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THESIS

USE OF COOPERATIVE UNMANNED SYSTEMS FOR MINE COUNTERMEASURES

by

Tong Hai Ling

September 2020

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13. ABSTRACT (maximum 200 words)

The maritime industry is critical to Singapore's survival. In 2019, the Ministry of Defence found that the maritime industry accounted for 7% of Singapore's GDP and supplied more than 90% of Singapore's food consumption in 2018. To protect the maritime trade, one of the many threats Singapore has to defend against is naval mines. Effective mine countermeasures (MCM) using unmanned systems would enhance safety and reduce the reliance on human involvement. This thesis uses agent-based simulation, cutting-edge design of experiments, and data analysis tools to explore the performance of different MCM concept of operations (CONOPS). The scenario is a defensive MCM mission where unmanned surface vehicles are deployed around the clock to neutralize naval mines along operational sea lines of communications. Results from 60,000 simulated MCM missions reveal that overlapping sensor range and path deviation are the main factors influencing kill probability. The main driving factors for risk are detector speed, revisit rate, and sectorization of neutralizers. Sectorization of neutralizers increases the risk to transiting vessels and has little impact on kill probability. It is recommended that decision makers focus on increasing the speed of detectors, optimizing the length of overlap for sensor range, and using strategies to reduce path deviation when improving a CONOPS for the MCM scenario presented in this thesis.

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USE OF COOPERATIVE UNMANNED SYSTEMS FOR MINE COUNTERMEASURES

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ABSTRACT

The maritime industry is critical to Singapore's survival. In 2019, the Ministry of Defence found that the maritime industry accounted for 7% of Singapore's GDP and supplied more than 90% of Singapore's food consumption in 2018. To protect the maritime trade, one of the many threats Singapore has to defend against is naval mines. Effective mine countermeasures (MCM) using unmanned systems would enhance safety and reduce the reliance on human involvement. This thesis uses agent-based simulation, cutting-edge design of experiments, and data analysis tools to explore the performance of different MCM concept of operations (CONOPS). The scenario is a defensive MCM mission where unmanned surface vehicles are deployed around the clock to neutralize naval mines along operational sea lines of communications. Results from 60,000 simulated MCM missions reveal that overlapping sensor range and path deviation are the main factors influencing kill probability. The main driving factors for risk are detector speed, revisit rate, and sectorization of neutralizers. Sectorization of neutralizers increases the risk to transiting vessels and has little impact on kill probability. It is recommended that decision makers focus on increasing the speed of detectors, optimizing the length of overlap for sensor range, and using strategies to reduce path deviation when improving a CONOPS for the MCM scenario presented in this thesis.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABS	Agent-Based Simulation
BIC	Bayesian Information Criterion
CONOPS	Concept of Operations
COTS	Commercial Off-the-Shelf
CSV	Comma Separated Value
DOE	Design of Experiment
DP	Design Point
DTA	Defence Technology Agency
EMDS	Expendable Mine Disposal System
EOD	Explosive Ordnance Disposal
IPB	Intelligence Preparation of the Battlefield
LARS	Launch and Recovery System
LCS	Littoral Combat Ship
MANA	Map Aware Non-Uniform Automata
MANA-V	Map Aware Non-Uniform Automata Version V
MCM	Mine Countermeasures
MINDEF	Ministry of Defence
MMS	Marine Mammal System
MOE	Measure of Effectiveness
NO/B	Nearly Orthogonal/Balanced
NOLH	Nearly Orthogonal Latin Hypercube
RSN	Republic of Singapore Navy
SEED	Simulation Experiments and Efficient Designs
SLOC	Sea Lines of Communications
TSAS	Towed Synthetic Aperture Sonar
UAV	Unmanned Aerial Vehicle
USN	United States Navy
USV	Unmanned Surface Vehicle
UUV	Unmanned Underwater Vehicle

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EXECUTIVE SUMMARY

The maritime industry plays an essential role in the survival of Singapore. As a country with no natural resources, Singapore depends on the sea for most of her needs. Seven percent of Singapore's gross domestic product (GDP) comes from the maritime industry and more than 90% of Singapore's food supply is imported via sea freight (Ministry of Defence, 2019). In fact, it has been estimated that more than S$2 billion worth of trade losses could result from closing Singapore's port for a day (Goh & Lam, 2015), threatening Singapore's economy. Thus, it is important to maintain maritime security around Singapore by ensuring its surrounding sea lanes and the Singapore Straits are available and safe for international shipping. In particular, it is essential that Singapore is able to effectively search and remove all naval mines deployed by hostile forces in the vital waterways surrounding Singapore.

