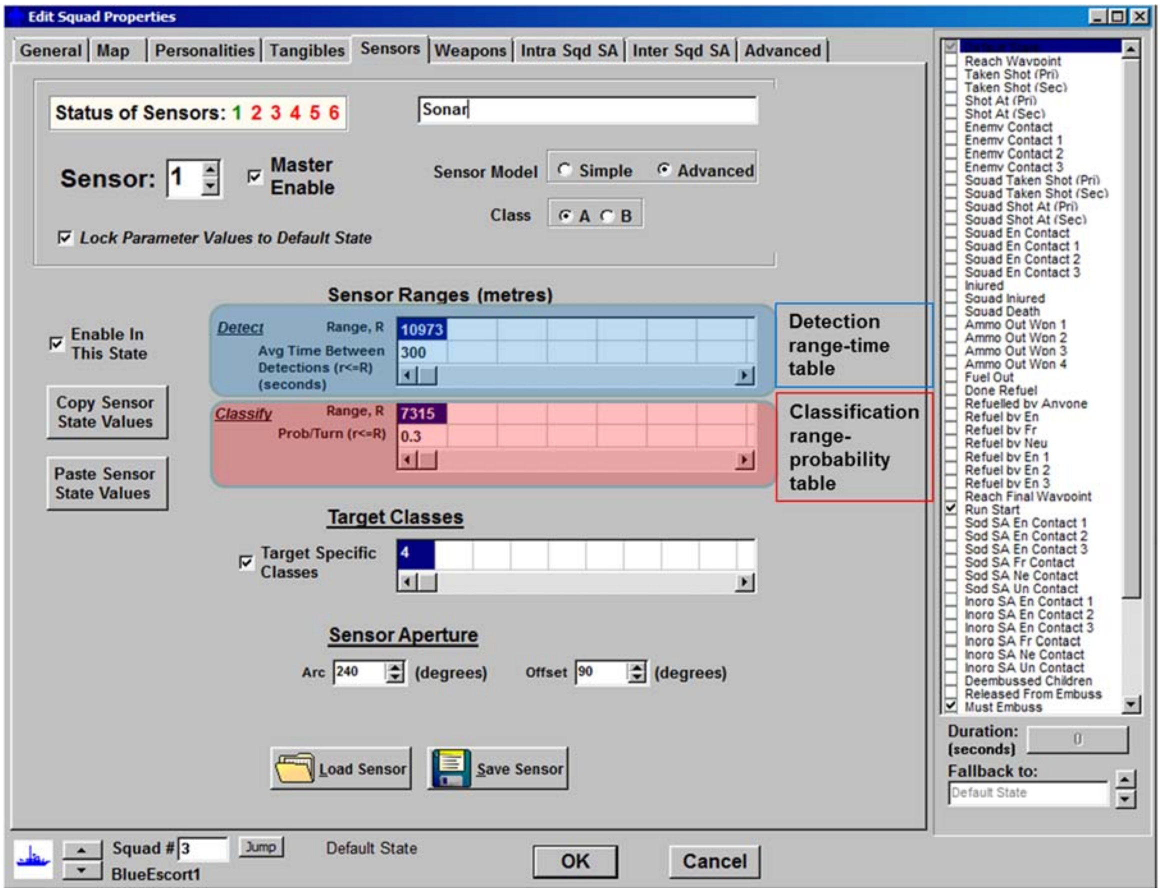


Figure 18. Setup panel for an advanced sensor model.

Detection ranges and classification range intervals for all the agents are summarized in Table 6.

Table 6. Sensor detection ranges and classification range intervals.

Sonar Type		Detection Range	Classification Range Interval	
			Minimum	Maximum
Ship hull-mounted sonar		12000 yards	6000 yards	10000 yards
Dipping sonar		12000 yards	4000 yards	10000 yards
Submarine hull-mounted sonar	**Counter-detection**	20000 yards	20000 yards	
	Detection	15000 yards	15000 yards	

D. STOP CONDITIONS

Stop conditions were introduced to the model to reduce runtime. The simulation stops when one of the following conditions happens (see Figure 19):

- The submarine is classified by one of the ASW units;
- The submarine reaches the TDZ around the HVU; or
- The HVU reaches its final waypoint.

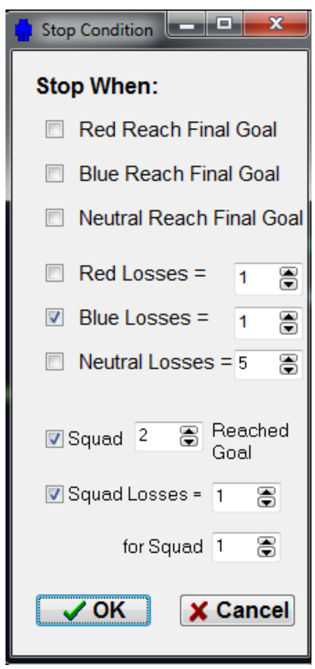


Figure 19. Stop conditions.

E. SCENARIO ASSUMPTIONS AND LIMITATIONS

Scenario assumptions and limitations are vital to a successful study. It is necessary to make acceptable assumptions and define limitations to create a model realistic enough to obtain useful insights.

1. Assumptions

a. Friendly Forces

(1) USVs are launched from surface warships and they are fully autonomous.

(2) USVs meet autonomous requirements, such as station-keeping.

(3) Helicopters and USVs use a *Sprint & Drift* tactic. They sprint ahead to the next dip location, and once there, they drift or hover on the water and lower and operate their dipping sonar.

(4) Dipping points are semi-randomized in the area of interest.

(5) Once an ASW unit detects an underwater contact, it can execute the classification process itself.

(6) Each unit has a chance of classifying the submarine for every detection event.

b. Enemy

(1) The submarine operates submerged during the simulation. By doing this, it minimizes detection by the ASW forces.

(2) The submarine's initial position is selected at random in its homebox.

(3) The submarine does not attack frigates, helicopters, or USVs. Its only target is the HVU.

2. Limitations

We defined the limitations of MANA when building the model. These limitations must be considered in the analysis chapter. The first and most important one is that it is very hard to implement an advanced naval formation, such as an ASW screen formation, in MANA. Another limitation is that the level of classification is limited to a binary response: *0* or *1*. For us, 0 represents the levels non-submarine (NONSUB) and doubtful (POSSUB and PROBSUB) levels, and 1 represents the certain submarine (CERTSUB) level. Also, it is difficult to simulate the underwater environment. The changes in the environmental conditions are simulated by varying detection chances and classification probabilities. Finally, the submarine's actual depth is not explicitly simulated. The submarine can hide below thermal layers, beneath undersea mountains, or on the sea floor. The submarine's concealment rate per detection event accounts for the submarine's stealthiness.

IV. MODEL EXPLORATION

A. DESIGN OF EXPERIMENTS

The Design of Experiments (DOE) is a practical approach for large-scale experiments to examine design factors and determine the relationship between design factors and output responses. In experimental terminology, design factors are the input variables, and output responses are the measures of effectiveness or performance [39].

Although cluster computers can run simulations very quickly, it is an impossible task to run all possible design points. The quality of the results can be determined by the model runs. An efficient design is needed to analyze a sufficient breadth of possible outcomes. Otherwise, we may limit the insights in the analysis.

In this thesis, a nearly orthogonal Latin hypercube (NOLH) spreadsheet developed by Susan Sanchez is used to generate the design points [40]. The advantage of using an NOLH design is that it has good space-filling properties and meets the orthogonality criteria necessary for good statistical properties of analysis methods. This design can provide efficient information about the experiment. A well-designed NOLH allows the analyst to efficiently explore more factors across the design space and fit a variety of diverse models to multiple different response variables. A scatterplot matrix in Figure 20 shows the space-filling properties of our NOLH design.

The NOLH design spreadsheet allows us to create an efficient design and saves time and effort. Different designs are available on this spreadsheet based on the number of design factors. A design with more design points is a favorable thing, but not required. We choose the 16-factor design to build our experimental design. The design points used in this study are provided in Appendix A.

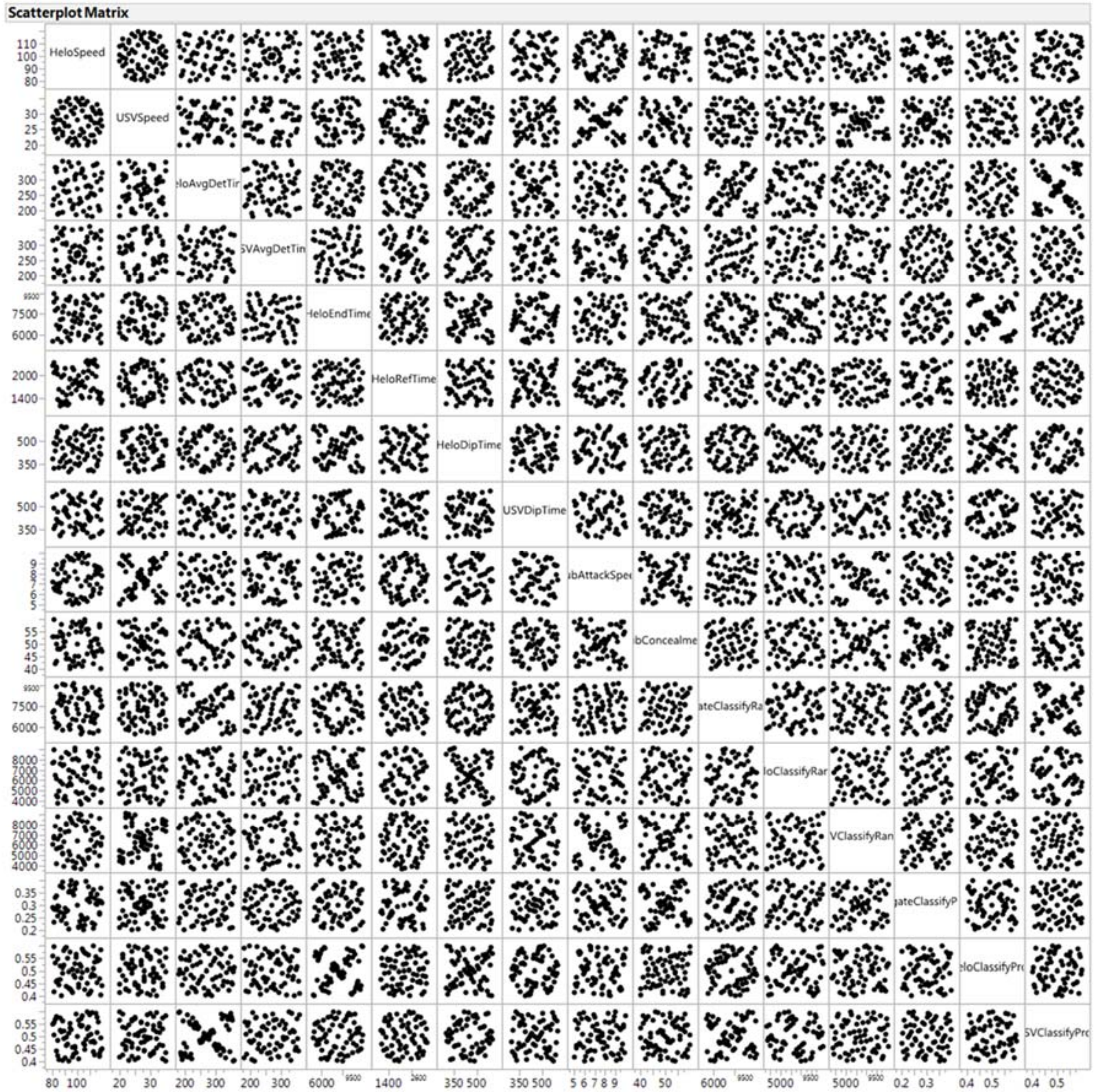


Figure 20. Scatterplot matrix for the design factors.

B. DESIGN FACTORS

In an ASW scenario, many factors may affect the outcome. In total, 16 factors were varied in the simulation for each scenario. Design factors can be divided into two groups: controllable and uncontrollable factors. These factors are varied over a range in order to explore their effects on the outcome. They are explained in the following sections. Table 7 shows the list of factors with their ranges, units, and explanations.

Table 7. Description of controllable and uncontrollable factors.

Factor	Explanation	Minimum	Maximum	Unit
Controllable Factors				
HeloSpeed	Helicopter Speed at Default State	80	120	knot
USVSpeed	USV Speed at Default State	20	35	knot
HeloAvgDetTime	Helicopter Sonar Average Time Between Detections at Default State	180	360	second
USVAvgDetTime	USV Sonar Average Time Between Detections at Default State	180	360	second
HeloEndTime	Helicopter Endurance (Duration Time of Escort Ships' Run Start State)	5400	9000	second
HeloRefTime	Helicopter Refuel Time (Duration Time of Escort Ships' Embussed Children State)	1200	2400	second
HeloDipTime	Helicopter Dipping Time (Duration Time of Helicopters' Spare1 State)	300	600	second
USVDipTime	USV Dipping Time (Duration Time of USVs' Spare1 State)	300	600	second
FrigateClassifyRange	Frigate Sonar Classification Range	5486	9144	meter
HeloClassifyRange	Helicopter Sonar Classification Range	3658	9144	meter
USVClassifyRange	USV Sonar Classification Range	3658	9144	meter
FrigateClassifyProb	Frigate Classification Probability	0.2	0.4	-
HeloClassifyProb	Helicopter Classification Probability	0.4	0.6	-
USVClassifyProb	USV Sonar Classification Probability	0.4	0.6	-
Uncontrollable Factors				
SubAttackSpeed	Submarine Attack Speed at Enemy Contact State	5	10	knot
SubConcealment	Submarine Personal Concealment per Detection	40	60	%

1. Controllable Factors

Controllable factors are related to the decisions of friendly assets, which can be decided upon in advance or during the mission. In this model, they are all related to the characteristics of the frigate, helicopter, and USV. Controllable factors included the movement speed, dipping time, endurance time, refuel time, average time between detections, classification range, and classification probability.

a. Movement Speed

The movement speed is varied in the experimental design to determine whether this factor has an effect on mission success. Because the most considerable strength of the helicopter is its high speed capability, it can execute the dipping process easily over a large area. However, its endurance is limited. Once the helicopter runs out of fuel, it moves back to the mother ship, refuels, and deploys to the station again. Four states are defined to simulate the dipping process. In "Default State," a helicopter moves to the next dipping location with a speed of 80 to 120 knots. In a trigger state, the speed of the helicopter is set to zero since it hovers over the water.

The helicopters are significantly faster than the USVs. This factor may give the helicopters an advantage over USVs in terms of mobility. USVs execute the dipping process the same way as the helicopter. When a USV is in "Default State," it moves to the next dipping location with a speed of 20 to 35 knots. In a trigger state, it drifts on the water with zero speed.

b. Sensors

The main focus of the defensive ASW operations is the ability to detect and classify the enemy submarine. Since using active sonar is the primary method to detect and classify the diesel-electric submarine, the frigate uses a hull-mounted sonar, and the helicopter and USV use dipping sonars in active mode. The sensor parameters are mostly controllable because the selection of the sensor type and capability can be decided during the design process. But, the effectiveness of a sonar is limited by environmental conditions. In our model, we consider the sensor parameters only partly controllable.

The helicopter and USV use the same sensor type in the model. The performance of the sonar for each platform can be evaluated by varying three factors: the time interval between consecutive detections, classification range, and classification probability. These factors relate to the helicopter and USV varied independently over the same range. So, we can explore three different cases: a better sonar performance for the USV, a better performance for the helicopter, and the same performance for both platforms.

We define the time interval between consecutive detections as the period between the event initiation and completion. This is a simplification of simulating detection chances. The other states are locked to the default state, so varying the average time between detections in the default state is enough. Thus, it is desirable to have the mean detection time as small as possible.

The classification ranges of the platforms provide a reduced danger area. If the platforms have a short classification range, then the submarine has a good chance of penetrating the ASW screen. In ASW, the classification range depends on underwater conditions, background noise in the ocean, and sonar capability.

The other sensor parameter is the classification probability. In ASW, this factor may depend on target characteristics or the training of the operators. For USVs, it may depend on the development and performance of automatic detection and classification systems and techniques.

c. Tactical Employment of ASW Assets

Six scenarios were built to explore the use of the combinations of frigates, helicopters, and USVs. The name of the scenarios is viewed as a categorical factor for a quick comparison of the scenarios. We expanded this factor into three different categorical factors for partition tree and regression analysis: the number of available frigates, helicopter presence, and USV presence. These factors relate to the tactical employment of the helicopters and USVs as well as the design of the ships. The factors related to the scenarios are shown in Table 8.

Table 8. The factors related to scenario setup.

Scenario	The Number of Available Frigates	Helicopter Presence (1=Yes, 0=No)	USV Presence (1=Yes, 0=No)
Baseline Scenario	2	1	0
Scenario Two	2	0	1
Scenario Three	2	1	1
Scenario Four	3	1	0
Scenario Five	3	0	1
Scenario Six	3	1	1

2. Uncontrollable Factors

Uncontrollable factors are related to the enemy and uncertainty in the combat environment. There are two factors regarding the enemy submarine: attack speed and personal concealment per detection opportunity.

a. Speed

The submarine patrols at 3 knots in its homebox. When it detects an ASW unit, it changes its state to "Enemy Contact State" and tries to penetrate the ASW screen by increasing its speed. The speed of the submarine in "Enemy Contact State" is a factor that ranges from 5 to 10 knots.

b. Stealth

The submarine is designed to submerge and maneuver quietly to avoid detection. In a noisy littoral environment, the submarine gains extra stealth. The submarine can find shadow zones to hide from active sonar and approach an enemy without being detected. This factor was simulated in MANA using the personal concealment per detection feature. This factor represents a probability of stealth per detection event. The stealth of the submarine is varied between 40% and 60% in the experimental design.

C. DATA ANALYSIS

After explaining the model development, experimental design, and design factors, we now focus on data analysis. In this section, model runs, our analysis tools, and measures of effectiveness are described briefly. This is followed by a comparison of the scenarios, regression analysis, and partition trees.

1. Model Runs

Using the NOLH design for 16-factors, 65 design points were created for each scenario. Each design point was run 1,000 times, resulting in 65,000 simulated ASW missions for each scenario. The time step in this model is fixed to one second because it was observed that large time steps led to unusual behaviors. Since there are six different scenarios being evaluated, a total of 390,000 runs were executed. On average, each model run takes approximately one minute of computer runtime on a personal computer. As expected, the more agents that are included in the model, the longer the runtime it takes. For example, the scenarios with three frigates take more time to run than the scenarios with two frigates. This is because each additional agent and its interactions with the others will require considerably larger computational effort.

On a personal computer it would take approximately 250–300 days to complete this experiment and get the data. Fortunately, the Naval Postgraduate School's Simulation Experiments & Efficient Design (SEED) Center offers a great computational resource for thesis students. The SEED Center can use over a hundred processors in parallel to make MANA runs. With this advantage, all of the runs were completed and the data was synthesized into a single comma-separated (CSV) file in just a few days.

2. Analysis Tool

The analysis tool used in this study is JMP, a statistical analysis tool developed by the JMP business unit of SAS Institute. It is very useful to the analyst for investigating and exploring the data. This software is used to interpret the data by performing analyses and creating graphs, data tables, charts, and reports. JMP automatically displays statistical text as well as graphs and charts; this makes it a user-friendly analysis tool. The edition utilized in this study is JMP Pro 12.

3. Measure of Effectiveness

In this study, mission success is considered classifying the submarine before it enters the TDZ around the HVU. Two measures can be defined to represent this goal: the proportion of successful classification and the time to classify the submarine. The first MOE is the success rate, which represents the proportion of classification. The result of each run is a binary output: 1 or 0. “1” means that the submarine is classified and “0” means that the underwater contact isn’t detected or isn’t classified as a submarine before the submarine enters the TDZ. The average of the binary data gives us the overall proportion of 1s in the output for each design point. If an ASW asset classifies the submarine, we assume this reduces the risk for the HVU. We also assess the effectiveness of each scenario by quantifying the time to classify the submarine. This measure is defined as our second MOE. That is, the earlier a submarine is detected, the better it is for the defenders. In some cases, early detection and classification is critical for decision-makers since it plays an important role in keeping the HVU out of harm’s way.

4. A Quick Comparison of the Scenarios

Two MOEs are used for evaluating the effectiveness of deployment tactics. The first MOE is the proportion of mission success, which represents the overall probability of classification before the submarine reaches the TDZ. The second MOE is the time to classify the submarine.

A single CSV file with 390,000 rows of raw data is imported into the analysis tool JMP. First, we create a summary data table with all the raw data by averaging the MOE1 (mission success) column for each scenario. For the Baseline Scenario, the mean of success in the overall replications is around 0.383. The success rate in the other scenarios differs due to the number and variety of the platforms. Scenario Six gives the highest success rate, since more platforms are employed than in the other scenarios. Table 9 shows the success rate based on different scenarios.

Table 9. The proportion of successful classification in the overall replications.

Scenario Name	Number of Replication	Number of Success	Success Rate
Baseline Scenario	65000	24953	0.383892308
Scenario Two	65000	24578	0.378123077
Scenario Three	65000	30752	0.473107692
Scenario Four	65000	29108	0.447815385
Scenario Five	65000	28664	0.440984615
Scenario Six	65000	34947	0.537646154

The scenarios are grouped to create different datasets. Because the factors and their ranges are identical for all scenarios, we can directly compare them. From this comparison, we can determine how a change in the configuration of ASW assets affects the MOE. Side-by-side box plots are particularly useful when comparing different datasets. They provide us a quick comparison of the scenarios. This comparison can help a tactical commanders choose an appropriate configuration of ASW assets. For each scenario, a box is created extending from the 25th percentile to the 75th percentile. The 50th percentile is the median, which is drawn inside the box. *Whiskers* are the lines that limit a subset of the data, outside the box.

We created two different side-by-side box plots: the proportion of successful classification versus scenario and time steps to classification versus scenario. Figure 21 displays a comparison of the average mission success versus scenario. The box plot for Scenario Six gives higher results on the average mission success scale than the others. While the Baseline Scenario and Scenario Two look similar to each other, Scenario Four and Scenario Five also look similar.

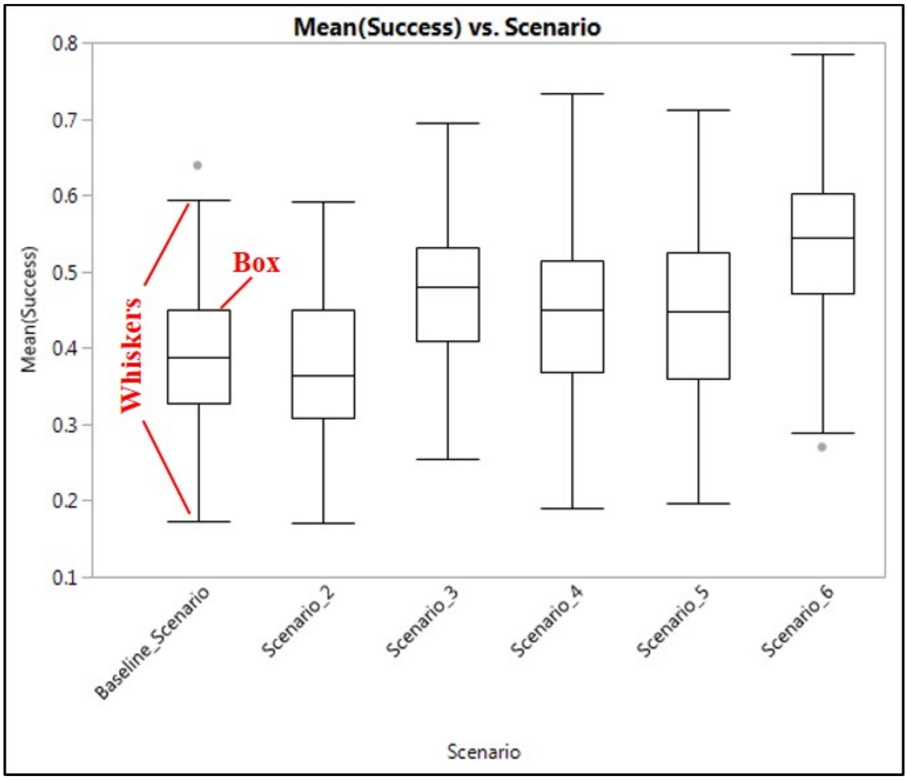


Figure 21. Comparative boxplots: Mean(success) vs. scenario.

We basically see that while assuming the helicopter and USV have the same sensor type and capability, the classification effectiveness of the ASW screen will be approximately the same. So, we turn to the second MOE, time to classify, to see if there is a difference. We take a subset of data for every level of the *Mission Success* column. This created two different data tables: *Mission Success=1* and *Mission Success=0.* Between them, the *Mission Success=1* data table is the one that we will use to quantify the second MOE. The *Steps* column gives the number of time steps in a scenario until the submarine is classified. The distributions of the "Steps" column by scenarios are provided in Appendix B. Figure 22 displays a comparison of the average steps versus scenario. When we look at the side-by-side box plot, firstly, we realize that the box plots of Scenario Three and Scenario Six resemble each other and that the average time steps are significantly less than in the other scenarios. Employing the helicopters and USVs together in an ASW screen formation will give us an early detection and classification capability. The early detection and classification of the submarine is a crucial factor in

ASW because they enable the task force commander to easily keep the HVU outside of the danger zone of the enemy submarine.

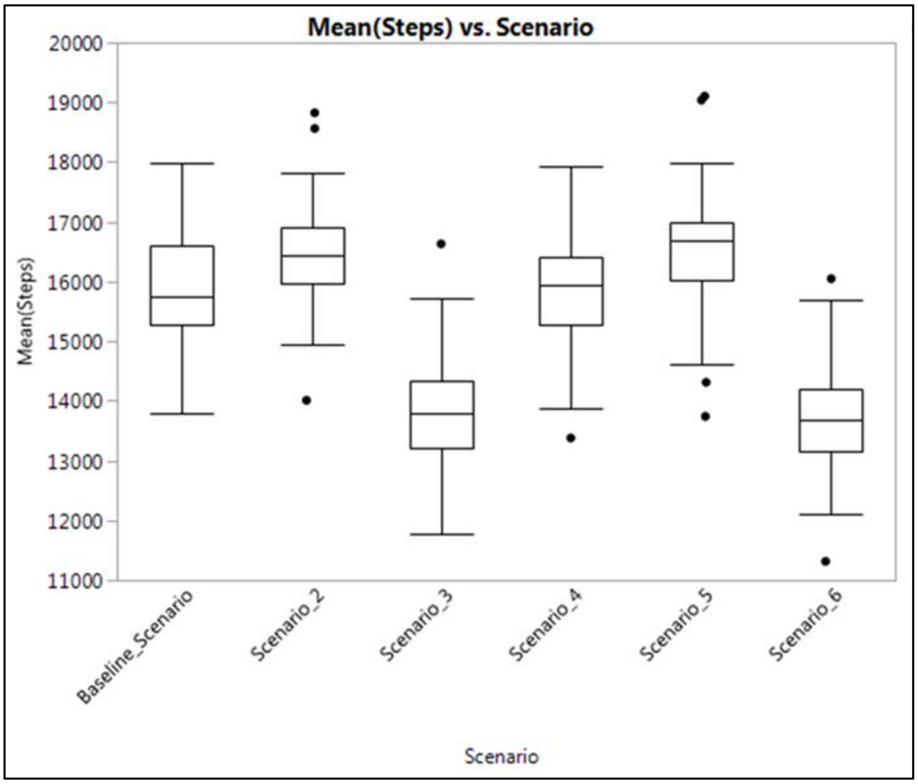


Figure 22. Comparative boxplots: Mean(steps) vs. scenario.

5. One-way Analysis of the Means by Scenarios

A *t*-test is used to examine the difference between two means and assumes that the samples are randomly drawn from normal populations; though the test is robust to nonnormality). In this study, the six scenarios are independent; therefore, another way of comparing the scenario means is by using a *t*-test. In this test, we use a significance level of $\alpha < 0.05$.

a. The Proportion of Successful Classification

The scenarios were built to explore how different combinations of frigates, helicopters, and USVs contribute to the detection and classification of the submarine. The proportion of classification is the first measure for the comparison of the scenarios. We use JMP to perform multiple pairwise comparisons of group means. Figure 23 shows the visual comparison of the scenario means in terms of the proportion of classification. Interpreting the comparison circles is a basic way to compare group means. If the comparison circles for different scenarios do not intersect or intersect slightly, the means of the scenarios are statistically significantly different. If the comparison circles for different scenarios intersect or intersect by an angle of higher than 90 degrees, the means of the scenarios are not significantly different. From Figure 23, we can interpret that the Baseline Scenario and Scenario Two are not significantly different. Scenario Six (with three of all the assets) is the only one that is significantly different than all the other scenarios.