Detecting and neutralizing naval mines is tedious, time-consuming, and dangerous. With the advancement in unmanned systems, navies around the world are exploring the use of unmanned systems to perform these dangerous missions. Therefore, effective use of unmanned systems is becoming increasingly crucial to a successful mine countermeasure (MCM) mission.

The objective of this study is to increase our understanding of the effectiveness and performance of MCM missions by exploring different concept of operations (CONOPS) of cooperative unmanned systems. The CONOPS studied are broadly classified into two different categories: Platform/Payload and Operational Strategy. Platforms investigated include unmanned surface vehicles (USV) that carry different payloads for different tasks. Operational strategy refers to search paths and platform behaviors. The study is based on high-level scenarios and the results are meaningful when compared within the scenarios studied in the experiments. Figure 1 summarizes the methodology used in the thesis to achieve the study objective.

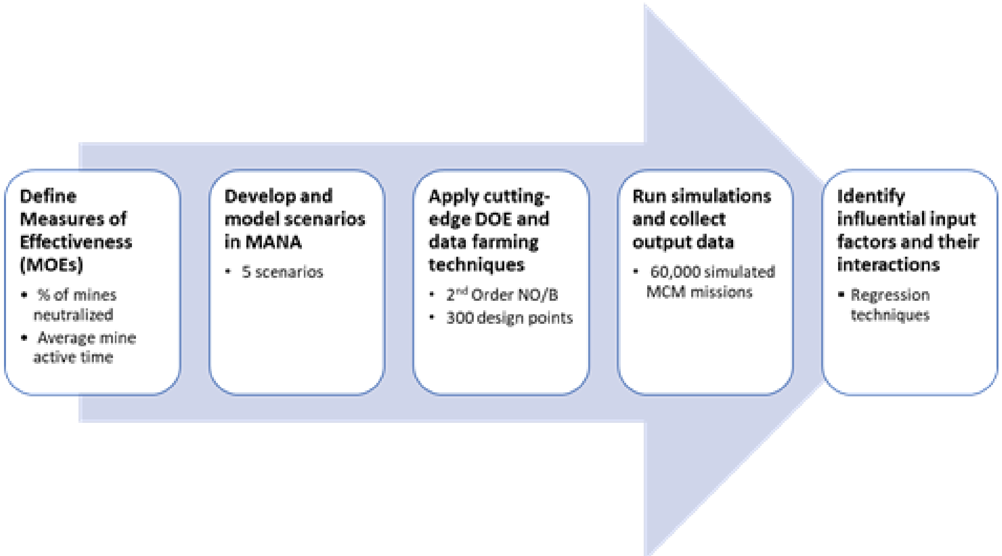

Figure 1. Thesis methodology

Scenario selection was based on defensive MCM to protect the vital waterways of the Singapore Straits from hostile forces. Five separate scenarios are modeled to study the impact of different platforms, sectorization of neutralizers, detector revisit rate, and detector search pattern.

This thesis uses agent-based simulation, cutting-edge design of experiment, and parallel computing to efficiently explore the effectiveness of studied CONOPS. A second order nearly orthogonal/balanced design developed by Alexander D. MacCalman was used to construct an experiment design with excellent space-filling properties, and which was ideal to fit second-order models (MacCalman, 2013). A total of 60,000 simulated MCM missions were carried out for this research and the results underwent rigorous statistical analysis to produce meaningful insights.

The thesis findings focus on how CONOPS can affect performance and risk to transiting vessels. In this case, performance refers to the percentage of mines neutralized while risk to transiting vessels refers to the average mine active time in the search area. It is important to note that while the findings may apply well beyond Singapore, the findings are made with reference to the scenarios studied and only apply when similar conditions are met. These findings include the following:

- Single sortie and two sortie operations perform equally well in terms of performance and risk to the transiting commercial vessels.
- The sectorizing of neutralizers by either detectors or areas has no impact on their performance, but it increases the risk to transiting commercial vessels.
- A reduction in revisit rate is detrimental to both performance and risk to transiting commercial vessels.
- All the CONOPS studied in this thesis are capable of handling the number of mines looked at with no impact to performance.
- The most critical factor in improving the performance of MCM missions is planning overlaps in the sensor range.
- The most critical factor in reducing the risk of transiting commercial vessels is detector speed.
- Interaction between path deviation and overlapping sensor range shows that when there are gaps in the sensor range, increasing path deviation leads to better detection; when there are overlaps in the sensor range, increasing path deviation leads to missing mines.

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I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Naval mines are effective force multipliers and are one of the most effective weapons used in the waters (Ocean Studies Board et al., 2000). They are small, easy to hide, require minimal maintenance once deployed, and can be easily deployed by many different platforms. Naval mines can quickly annihilate or seriously damage surface and submarine forces. Consequently, their use can bring sea commerce to an abrupt halt. Given the low cost to high damage ratio, ease of deployment, and versatile usage in the surrounding waters, mines are one of the most effective and deadly weapons used to defend/attack important targets. Figure 1 shows a photograph of an ordnance team with a training mine. Naval mines have evolved significantly from simple contact mines to modern influence mines with magnetic, acoustic, and pressure sensors (Goh & Lam, 2015). Moreover, modern naval mines can be planted by hostile countries as well as by organized terrorists (Inbar, 2011).

U.S. Navy diver David Ahearn attaches an inert satchel charge to a training mine, during training exercises in waters off Naval Base Guantanamo Bay, Cuba, on Feb. 15, 1997.

Figure 1. Ordnance team and training mine. Source: Mckaskle (1997).

The maritime industry plays an essential role in the survival of Singapore. As a country with no natural resources, Singapore depends on the sea for most of her needs. Seven percent of Singapore’s gross domestic product (GDP) comes from the maritime industry and more than 90% of Singapore’s food supply is imported via sea freight (Figure 2). In fact, it has been estimated that more than S$2 billion worth of trade losses could result from closing Singapore’s port for a day (Goh & Lam, 2015), threatening Singapore’s economy. Thus, it is important to maintain maritime security around Singapore by ensuring its surrounding sea lanes and the Singapore Straits are available and safe for international shipping. In particular, it is essential that Singapore is able to effectively search and quickly remove all naval mines deployed by hostile forces in the vital waterways surrounding Singapore.