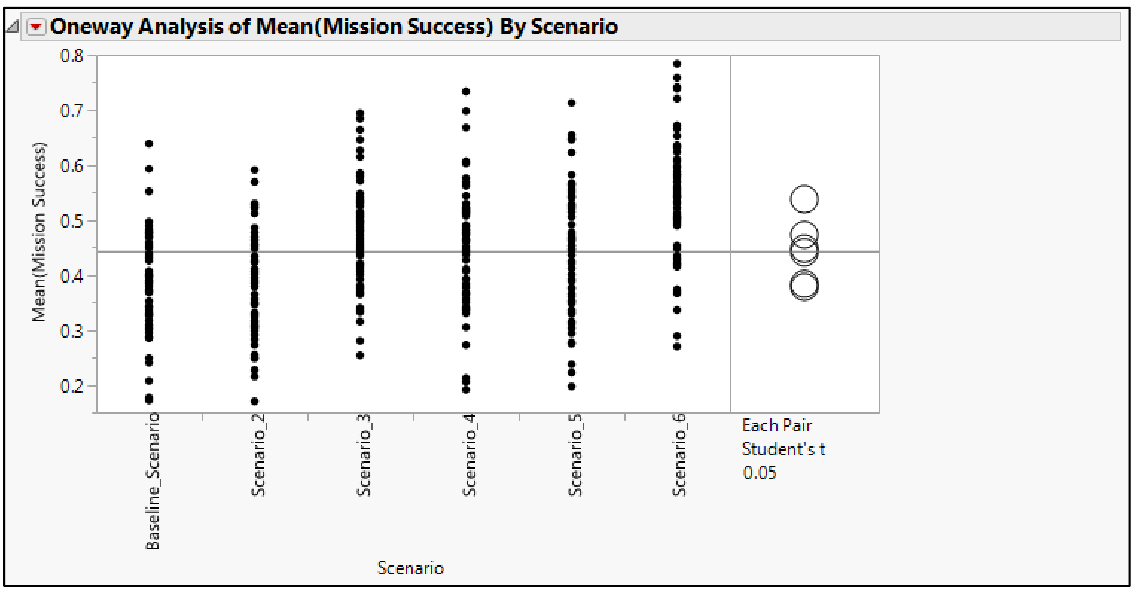


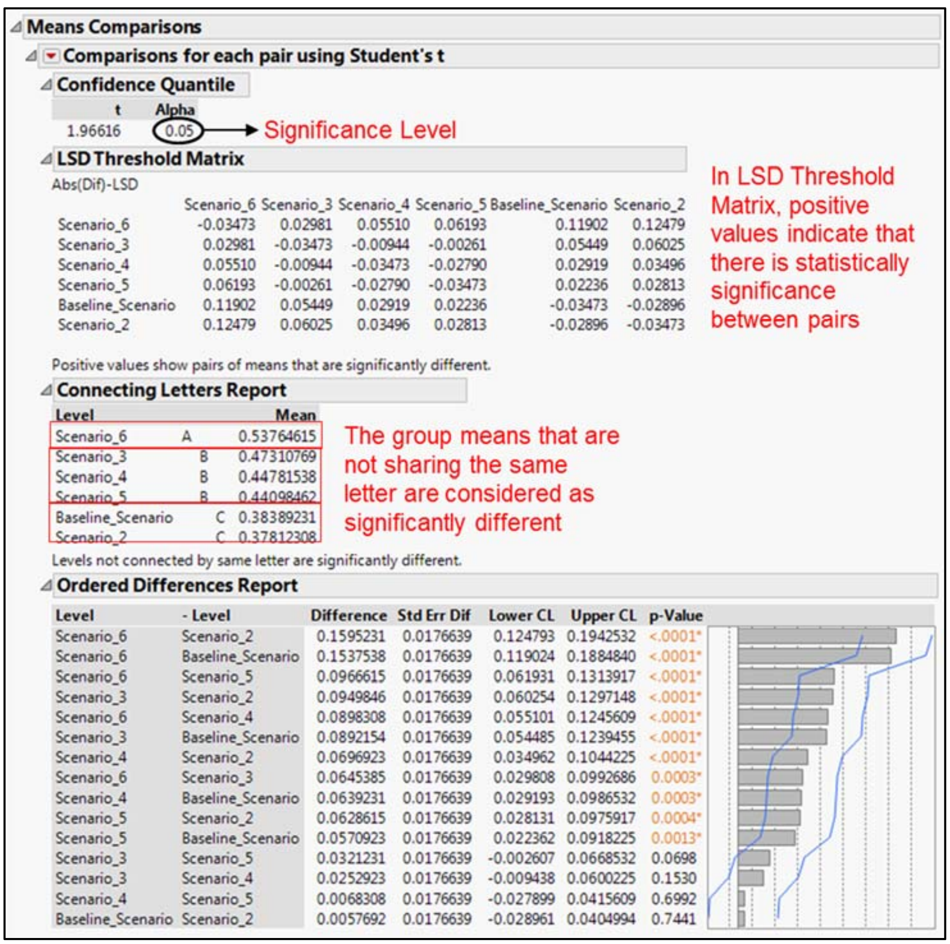
Figure 23. The visual comparison of the scenario means in terms of the proportion of classification.

From the detailed results, as shown in Figure 24, we can see that there are four comparisons among all pairwise comparisons where no statistically significant difference is found:

- **Baseline Scenario** where two frigates and two helicopters are employed and **Scenario Two** where two frigates and two USVs are employed.

- **Scenario Four** where three frigates and three helicopters are employed and **Scenario Five** where three frigates and three USVs are employed.
- **Scenario Three** where two frigates, two helicopters, and two USVs are employed and **Scenario Four** where three frigates and three helicopters are employed.
- **Scenario Three** where two frigates, two helicopters, and two USVs are employed and **Scenario Five** where three frigates and three USVs are employed.

The other pairwise comparisons show that there is a statistically significant difference. A detailed report that compares each pair is provided in Appendix C.



Means Comparisons

Comparisons for each pair using Student's t

Confidence Quantile

t	Alpha
1.96616	0.05

LSD Threshold Matrix

Abs(Dif)-LSD

	Scenario_6	Scenario_3	Scenario_4	Scenario_5	Baseline_Scenario	Scenario_2
Scenario_6	-0.03473	0.02981	0.05510	0.06193	0.11902	0.12479
Scenario_3	0.02981	-0.03473	-0.00944	-0.00261	0.05449	0.06025
Scenario_4	0.05510	-0.00944	-0.03473	-0.02790	0.02919	0.03496
Scenario_5	0.06193	-0.00261	-0.02790	-0.03473	0.02236	0.02813
Baseline_Scenario	0.11902	0.05449	0.02919	0.02236	-0.03473	-0.02896
Scenario_2	0.12479	0.06025	0.03496	0.02813	-0.02896	-0.03473

Positive values show pairs of means that are significantly different.

Connecting Letters Report

Level		Mean
Scenario_6	A	0.53764615
Scenario_3	B	0.47310769
Scenario_4	B	0.44781538
Scenario_5	B	0.44098462
Baseline_Scenario	C	0.38389231
Scenario_2	C	0.37812308

Levels not connected by same letter are significantly different.

Ordered Differences Report

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
Scenario_6	Scenario_2	0.1595231	0.0176639	0.124793	0.1942532	<.0001*
Scenario_6	Baseline_Scenario	0.1537538	0.0176639	0.119024	0.1884840	<.0001*
Scenario_6	Scenario_5	0.0966615	0.0176639	0.061931	0.1313917	<.0001*
Scenario_3	Scenario_2	0.0949846	0.0176639	0.060254	0.1297148	<.0001*
Scenario_6	Scenario_4	0.0898308	0.0176639	0.055101	0.1245609	<.0001*
Scenario_3	Baseline_Scenario	0.0892154	0.0176639	0.054485	0.1239455	<.0001*
Scenario_4	Scenario_2	0.0696923	0.0176639	0.034962	0.1044225	<.0001*
Scenario_6	Scenario_3	0.0645385	0.0176639	0.029808	0.0992686	0.0003*
Scenario_4	Baseline_Scenario	0.0639231	0.0176639	0.029193	0.0986532	0.0003*
Scenario_5	Scenario_2	0.0628615	0.0176639	0.028131	0.0975917	0.0004*
Scenario_5	Baseline_Scenario	0.0570923	0.0176639	0.022362	0.0918225	0.0013*
Scenario_3	Scenario_5	0.0321231	0.0176639	-0.002607	0.0668532	0.0698
Scenario_3	Scenario_4	0.0252923	0.0176639	-0.009438	0.0600225	0.1530
Scenario_4	Scenario_5	0.0068308	0.0176639	-0.027899	0.0415609	0.6992
Baseline_Scenario	Scenario_2	0.0057692	0.0176639	-0.028961	0.0404994	0.7441

Figure 24. Comparison of each pair for the proportion of successful classification using Student's *t*-test.

The Connecting Letters Report is the simple way to analyze the differences between group means. The highest group mean is always shown on the top. Scenario Six has the highest group mean amongst the other scenarios—this is where the largest number of sensors are employed in the ASW screen formation. Scenario Three, Scenario Four, and Scenario Five form the first group, and Baseline Scenario and Scenario Two form the second group that share the same letter in the report. From these results, we can say that the scenarios that have the same number of sensors are not considered as significantly different.

b. Time to Classify the Submarine

Figure 25 shows the visual comparison of the scenario means for the time to classify measure of effectiveness. By looking at the comparison circles, one can see that Baseline Scenario and Scenario Four, Scenario Two and Scenario Five, and Scenario Three and Scenario Six do not display a significantly different group means. If time is an important factor on the mission, the ASW screen planning method should be considered an important factor.

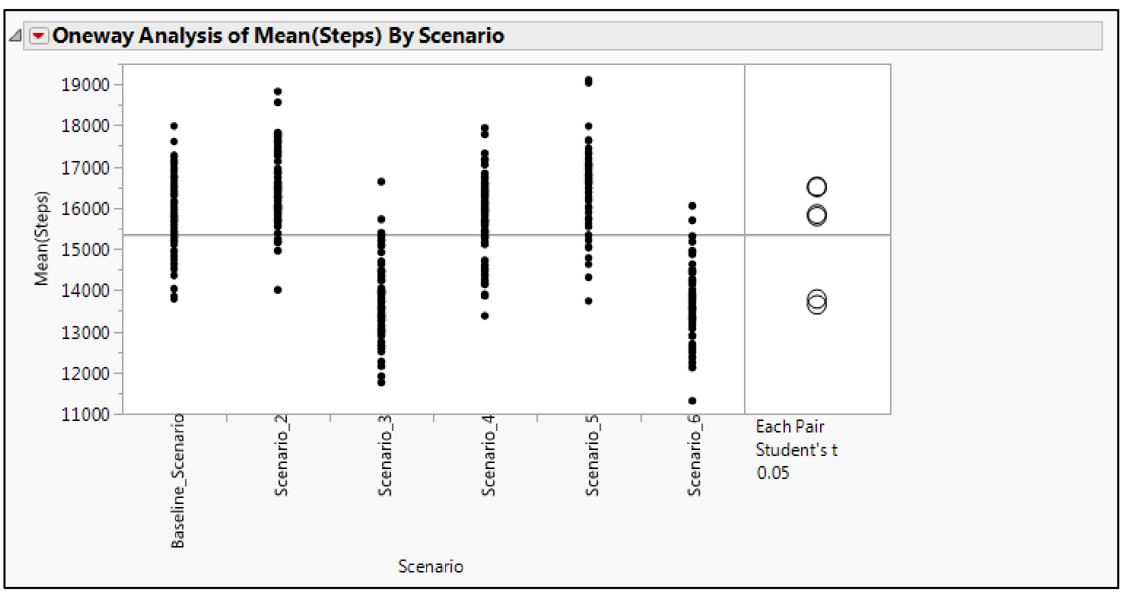


Figure 25. The visual comparison of the scenario means in terms of the time to classify.

From the detailed results, as shown in Figure 26, one can say that there are three comparisons among all pairwise comparisons where no statistically significant difference is found:

- **Baseline Scenario** and **Scenario Four**, where the frigates are employed in the inner screen and the helicopters in the outer screen.
- **Scenario Five** and **Scenario Two**, where the frigates are employed in the inner screen and the USVs in the intermediate screen.
- **Scenario Three** and **Scenario Six**, where the frigates are employed in inner screen, the USVs in the intermediate screen, and the helicopters in the outer screen.

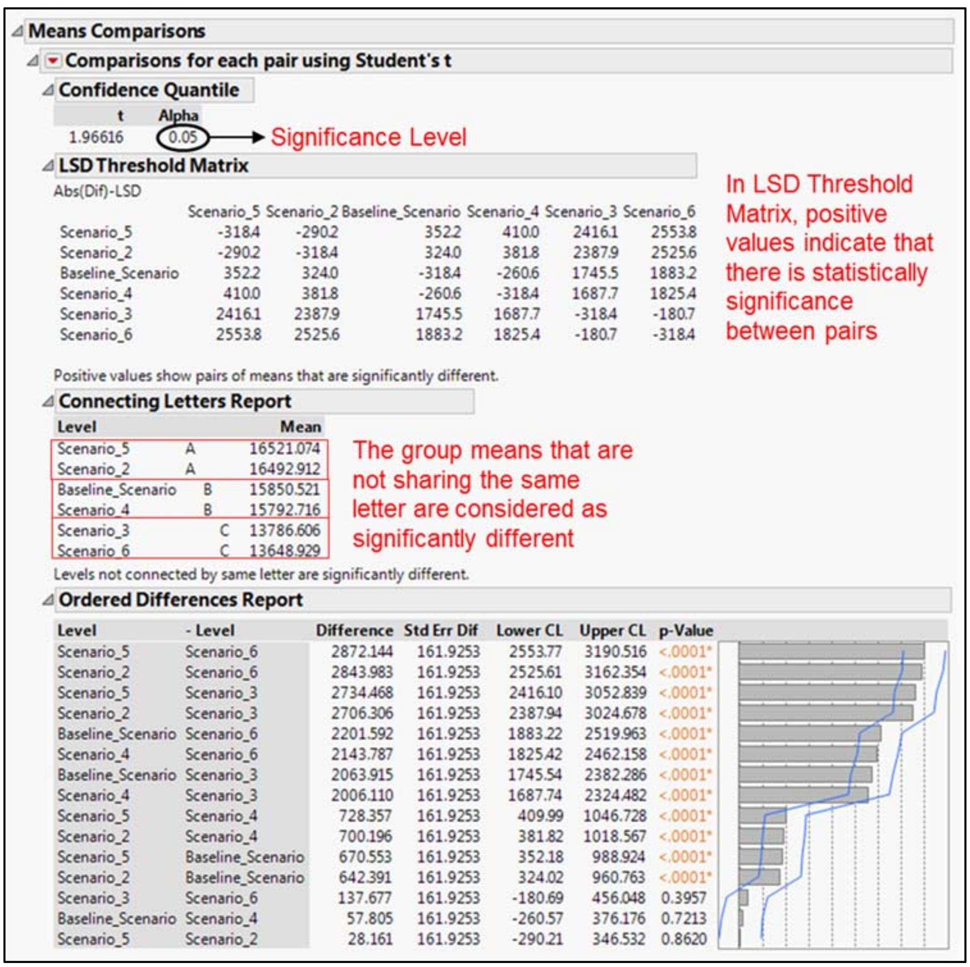


Figure 26. Comparison of each pair for time to classify using Student's *t*-test.

The other pairwise comparisons show that there is a statistically significant difference. A detailed report that compares each pair is provided in Appendix D.

6. Regression Analysis

Regression analysis is used in simulation analysis for quantifying the relationships among variables. Multiple linear regression is used in this analysis.

a. Multiple Linear Regression

Multiple linear regression is used to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. The mean response is modeled as a function of multiple variables. A multiple linear regression with p explanatory variables has an equation of the form $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p$, where $x_1, x_2 \ldots x_p$ are the explanatory variables and y is the response variable.

MANA uses a random number generator to randomize many properties in the scenarios. Therefore, the scenarios can produce different results for any design point each time they are run. The mission success is the response variable to conduct a multiple linear regression. Since the response variable has two levels, it is hard to fit a linear regression model. Another way to fit a linear regression is to summarize the data by calculating the means of each input combination. Therefore, a probability of mission success is produced for each design point. This new data table consists of 390 rows and a new response variable named *Mean(Mission Success)*, which is a continuous variable that ranges from zero to one. By fitting a linear regression model, we can predict the probability that the response is equal to one (success).

In this new table, the data points for Scenario Two and Scenario Four are excluded. We assume that the frigates and helicopters have already employed in all the scenarios. The number of frigates and USV presence are considered as categorical factors to explore their effectiveness on the response.

We examine the distribution of the mean of the response using the distribution platform in JMP. Figure 27 shows that the mean of the response is approximately normally distributed with a mean of 0.461 and standard deviation of 0.114.

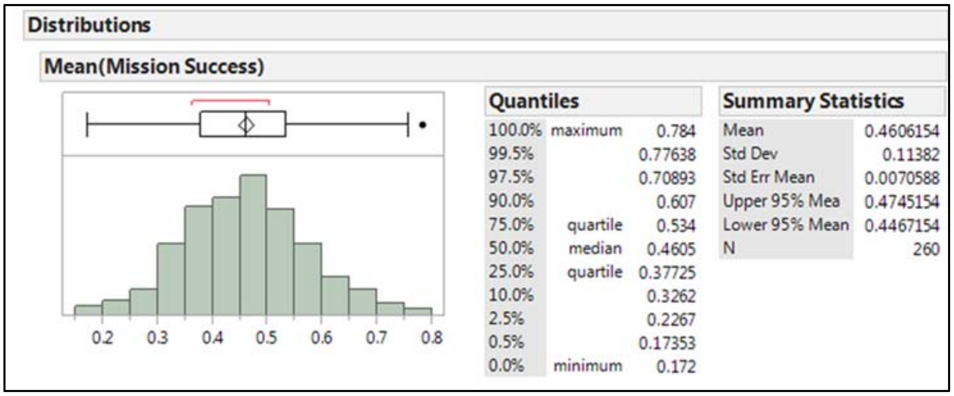
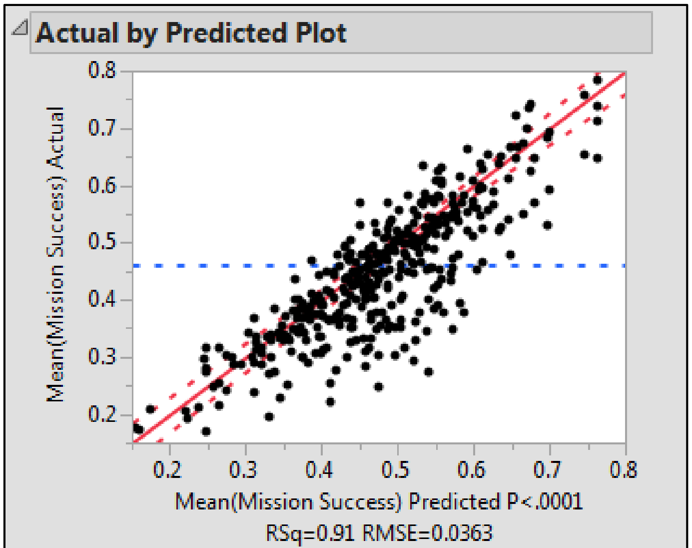


Figure 27. Distribution for the mean response.

b. Main Effects Model

In order to understand the relationship between the input factors and response, a model is fitted using only the main factors without any interactions. We look at the actual by predicted plot to evaluate the goodness of fit of the model. From Figure 28, the actual by predicted plot shows that the model fits the data quite well. In this model, the R-squared value is around 0.91. The R-squared value is a statistical measure which represents how well the regression line approximates the data points. This model explains 91% of the variance of the data.



Summary of Fit

RSquare	0.905435
RSquare Adj	0.898372
Root Mean Square Error	0.036285
Mean of Response	0.460615
Observations (or Sum Wgts)	260

Figure 28. Actual by predicted plot and the summary of the fit for the main effects model.

Is this main effect model the correct model to capture the relationship between the input factors and response variable? To answer this question, we examined four different assumptions related to the residuals. A residual value represents the distance between the observed value and the fitted value in the model. A graphical representation is an effective way to evaluate the adequacy of the model. Figure 29 displays the distribution of the residuals with graphs, quantiles, and summary statistics. From Figure 29, we see two assumptions are satisfied: the residuals are approximately normally distributed, and the mean of the residuals is approximately equal to zero. A normal Q-Q plot is also used to assess the normality. We can see that the approximate linearity of the points on this plot indicates that the residuals are normally distributed.

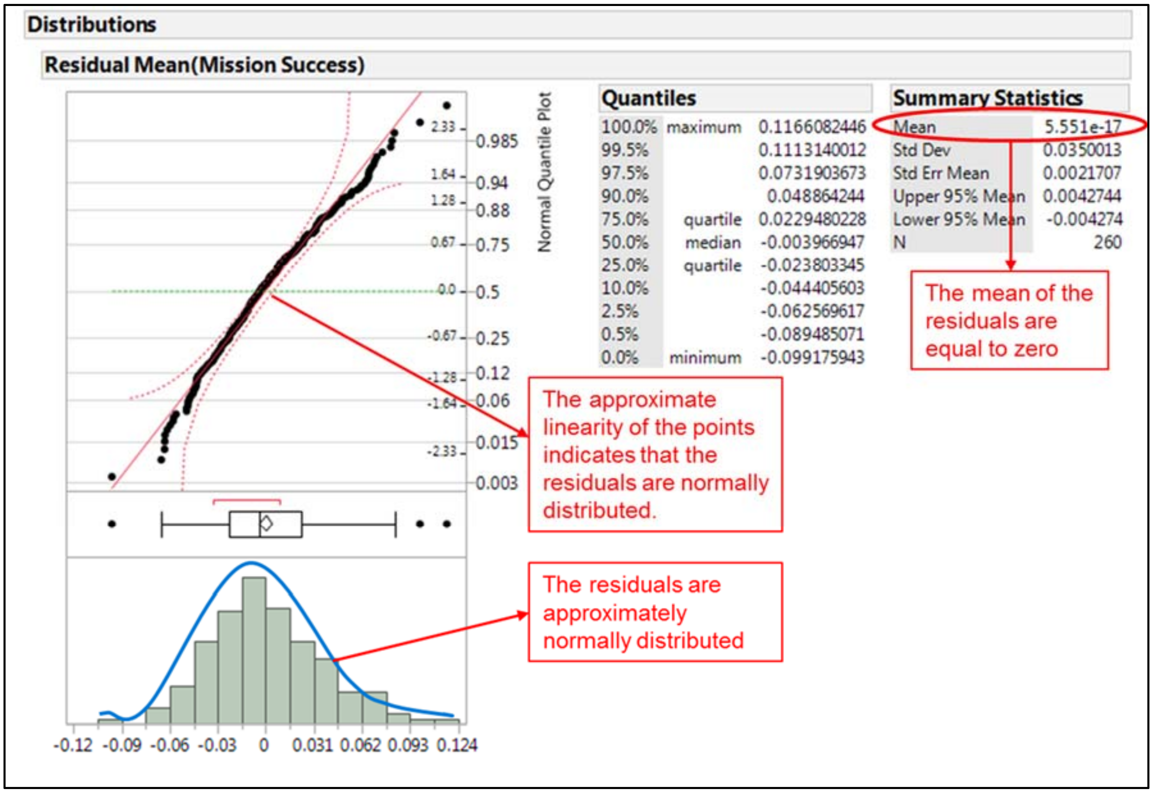


Figure 29. Distribution of the residuals for the main effects model.

For fitting a valid model, the error terms must be uncorrelated and have constant variance. To check these assumptions, we created the residual by predicted plot shown in Figure 30. We see that the residuals are scattered randomly about zero and they have constant variance. The assumption of uncorrelated errors is also satisfied because there is no evidence of sequencing of points.

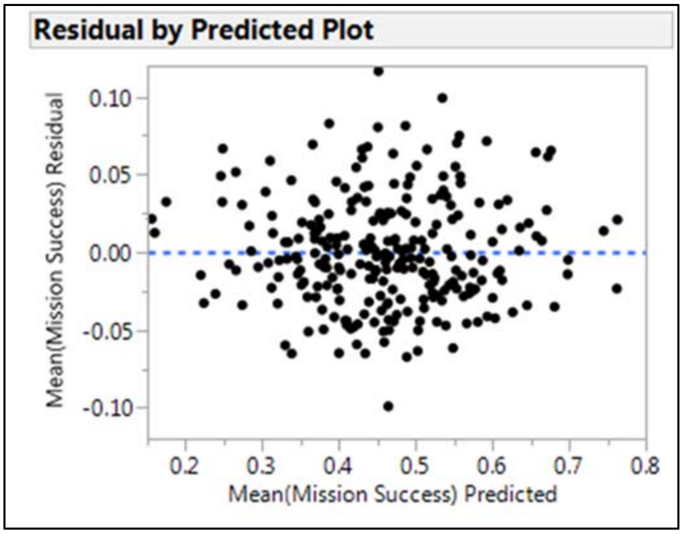


Figure 30. Residual by predicted plot for the main effects model.

The sorted parameter estimates report is useful in screening situations. This report shows the estimates of the parameters and conducts a hypothesis test for each model parameter to test the claim that the parameter estimate is equal to zero. In Figure 31, the parameter estimates are sorted according to their significance level. The most significant effects can be seen at the top of the report. There are 13 highly significant factors, one significant factor, and four insignificant factors. The most statistically significant factor is *Frigate Sonar Classification Range,* which represents the reality in an ASW screen formation. *USV Presence* is the second one that highly affects the response. All USV-related factors are marked in Figure 31. Among these factors, *USV Speed* is the only statistically insignificant factor in the model. The value of each estimate has a direct interpretation on the response. For example, the presence of a USV increases the probability of mission success by 0.089.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Frigate Sonar Classification Range	0.0000501	2.099e-6	23.87	<.0001*
USVPresence[1-0]	0.0893869	0.004501	19.86	<.0001*
Helicopter Sonar Classification Range	0.0000257	1.4e-6	18.36	<.0001*
Frigate Classification Probability	0.6106949	0.038383	15.91	<.0001*
Submarine Personel Concealment per Detection	-0.005531	0.000384	-14.41	<.0001*
#Frigate[3-2]	0.0642308	0.004501	14.27	<.0001*
Submarine Attack Speed	-0.015877	0.001537	-10.33	<.0001*
USV Sonar Classification Range	0.0000138	1.4e-6	9.86	<.0001*
Helicopter Average Time Between Detections	-0.000296	4.266e-5	-6.95	<.0001*
Helicopter Dipping Time	0.0001482	2.56e-5	5.79	<.0001*
Helicopter Classification Probability	0.1652491	0.038411	4.30	<.0001*
USV Average Time Between Detections	-0.00014	4.266e-5	-3.27	0.0012*
USV Sonar Classification Probability	0.1014717	0.038395	2.64	0.0088*
USV Dipping Time	0.0000563	2.561e-5	2.20	0.0289*
Helicopter Speed	0.000203	0.000192	1.06	0.2916
Helicopter Endurance	1.4141e-6	2.133e-6	0.66	0.5080
USV Speed	0.0003367	0.000509	0.66	0.5093
Helicopter Refuel Time	-4.184e-6	6.399e-6	-0.65	0.5138

Figure 31. The sorted parameter estimates for the main effects model.

JMP produces a prediction expression which shows the equation used to predict the response (see Figure 32). This expression can be very useful in the decision-making process.

Prediction Expression

-0.1629833231228

+ Match(#Frigate) { 2 ⇒ 0; 3 ⇒ 0.06423076923077; else ⇒ . }

+ Match(USVPresence) { 0 ⇒ 0; 1 ⇒ 0.08938693746909; else ⇒ . }

+ 0.00020299882666 * Helicopter Speed

+ 0.00033669543304 * USV Speed

+ -0.000296496107 * Helicopter Average Time Between Detections

+ -0.000139538825 * USV Average Time Between Detections

+ 0.00000141407401 * Helicopter Endurance

+ -0.0000041844127 * Helicopter Refuel Time

+ 0.00014816251092 * Helicopter Dipping Time

+ 0.0000563050785 * USV Dipping Time

+ -0.015876524082 * Submarine Attack Speed

+ -0.0055306653183 * Submarine Personel Concealment per Detection

+ 0.00005010821762 * Frigate Sonar Classification Range

+ 0.00002570762924 * Helicopter Sonar Classification Range

+ 0.00001379568173 * USV Sonar Classification Range

+ 0.61069488533826 * Frigate Classification Probability

+ 0.16524913885334 * Helicopter Classification Probability

+ 0.10147174064001 * USV Sonar Classification Probability

Figure 32. Prediction expression for the main effects model.

c. Second Order Model

In this section, a second order regression model is developed over the data set. We included main effects, two-way interactions, and second-order polynomial terms in the model. A stepwise regression technique is used to select a subset of effects to fit a better model. When the additional terms are added to the model, the R-squared value will increase. It is good to have a higher R-squared value, but it is also desirable to have fewer terms in the model to avoid overfitting the data. In brief, we are trying to fit a valid parsimonious model. Therefore, we created a table using the stepwise regression step history report and then, we plotted R-squared vs. the number of terms. As Figure 33 suggests, after the 23rd term, the R-squared value reaches a point where adding more terms will not improve our model much.

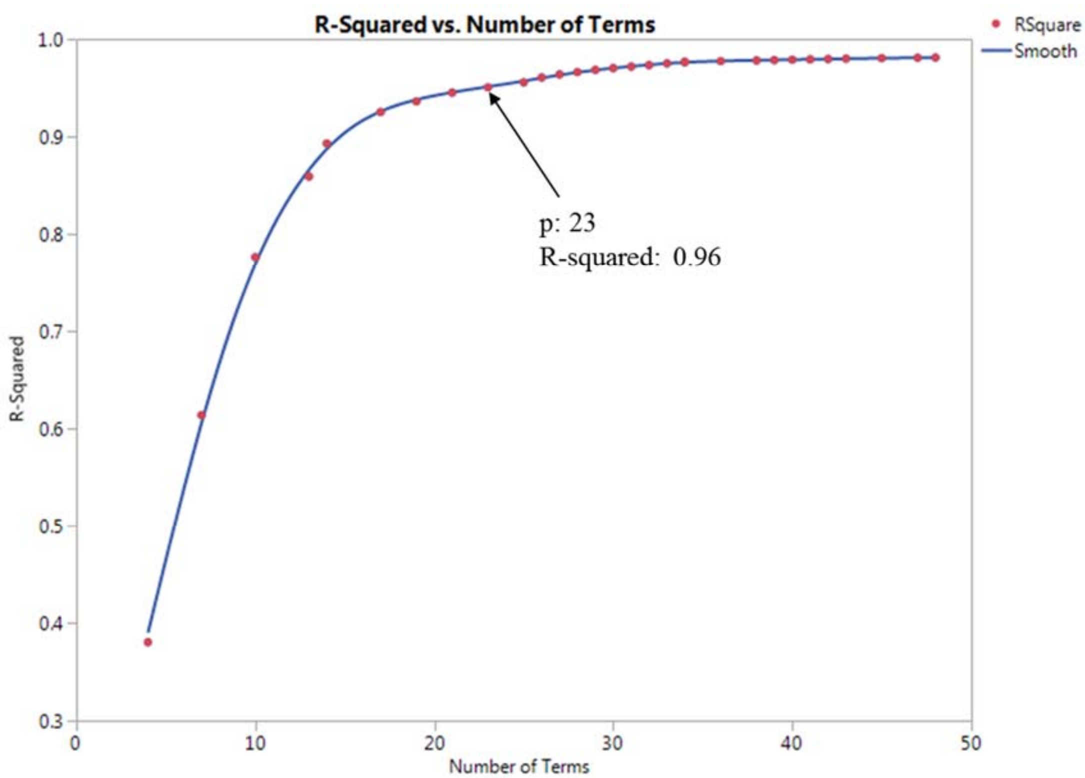
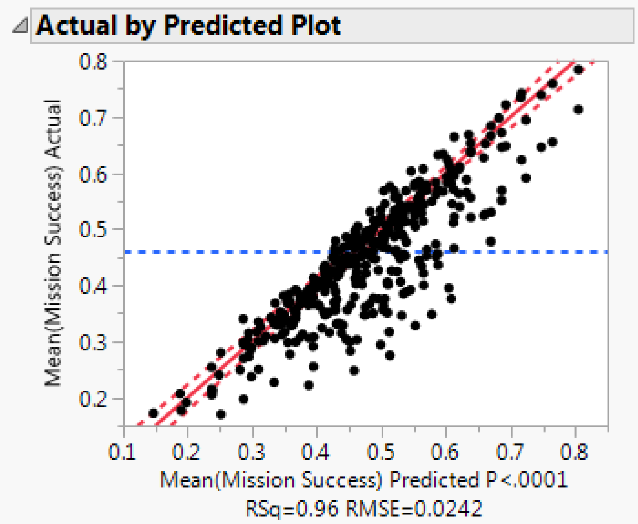


Figure 33. R-squared value increases with the added terms.

The actual by predicted plot and summary of fit for this model is shown in Figure 34. The second order model's predictions seem very good. The R-squared value is around 0.96. The second order model explains 96% of the variance of the output.



Summary of Fit

RSquare	0.958707
RSquare Adj	0.954874
Root Mean Square Error	0.024179
Mean of Response	0.460615
Observations (or Sum Wgts)	260

Figure 34. Actual by predicted plot and the summary of the fit for the second order model.

The R-squared value is really high, but it does not fully guarantee that the second order model fits the data well. We need to check the residual distributions to investigate how well this model fits the data. Figure 35 displays the distribution of the residuals with graphs, quantiles, and summary statistics. This figure confirms that the residuals are distributed around zero and follow a normal distribution. For smaller samples, JMP provides the Shapiro-Wilks test, which tests whether the data comes from a normal distribution. Because the *p*-value is greater than .05, we retain the null hypothesis that the residuals come from a normally distributed population.

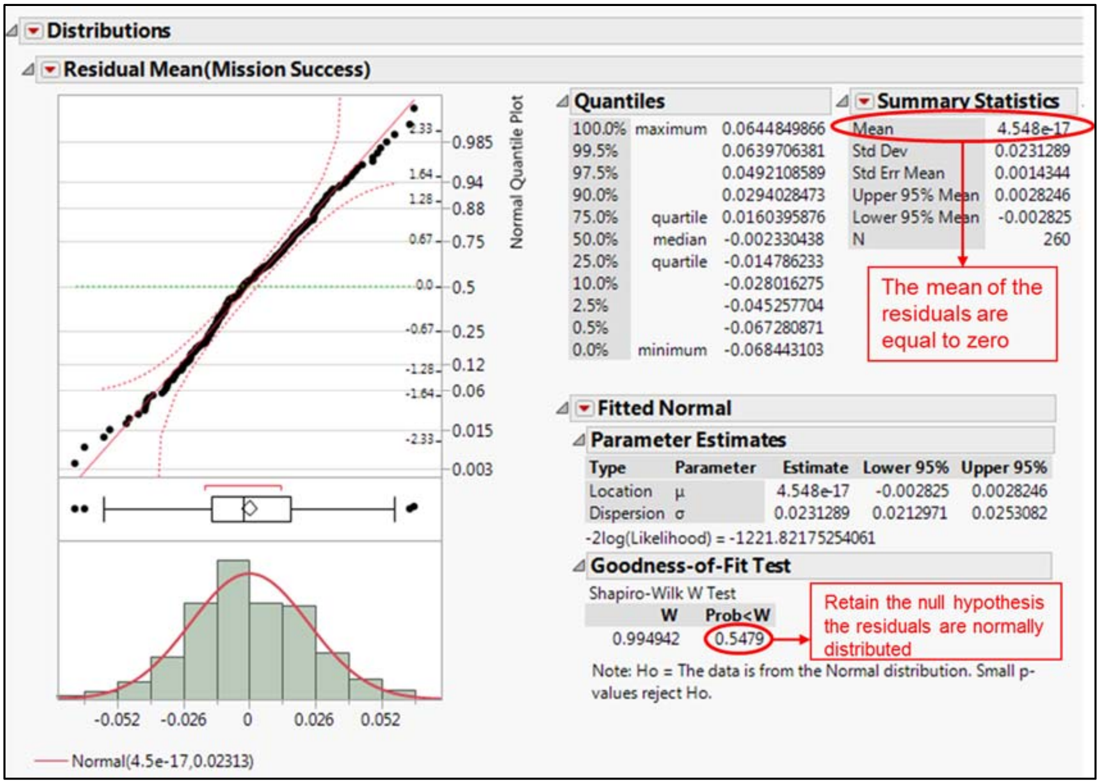


Figure 35. Distribution of the residuals for the second order model.

The residual by predicted plot in Figure 36 indicates that the residuals have constant variance and follow a random pattern. Therefore, the second order model satisfies the assumptions well.

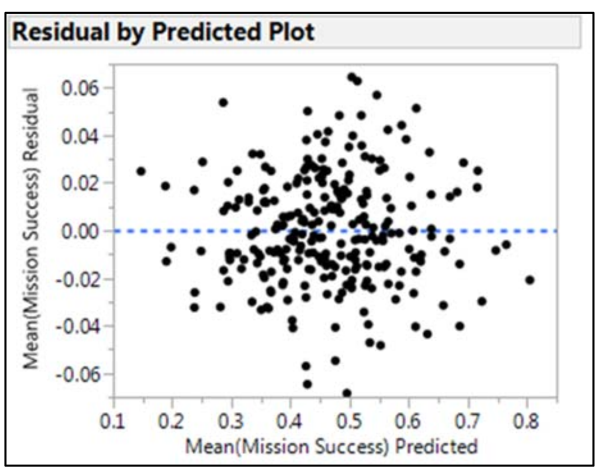
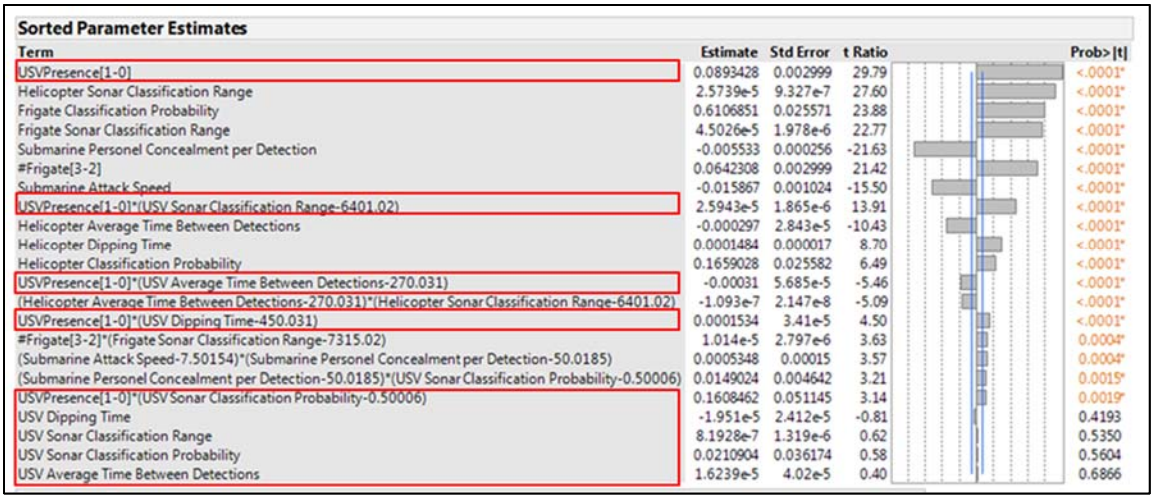


Figure 36. Residual by predicted plot for the second order model.

The sorted parameter estimates are shown in Figure 37. There are 15 highly significant factors, four significant factors, and four insignificant factors. The most statistically significant factor is *USV Presence* in the second order model, while *Frigate Sonar Classification Range* is the most statistically significant in the main effects model. *USV Speed* factor is not included in the second order model as distinct from the main effects model.



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
USVPresence[1-0]	0.0893428	0.002999	29.79	<.0001*
Helicopter Sonar Classification Range	2.5739e-5	9.327e-7	27.60	<.0001*
Frigate Classification Probability	0.6106851	0.025571	23.88	<.0001*
Frigate Sonar Classification Range	4.5026e-5	1.978e-6	22.77	<.0001*
Submarine Personel Concealment per Detection	-0.005533	0.000256	-21.63	<.0001*
#Frigate[3-2]	0.0642308	0.002999	21.42	<.0001*
Submarine Attack Speed	-0.015867	0.001024	-15.50	<.0001*
USVPresence[1-0]*(USV Sonar Classification Range-6401.02)	2.5943e-5	1.865e-6	13.91	<.0001*
Helicopter Average Time Between Detections	-0.000297	2.843e-5	-10.43	<.0001*
Helicopter Dipping Time	0.0001484	0.000017	8.70	<.0001*
Helicopter Classification Probability	0.1659028	0.025582	6.49	<.0001*
USVPresence[1-0]*(USV Average Time Between Detections-270.031)	-0.00031	5.685e-5	-5.46	<.0001*
(Helicopter Average Time Between Detections-270.031)*(Helicopter Sonar Classification Range-6401.02)	-1.093e-7	2.147e-8	-5.09	<.0001*
USVPresence[1-0]*(USV Dipping Time-450.031)	0.0001534	3.41e-5	4.50	<.0001*
#Frigate[3-2]*(Frigate Sonar Classification Range-7315.02)	1.014e-5	2.797e-6	3.63	0.0004*
(Submarine Attack Speed-7.50154)*(Submarine Personel Concealment per Detection-50.0185)	0.0005348	0.00015	3.57	0.0004*
(Submarine Personel Concealment per Detection-50.0185)*(USV Sonar Classification Probability-0.50006)	0.0149024	0.004642	3.21	0.0015*
USVPresence[1-0]*(USV Sonar Classification Probability-0.50006)	0.1608462	0.051145	3.14	0.0019*
USV Dipping Time	-1.951e-5	2.412e-5	-0.81	0.4193
USV Sonar Classification Range	8.1928e-7	1.319e-6	0.62	0.5350
USV Sonar Classification Probability	0.0210904	0.036174	0.58	0.5604
USV Average Time Between Detections	1.6239e-5	4.02e-5	0.40	0.6866

Figure 37. The sorted parameter estimates for the second order model.

7. Regression Tree

When the model has non-linearity and lots of interactions among factors, building a single regression model may not be enough. An alternative technique for exploring the effects of the factors on the response is building a regression tree. The purpose is to fit a model that predicts the response variable based on design factors. In regression tree analysis, the data is recursively partitioned into smaller regions, where the interactions are easy to understand; then, a predictive model is fitted for each cell of the partition. A tree of decision rules is formed until the desired fit is obtained. A regression tree is a useful technique because an analyst can easily present the results and insights.

We build a regression tree for the probability of successful classification given all design factors. The data is partitioned into two segments based on the *LogWorth* statistic, which is defined as $-\log_{10}(p\text{-value})$. This statistic is reported in node Candidate reports, as shown in Figure 38. The *Frigate Sonar Classification Range* column has the largest LogWorth, which is noted by an asterisk. Therefore, this factor defines the first optimum split.

All Rows

Count	260
Mean	0.4606154
Std Dev	0.11382

Candidates

Term	Candidate SS		LogWorth	Cut Point
#Frigate	0.2681634615		5.77934102	2
USVPresence	0.5209347846		11.56889989	0
Helicopter Speed	0.1062958815		1.33357843	100
USV Speed	0.0311524159		0.22346943	22
Helicopter Average Time Between Detections	0.1268804907		1.72272943	228
USV Average Time Between Detections	0.1215830805		1.61955524	191
Helicopter Endurance	0.0370256410		0.23647750	7594
Helicopter Refuel Time	0.1131237863		1.45762245	2269
Helicopter Dipping Time	0.1254575034		1.69488607	567
USV Dipping Time	0.0806772924		0.87458623	309
Submarine Attack Speed	0.2429445949		4.24414142	6.3
Submarine Personel Concealment per Detection	0.2692261597		4.86637589	57
Frigate Sonar Classification Range	0.6422193893	*	15.54367025	6458
Helicopter Sonar Classification Range	0.3779089892		7.63367185	8630
USV Sonar Classification Range	0.1902161778		3.04329916	6915
Frigate Classification Probability	0.3654461597		7.30213508	0.303
Helicopter Classification Probability	0.0520842684		0.42995882	0.528
USV Sonar Classification Probability	0.0832794278		0.91874820	0.428

Figure 38. Candidates report for the root node.

The first five splits of the regression tree are shown in Figure 39. The interpretation of the regression tree is straightforward. Each leaf in the decision tree includes the probability of successful classification in the *Mean* row. The first split of the partition tree occurs with the factor *Frigate Sonar Classification Range,* as stated above. This factor is the most significant one in the regression tree model as well as in the main effects regression model. The original 260 design points are split into two parts: a left leaf that has 68 design points and a right leaf that has 192 design points. If the frigate sonar classification range is less than or equal to 6,343 meters, the ASW screen has a lower probability of successful classification. The higher probability of successful classification is evident when the frigate sonar classification range is higher than or equal to 6,343 meters. For the left leaf, the next split would happen on the factor *Frigate Sonar Classification Probability*. For the right leaf, the next split would happen on the factor *USV Presence* which is a two-level categorical variable. When USVs are not present in the model, the probability of successful classification is 0.4461. When USVs are present in the model, the probability of successful classification increases to 0.5246. The next split occurs for the *USV Sonar Classification Range*. The probability of successful classification is 0.4912 when the USV sonar classification range is less than 7,001 meters, while the probability of successful classification is 0.5769 when the USV sonar classification range is greater than or equal to 7,001 meters.

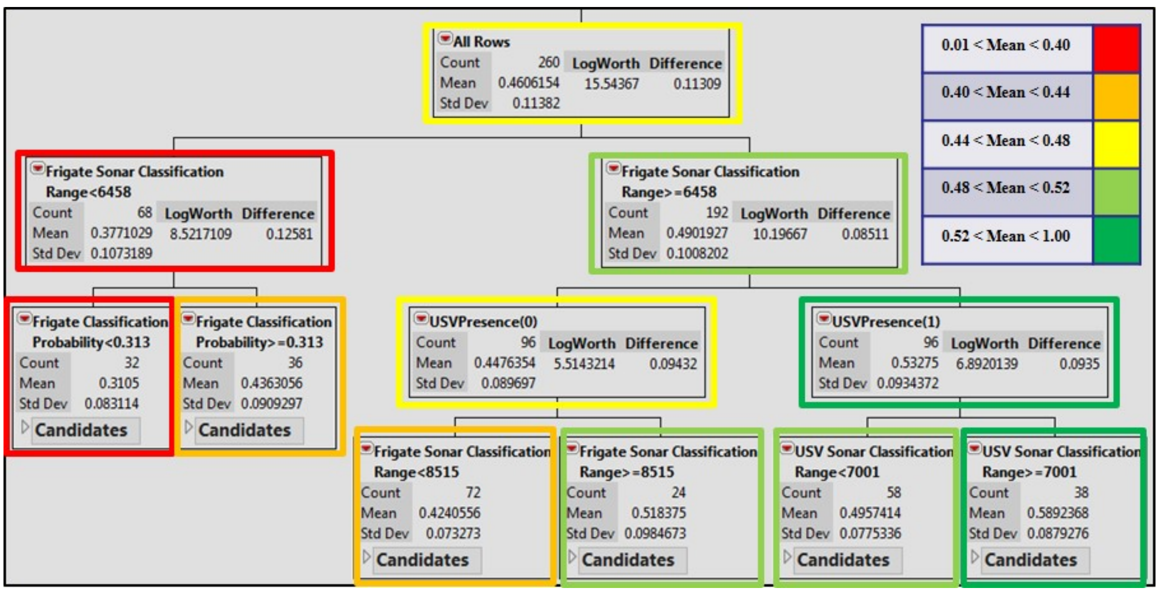


Figure 39. The first five splits of the regression tree. Colors and associated means are explained in the legend (located at the top right).

We performed the splitting process repeatedly to find a better R-squared value. But, this big tree seems complex, making it difficult to display and interpret. Finally, we come up with 23 splits and observe an R-squared value of 0.766. Figure 40 shows a plot of R-squared versus the number of splits named as split history. Figure 41 displays a report showing each factor's contribution to the fit in the model.

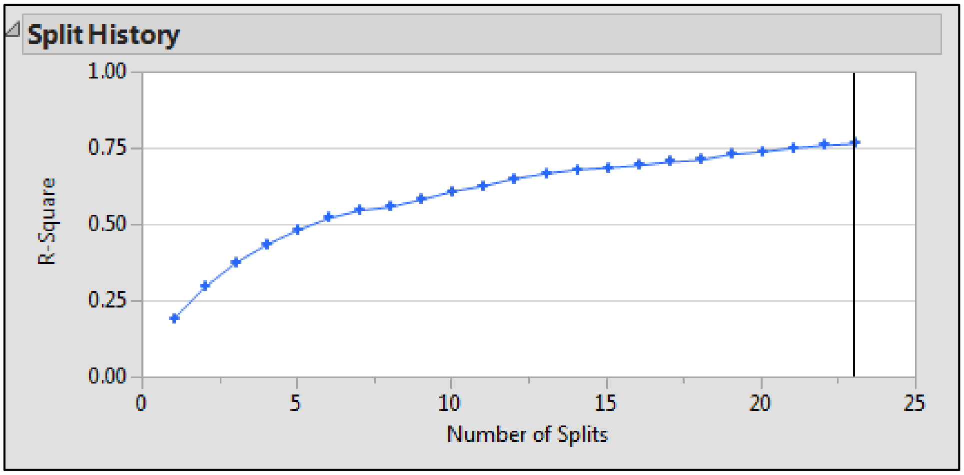


Figure 40. Split history for the regression tree model.

Column Contributions

Term	Number of Splits	SS	Portion
Frigate Sonar Classification Range	3	0.88241475	0.3433
USVPresence	3	0.52455645	0.2041
Frigate Classification Probability	1	0.26812864	0.1043
USV Sonar Classification Range	2	0.26447486	0.1029
#Frigate	4	0.18912282	0.0736
Submarine Personel Concealment per Detection	2	0.16873481	0.0656
Helicopter Sonar Classification Range	2	0.07726155	0.0301
USV Sonar Classification Probability	1	0.05546453	0.0216
Submarine Attack Speed	1	0.0421085	0.0164
Helicopter Classification Probability	1	0.02839225	0.0110
Helicopter Speed	1	0.0274769	0.0107
Helicopter Refuel Time	1	0.02219761	0.0086
Helicopter Dipping Time	1	0.02021761	0.0079
USV Speed	0	0	0.0000
Helicopter Average Time Between Detections	0	0	0.0000
USV Average Time Between Detections	0	0	0.0000
Helicopter Endurance	0	0	0.0000
USV Dipping Time	0	0	0.0000

Figure 41. Column contributions report shows each factor's contribution to the fit in the model.

V. CONCLUSIONS

A. SUMMARY

This research explores how USVs can complement and extend existing ASW screen effectiveness in detecting and classifying diesel-electric submarines. When an HVU is screened by a task force that is conducting protective ASW operations, the submarine threat level can be greatly reduced with high detection and classification capabilities.

In this study, the modeling first focuses on building an existing ASW screening scenario. This baseline scenario provides a standardized benchmark to evaluate the other scenarios. A generic scenario was built to increase the understandability. The scenarios are implemented in the simulation modeling platform MANA. We have to state that the scenarios built in MANA may not necessarily represent the real ASW operations and the assumptions we made about the detection and classification of the submarine may not be necessarily true. Thus, this simulation study cannot answer the detailed questions, but it provides some useful insights about the employment of USVs in ASW screen formation.

B. ANSWERING RESEARCH QUESTIONS

The following research questions were presented in Chapter 1:

1. Can USVs give the same effectiveness as ASW helicopters against diesel-electric submarines ahead of naval convoys or HVUs?
2. What are the main advantages and disadvantages of employing USVs in an ASW screen formation?
3. Which characteristics of USVs are the most significant in ASW?
4. How do changes in decision parameters affect the probability of classifying a diesel-electric submarine?
5. What strengths and drawbacks does the simulation software MANA have for modelling ASW scenarios?

To answer the first question, we conduct a comparison analysis of the scenarios where different numbers and varieties of platforms are employed in an ASW screen formation. In protective ASW operations, employing different platform and sensor types can help an ASW commanders detect and classify the stealthy submarine. These platforms and their sensors support and complement each other to improve ASW effectiveness. With side-by-side box plots and one-way analysis of the means by scenarios, we find that when the helicopters are replaced with USVs, which have the same sensor type and capability, they can provide the same classification effectiveness in an ASW screen formation. The operating range of the USVs is considered shorter than the operating range of the helicopters because of the autonomy requirements of USVs. Therefore, USVs are employed in the intermediate screen while the helicopters are employed on the outer screen. This gives the helicopters a great advantage against USVs because the helicopters can extend the reach of the frigates to the farther point in the ASW screen and provide an early detection and classification of the diesel-electric submarine.

Addressing the second question, we show the primary advantage of employing USVs in ASW screen formation is freeing the helicopters to perform other missions, such as intelligence, surveillance and reconnaissance (ISR). The main disadvantage of employing USVs is that they are not nearly as efficient as the helicopters in early detection and classification when an early classification of the enemy submarine is critical for decision makers. The other disadvantage would be that USVs require a high level of autonomy and onboard processing for this mission, which means a higher cost for the development of the dipping sonar and system design.

The proportion of successful classification is used to measure the effectiveness of ASW screen formation in the regression model. Based on this MOE, the most significant characteristic of USVs is the classification range of dipping sonar. In ASW, the classification range will depend on underwater conditions, background noise in the ocean, and sonar capability. The sonar parameters are mostly controllable because the selection of the sonar type and capability can be decided on during the design process. But, the effectiveness of sonar is limited by environmental conditions. On the other hand, USV speed is viewed as an insignificant characteristic in the model. The reader must realize that USVs are self-deployed to the intermediate screen ahead of the HVU with sufficient time and satisfy the requirements of station-keeping.

Many decision and noise factors have a significant effect on the response in our protective ASW scenario. The sonar parameters of the frigates are really significant in the model. The first split of the partition tree occurs with the factor frigate sonar classification range. This factor has the greatest effect on mission success. The number of frigates is another significant factor which affects the outcome. Employing one more frigate in the screen will affect the outcome significantly. Among the noise factors, the stealthiness of the diesel-electric submarine plays an important role in the model, which is a significant factor in littoral ASW operations. The submarine is designed to submerge and maneuver quietly to avoid detection. In a noisy littoral environment, the submarine gains extra stealth. The submarine can find shadow zones to hide from active sonar and approach an enemy without being detected.

Addressing the final research question, the combat simulation platform MANA has a number of strengths to simulate maritime scenarios. It is easy to use and navigate. In a maritime scenario, the ships may patrol on randomly assigned routes in a box; it is straightforward to simulate patrol boxes and random search patterns for a specific agent. On the other hand, MANA has several drawbacks which need to be fixed to simulate maritime scenarios. First of all, to form an ASW screen effectively, the ships need to know and update target bearing, range, course, and speed in their situational awareness maps at each time step. Detailed information in an agent's situational awareness map will help the agent decide on their next movements. Specific built-in naval formation types can be added to the next versions of MANA

The next drawback is that, in an ASW scenario, the level of acoustic classification is limited to two levels: submarine and non-submarine. Therefore, it is hard to implement ASW contact classification procedures. In a realistic ASW scenario, there are four basic levels about the certainty of classification: certain submarine, probable submarine, possible submarine, and non-submarine. Classification procedures are important for deciding on ASW force tactics.

C. FURTHER RESEARCH

The underwater environment and the thermal layer and their effects on the sonar are not simulated explicitly in the model. Since the littoral waters are complex and chaotic due to several reasons that are mentioned in Chapter II, underwater conditions can have a significant effect on the effectiveness of sonar. For future work, underwater conditions can be simulated to prove how these conditions effect the detection and classification of submarines.

In this study, we are only interested in detecting and classifying the enemy submarine. The phases after the classification phase are not explicitly addressed in this study. USVs can contribute much more effectiveness in ASW operations. They can also serve as armed escorts ahead of HVUs with increased size and payload. Considering this fact, localization, tracking, and kill phases can be simulated in future models.

APPENDIX A. NOLH DESIGN SPREADSHEET

The NOLH design spreadsheet is a useful tool for designing large-scale simulation experiments. In this thesis, the design points are generated by using the NOLH design for 16 factors.

low level	80	20	180	180	5400	1200	300	300	5	40	5486	3658	3658	0.2	0.4	0.4
high level	120	35	360	360	9000	2400	600	600	10	60	9144	9144	9144	0.4	0.6	0.6
decimals	0	0	0	0	0	0	0	0	1	0	0	0	0	3	3	3
factor name	HeloSpeed	USVSpeed	HeloAvgDetTime	USVAvgDetTime	HeloEndTime	HeloRefTime	HeloDipTime	USVDipTime	SubAttackSpeed	SubConcealment	FrigateClassifyRange	HeloClassifyRange	USVClassifyRange	FrigateClassifyProb	HeloClassifyProb	USVClassifyProb
	109	21	245	239	5850	2119	539	445	9.8	54	7486	8801	4687	0.325	0.563	0.538
	118	31	200	256	6638	1500	464	525	8.6	58	8287	6315	4944	0.269	0.469	0.431
	116	25	352	219	6469	2231	347	436	7	52	8401	8458	6230	0.303	0.453	0.578
	106	33	309	262	5625	1706	380	380	5.6	60	8801	7087	4087	0.241	0.572	0.466
	117	27	214	183	5738	1388	375	483	8	50	5715	8287	7172	0.319	0.541	0.559
	101	34	222	267	5963	1988	342	558	9.5	42	6972	7944	8544	0.213	0.434	0.409
	111	23	276	186	6300	1594	567	427	5.8	49	6743	8630	8887	0.347	0.419	0.509
	113	31	346	236	6750	2306	511	305	6.3	46	5543	7172	7601	0.206	0.509	0.438
	108	20	183	326	6863	1931	417	328	9	46	8572	5801	5458	0.247	0.503	0.6
	119	30	267	318	5400	1538	577	413	8.4	40	7944	3829	5972	0.369	0.403	0.494
	101	20	354	276	6131	1725	394	506	5.1	45	8115	4687	4858	0.209	0.447	0.566
	119	28	304	346	6019	1275	413	544	6.6	48	7429	5030	6144	0.316	0.584	0.444
	102	23	239	295	6806	1781	356	384	9.8	59	6000	3915	9058	0.234	0.525	0.547
	111	28	256	340	6356	2363	314	300	7.6	51	6401	5287	6487	0.334	0.478	0.478
	103	25	321	352	6975	1463	441	581	5.7	57	5486	6058	8973	0.259	0.516	0.572
	107	29	278	309	5906	2344	600	469	7.3	56	6801	4258	7430	0.397	0.569	0.488
	114	27	250	203	7819	2400	534	591	7.9	52	6629	5201	5887	0.328	0.534	0.475
	103	33	228	242	7481	1744	548	539	6.8	55	5886	3658	3658	0.216	0.472	0.541
	109	26	281	233	8213	2269	309	422	7.7	56	7258	4087	4772	0.375	0.406	0.503
	104	31	335	191	7369	1406	431	352	9.1	58	5657	5972	4601	0.25	0.494	0.544
	113	23	253	197	8944	1650	305	511	6.5	42	7029	4601	7001	0.363	0.6	0.481
	112	32	180	208	7256	2044	445	567	5.9	47	8858	5372	7687	0.228	0.488	0.597
	120	26	323	225	8888	1350	516	338	7.8	47	7544	5115	6744	0.309	0.441	0.45
	104	35	329	248	7875	1838	473	366	10	41	8058	4772	8373	0.244	0.588	0.584
	105	24	197	287	8325	2081	581	347	5.5	43	6458	7258	4344	0.2	0.578	0.472
	110	29	208	360	8156	1425	492	408	6.9	49	5600	8373	5544	0.313	0.409	0.588
	114	21	315	323	7313	2288	398	586	8.8	45	6286	6915	5287	0.222	0.481	0.425
	116	33	293	329	8719	1575	338	497	8.7	47	6858	9058	4001	0.344	0.538	0.516
	118	24	203	290	7706	1444	422	323	6.1	57	8687	6658	8630	0.263	0.544	0.419
	108	34	242	312	8606	2381	403	459	5.3	56	7715	7344	8287	0.322	0.45	0.531
	106	22	307	281	8831	1688	530	530	9.6	59	8458	6572	7773	0.219	0.425	0.447
	115	30	349	335	7988	1969	572	502	8.3	52	8515	7858	7087	0.306	0.556	0.594
	100	28	270	270	7200	1800	450	450	7.5	50	7315	6401	6401	0.3	0.5	0.5
	91	34	295	301	8550	1481	361	455	5.2	46	7144	4001	8115	0.275	0.438	0.463
	82	24	340	284	7763	2100	436	375	6.4	42	6343	6487	7858	0.331	0.531	0.569
	84	30	188	321	7931	1369	553	464	8	48	6229	4344	6572	0.297	0.547	0.422
	94	22	231	278	8775	1894	520	520	9.4	40	5829	5715	8715	0.359	0.428	0.534
	83	28	326	357	8663	2213	525	417	7	50	8915	4515	5630	0.281	0.459	0.441
	99	21	318	273	8438	1613	558	342	5.5	58	7658	4858	4258	0.388	0.566	0.591
	89	32	264	354	8100	2006	333	473	9.2	51	7887	4172	3915	0.253	0.581	0.491
	88	24	194	304	7650	1294	389	595	8.8	54	9087	5630	5201	0.394	0.491	0.563
	93	35	357	214	7538	1669	483	572	6	54	6058	7001	7344	0.353	0.497	0.4
	81	25	273	222	9000	2063	323	488	6.6	60	6686	8973	6830	0.231	0.597	0.506
	99	35	186	264	8269	1875	506	394	9.9	55	6515	8115	7944	0.391	0.553	0.434
	81	27	236	194	8381	2325	488	356	8.4	53	7201	7773	6658	0.284	0.416	0.556
	98	32	301	245	7594	1819	544	516	5.2	41	8630	8887	3744	0.366	0.475	0.453
	89	27	284	200	8044	1238	586	600	7.4	49	8230	7515	6315	0.266	0.522	0.522
	97	30	219	188	7425	2138	459	319	9.3	43	9144	6744	3829	0.341	0.484	0.428
	93	26	262	231	8494	1256	300	431	7.7	44	7829	8544	5372	0.203	0.431	0.513
	86	28	290	338	6581	1200	366	309	7.1	48	8001	7601	6915	0.272	0.466	0.525
	98	22	312	298	6919	1856	352	361	8.2	45	8744	9144	9144	0.384	0.528	0.459
	91	29	259	307	6188	1331	591	478	7.3	44	7372	8715	8030	0.225	0.594	0.497
	96	24	205	349	7031	2194	469	548	5.9	43	8973	6830	8201	0.35	0.506	0.456
	87	32	287	343	5456	1950	595	389	8.5	58	7601	8201	5801	0.238	0.4	0.519
	88	23	360	332	7144	1556	455	333	9.1	53	5772	7430	5115	0.372	0.513	0.403
	80	29	217	315	5513	2250	384	563	7.2	53	7086	7687	6058	0.291	0.559	0.55
	96	20	211	293	6525	1763	427	534	5	59	6572	8030	4429	0.356	0.413	0.416
	95	31	343	253	6075	1519	319	553	9.5	57	8172	5544	8458	0.4	0.422	0.528
	90	26	332	180	6244	2175	408	492	8.1	51	9030	4429	7258	0.288	0.591	0.413
	86	34	225	217	7088	1313	502	314	6.2	55	8344	5887	7515	0.378	0.519	0.575
	84	22	248	211	5681	2025	563	403	6.3	53	7772	3744	8801	0.256	0.463	0.484
	83	31	338	250	6694	2156	478	577	8.9	43	5943	6144	4172	0.338	0.456	0.581
	92	21	298	228	5794	1219	497	441	9.7	44	6915	5458	4515	0.278	0.55	0.469
	94	33	233	259	5569	1913	370	370	5.4	41	6172	6230	5030	0.381	0.575	0.553
	85	25	191	205	6413	1631	328	398	6.7	48	6115	4944	5715	0.294	0.444	0.406

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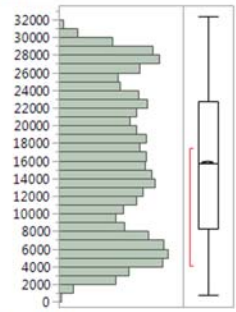
APPENDIX B. DISTRIBUTIONS OF “STEPS” COLUMNS BY SCENARIOS

Distributions Scenario=Baseline_Scenario

Steps



Quantiles

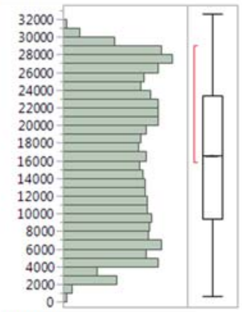
100.0%	maximum	32390
99.5%		30577.84
97.5%		29265.15
90.0%		27443.2
75.0%	quartile	22729.5
50.0%	median	15723
25.0%	quartile	8344
10.0%		4855
2.5%		2420.85
0.5%		1905.77
0.0%	minimum	736

Summary Statistics

Mean	15839.072
Std Dev	8170.8629
Std Err Mean	51.72572
Upper 95% Mean	15940.458
Lower 95% Mean	15737.687
N	24953

Distributions Scenario=Scenario_2

Steps



Quantiles

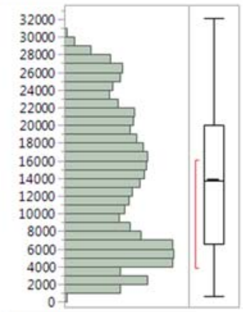
100.0%	maximum	32581
99.5%		30416.315
97.5%		29176.525
90.0%		27414.1
75.0%	quartile	23377.25
50.0%	median	16606.5
25.0%	quartile	9461
10.0%		5475.7
2.5%		2876.475
0.5%		2034.895
0.0%	minimum	635

Summary Statistics

Mean	16476.855
Std Dev	8004.9544
Std Err Mean	51.060562
Upper 95% Mean	16576.937
Lower 95% Mean	16376.773
N	24578

Distributions Scenario=Scenario_3

Steps



Quantiles

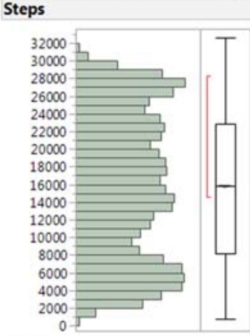
100.0%	maximum	32076
99.5%		29132.47
97.5%		27770
90.0%		25078
75.0%	quartile	19991.75
50.0%	median	13740
25.0%	quartile	6591
10.0%		3966.3
2.5%		1597.65
0.5%		1168.295
0.0%	minimum	614

Summary Statistics

Mean	13785.152
Std Dev	7742.7812
Std Err Mean	44.153009
Upper 95% Mean	13871.694
Lower 95% Mean	13698.61
N	30752

Distributions Scenario=Scenario_4

Steps



Quantiles

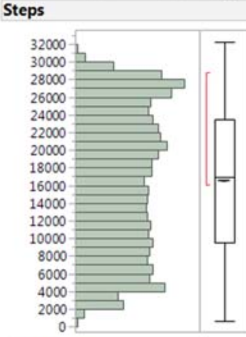
100.0%	maximum	32576
99.5%		30198.46
97.5%		28952.275
90.0%		27143
75.0%	quartile	22796
50.0%	median	15817.5
25.0%	quartile	8159.5
10.0%		4619
2.5%		2301
0.5%		1757.18
0.0%	minimum	735

Summary Statistics

Mean	15768.115
Std Dev	8182.1288
Std Err Mean	47.957897
Upper 95% Mean	15862.115
Lower 95% Mean	15674.116
N	29108

Distributions Scenario=Scenario_5

Steps



Quantiles

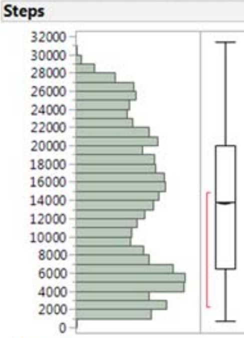
100.0%	maximum	32250
99.5%		30017.35
97.5%		28900.375
90.0%		27271.5
75.0%	quartile	23420.75
50.0%	median	16937
25.0%	quartile	9575.5
10.0%		5275.5
2.5%		2896.5
0.5%		1600.95
0.0%	minimum	677

Summary Statistics

Mean	16525.04
Std Dev	7978.5985
Std Err Mean	47.125743
Upper 95% Mean	16617.409
Lower 95% Mean	16432.672
N	28664

Distributions Scenario=Scenario_6

Steps



Quantiles

100.0%	maximum	31361
99.5%		28680.04
97.5%		27325.3
90.0%		24682
75.0%	quartile	19981
50.0%	median	13828
25.0%	quartile	6429
10.0%		3583
2.5%		1457.7
0.5%		1152
0.0%	minimum	746

Summary Statistics

Mean	13642.8
Std Dev	7736.1432
Std Err Mean	41.382769
Upper 95% Mean	13723.911
Lower 95% Mean	13561.688
N	34947

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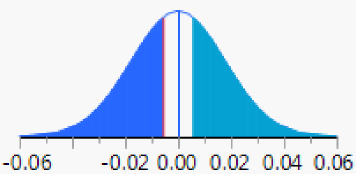
APPENDIX C. DETAILED COMPARISONS REPORT FOR T-TEST (MOE1–THE PROPORTION OF SUCCESSFUL CLASSIFICATION)

This detailed report provides the paired *t*-test comparisons of the scenarios. The statistical text includes the difference between the levels, standard error, and confidence intervals, t-ratios, *p-values*, and degrees of freedom. A plot is also provided for the comparison on the right of each report.

Detailed Comparisons Report

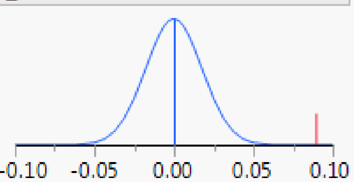
Comparing Scenario_2 with Baseline_Scenario

Difference	-0.00577	t Ratio	-0.32661
Std Err Dif	0.01766	DF	384
Upper CL Dif	0.02896	Prob > |t|	0.7441
Lower CL Dif	-0.04050	Prob > t	0.6279
Confidence	0.95	Prob < t	0.3721



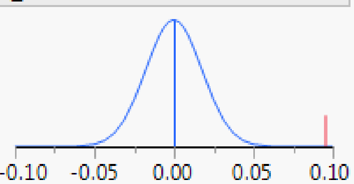
Comparing Scenario_3 with Baseline_Scenario

Difference	0.089215	t Ratio	5.050708
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.123946	Prob > |t|	<.0001*
Lower CL Dif	0.054485	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



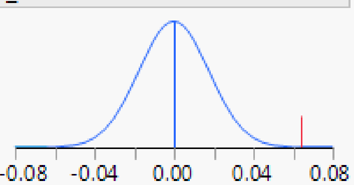
Comparing Scenario_3 with Scenario_2

Difference	0.094985	t Ratio	5.377318
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.129715	Prob > |t|	<.0001*
Lower CL Dif	0.060254	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



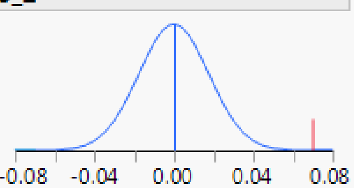
Comparing Scenario_4 with Baseline_Scenario

Difference	0.063923	t Ratio	3.618846
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.098653	Prob > |t|	0.0003*
Lower CL Dif	0.029193	Prob > t	0.0002*
Confidence	0.95	Prob < t	0.9998



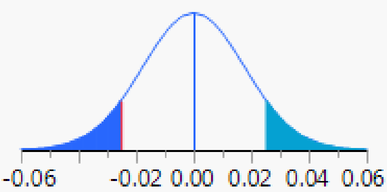
Comparing Scenario_4 with Scenario_2

Difference	0.069692	t Ratio	3.945457
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.104422	Prob > |t|	<.0001*
Lower CL Dif	0.034962	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



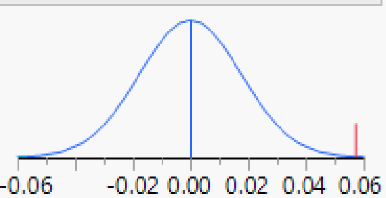
Comparing Scenario_4 with Scenario_3

Difference	-0.02529	t Ratio	-1.43186
Std Err Dif	0.01766	DF	384
Upper CL Dif	0.00944	Prob > |t|	0.1530
Lower CL Dif	-0.06002	Prob > t	0.9235
Confidence	0.95	Prob < t	0.0765



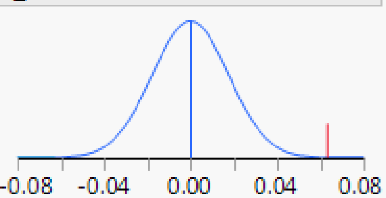
Comparing Scenario_5 with Baseline_Scenario

Difference	0.057092	t Ratio	3.232139
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.091822	Prob > |t|	0.0013*
Lower CL Dif	0.022362	Prob > t	0.0007*
Confidence	0.95	Prob < t	0.9993



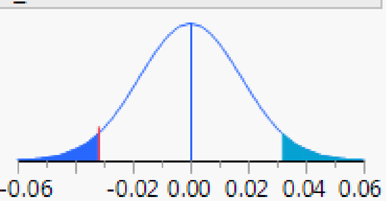
Comparing Scenario_5 with Scenario_2

Difference	0.062862	t Ratio	3.55875
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.097592	Prob > |t|	0.0004*
Lower CL Dif	0.028131	Prob > t	0.0002*
Confidence	0.95	Prob < t	0.9998



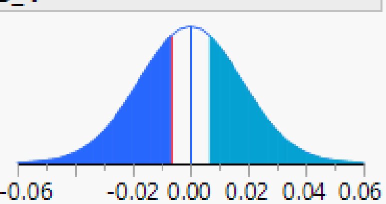
Comparing Scenario_5 with Scenario_3

Difference	-0.03212	t Ratio	-1.81857
Std Err Dif	0.01766	DF	384
Upper CL Dif	0.00261	Prob > |t|	0.0698
Lower CL Dif	-0.06685	Prob > t	0.9651
Confidence	0.95	Prob < t	0.0349*



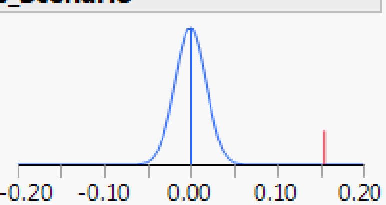
Comparing Scenario_5 with Scenario_4

Difference	-0.00683	t Ratio	-0.38671
Std Err Dif	0.01766	DF	384
Upper CL Dif	0.02790	Prob > |t|	0.6992
Lower CL Dif	-0.04156	Prob > t	0.6504
Confidence	0.95	Prob < t	0.3496



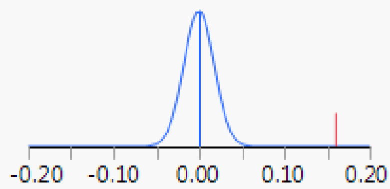
Comparing Scenario_6 with Baseline_Scenario

Difference	0.153754	t Ratio	8.704393
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.188484	Prob > |t|	<.0001*
Lower CL Dif	0.119024	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



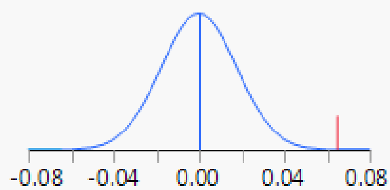
Comparing Scenario_6 with Scenario_2

Difference	0.159523	t Ratio	9.031003
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.194253	Prob > |t|	<.0001*
Lower CL Dif	0.124793	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



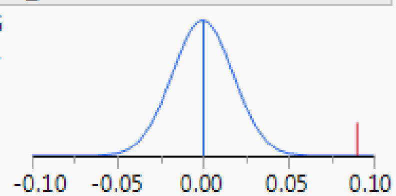
Comparing Scenario_6 with Scenario_3

Difference	0.064538	t Ratio	3.653685
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.099269	Prob > |t|	0.0003*
Lower CL Dif	0.029808	Prob > t	0.0001*
Confidence	0.95	Prob < t	0.9999



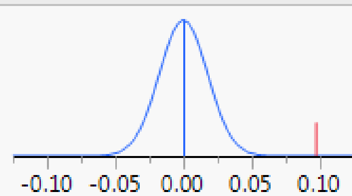
Comparing Scenario_6 with Scenario_4

Difference	0.089831	t Ratio	5.085546
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.124561	Prob > |t|	<.0001*
Lower CL Dif	0.055101	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Comparing Scenario_6 with Scenario_5

Difference	0.096662	t Ratio	5.472253
Std Err Dif	0.017664	DF	384
Upper CL Dif	0.131392	Prob > |t|	<.0001*
Lower CL Dif	0.061931	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



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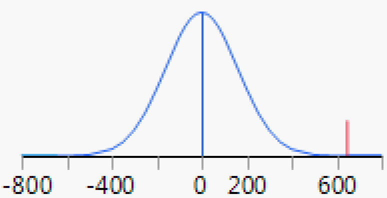
APPENDIX D. DETAILED COMPARISONS REPORT FOR T-TEST (MOE2–TIME TO CLASSIFY THE SUBMARINE)

Detailed Comparisons Report

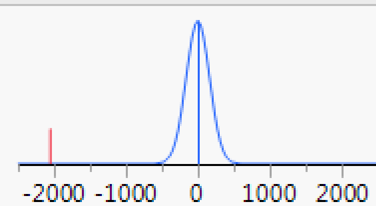
Comparing Scenario_2 with Baseline_Scenario

Difference	642.391	t Ratio	3.967209
Std Err Dif	161.925	DF	384
Upper CL Dif	960.763	Prob > |t|	<.0001*
Lower CL Dif	324.020	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



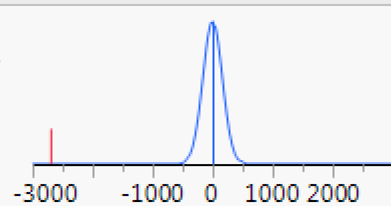
Comparing Scenario_3 with Baseline_Scenario

Difference	-2063.9	t Ratio	-12.7461
Std Err Dif	161.9	DF	384
Upper CL Dif	-1745.5	Prob > |t|	<.0001*
Lower CL Dif	-2382.3	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



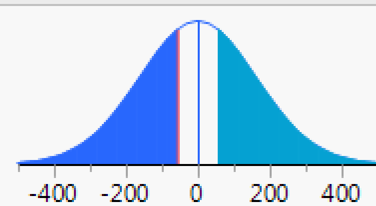
Comparing Scenario_3 with Scenario_2

Difference	-2706.3	t Ratio	-16.7133
Std Err Dif	161.9	DF	384
Upper CL Dif	-2387.9	Prob > |t|	<.0001*
Lower CL Dif	-3024.7	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



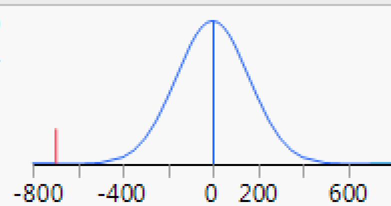
Comparing Scenario_4 with Baseline_Scenario

Difference	-57.80	t Ratio	-0.35698
Std Err Dif	161.93	DF	384
Upper CL Dif	260.57	Prob > |t|	0.7213
Lower CL Dif	-376.18	Prob > t	0.6393
Confidence	0.95	Prob < t	0.3607



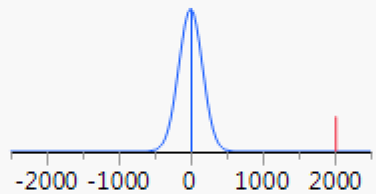
Comparing Scenario_4 with Scenario_2

Difference	-700.2	t Ratio	-4.32419
Std Err Dif	161.9	DF	384
Upper CL Dif	-381.8	Prob > |t|	<.0001*
Lower CL Dif	-1018.6	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



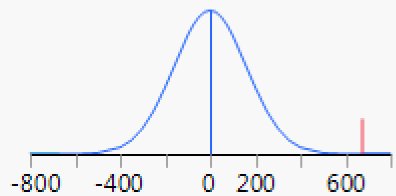
Comparing Scenario_4 with Scenario_3

Difference	2006.11	t Ratio	12.38911
Std Err Dif	161.93	DF	384
Upper CL Dif	2324.48	Prob > |t|	<.0001*
Lower CL Dif	1687.74	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



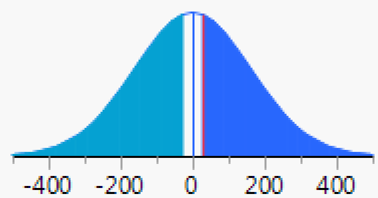
Comparing Scenario_5 with Baseline_Scenario

Difference	670.553	t Ratio	4.141124
Std Err Dif	161.925	DF	384
Upper CL Dif	988.924	Prob > |t|	<.0001*
Lower CL Dif	352.181	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



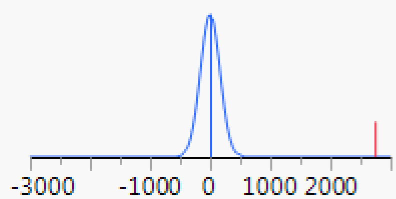
Comparing Scenario_5 with Scenario_2

Difference	28.16	t Ratio	0.173915
Std Err Dif	161.93	DF	384
Upper CL Dif	346.53	Prob > |t|	0.8620
Lower CL Dif	-290.21	Prob > t	0.4310
Confidence	0.95	Prob < t	0.5690



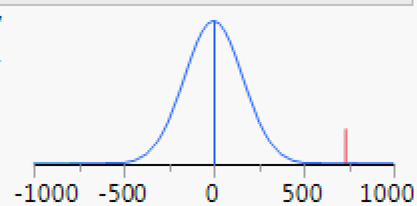
Comparing Scenario_5 with Scenario_3

Difference	2734.47	t Ratio	16.88722
Std Err Dif	161.93	DF	384
Upper CL Dif	3052.84	Prob > |t|	<.0001*
Lower CL Dif	2416.10	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



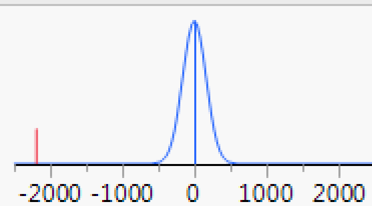
Comparing Scenario_5 with Scenario_4

Difference	728.36	t Ratio	4.498107
Std Err Dif	161.93	DF	384
Upper CL Dif	1046.73	Prob > |t|	<.0001*
Lower CL Dif	409.99	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



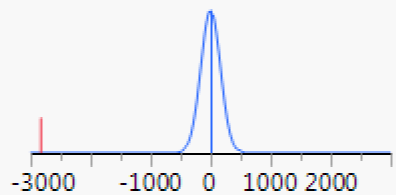
Comparing Scenario_6 with Baseline_Scenario

Difference	-2201.6	t Ratio	-13.5963
Std Err Dif	161.9	DF	384
Upper CL Dif	-1883.2	Prob > |t|	<.0001*
Lower CL Dif	-2520.0	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



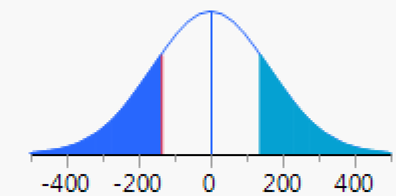
Comparing Scenario_6 with Scenario_2

Difference	-2844.0	t Ratio	-17.5636
Std Err Dif	161.9	DF	384
Upper CL Dif	-2525.6	Prob > |t|	<.0001*
Lower CL Dif	-3162.4	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



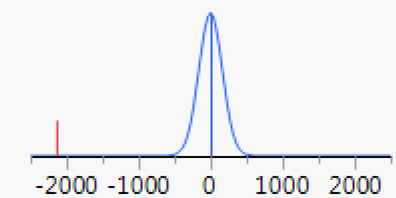
Comparing Scenario_6 with Scenario_3

Difference	-137.68	t Ratio	-0.85025
Std Err Dif	161.93	DF	384
Upper CL Dif	180.69	Prob > |t|	0.3957
Lower CL Dif	-456.05	Prob > t	0.8021
Confidence	0.95	Prob < t	0.1979



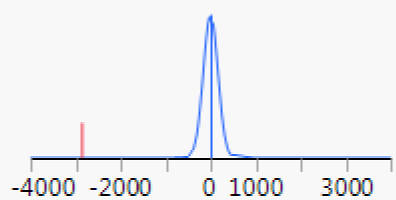
Comparing Scenario_6 with Scenario_4

Difference	-2143.8	t Ratio	-13.2394
Std Err Dif	161.9	DF	384
Upper CL Dif	-1825.4	Prob > |t|	<.0001*
Lower CL Dif	-2462.2	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



Comparing Scenario_6 with Scenario_5

Difference	-2872.1	t Ratio	-17.7375
Std Err Dif	161.9	DF	384
Upper CL Dif	-2553.8	Prob > |t|	<.0001*
Lower CL Dif	-3190.5	Prob > t	1.0000
Confidence	0.95	Prob < t	<.0001*



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