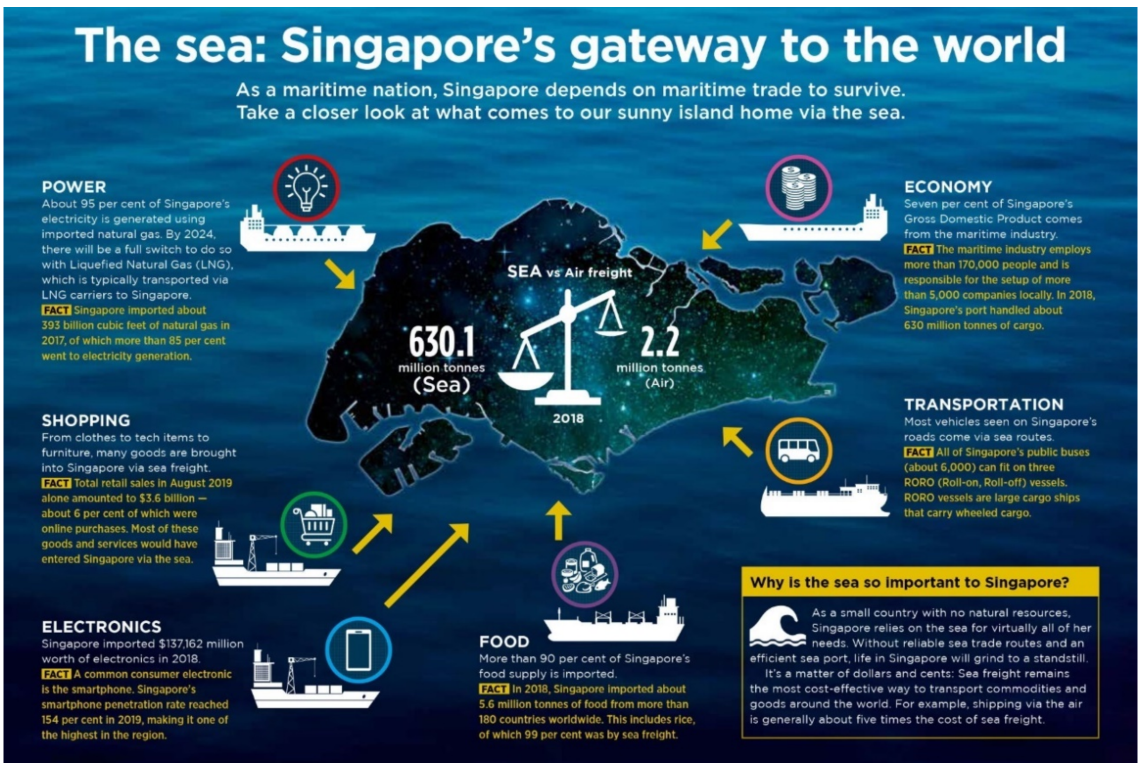

Figure 2. Singapore maritime infographic. Source: Ministry of Defence [MINDEF] (2019).

B. THE PROBLEM

Detecting and neutralizing naval mines is tedious, time-consuming, and dangerous. With the advancement in unmanned systems, navies around the world are exploring the use of unmanned systems to perform these dangerous missions. Therefore, effective use of unmanned systems is becoming increasingly crucial to a successful mine countermeasure (MCM) mission.

The objective of this study is to increase the effectiveness and performance of MCM missions by exploring different concept of operations (CONOPS) of cooperative unmanned systems.

C. SCOPE

The CONOPS studied are broadly classified into two different categories: Platform/ Payload and Operational Strategy. Platforms investigated include unmanned surface vehicles (USV) that carry different payloads for different tasks. Operational strategy refers to search paths and platform behaviors. The study is based on high-level scenarios and the results are meaningful when compared within the scenarios studied in the experiments.

D. METHODOLOGY

The following process was implemented to answer the thesis problem statement (Treml, 2013):

1. Define Measures of Effectiveness (MOE) for MCM operations.
2. Develop and model scenarios in Map Aware Non-Uniform Automata Version V (MANA-V) to study MCM operations.
3. Apply design of experiment (DOE) and data farming techniques to form efficient design matrices of the study parameters.
4. Run simulations and collect output data.
5. Identify influential input factors and their interactions according to the defined MOEs.
6. Use regression techniques to create meta-models.

7. Analyze how factors affect CONOPS and which CONOPS result in better performance based on defined MOEs.

E. THESIS ORGANIZATION

Chapter II highlights important concepts and tools critical to this thesis. The chapter introduces MCM, reviews unmanned vehicles, and discusses the modeling approach. Chapter III focuses on model development. The author defines the scenario, explains the characteristics, discusses the factors, their ranges, and key model assumptions. Chapter IV covers factor selection, DOE, and the use of Second Order Nearly Orthogonal/Balanced (NO/B) designs to efficiently explore the factor space. Chapter V analyzes the simulation results and provides insight into the different CONOPS. Chapter VI concludes the study and suggests future research.

II. INTRODUCTION TO MINE COUNTERMEASURES, UNMANNED SYSTEMS IN MINE COUNTERMEASURES, AND THE MODELING ENVIRONMENT

A. MINE COUNTERMEASURES: AN OVERVIEW

The two basic kinds of mine countermeasures (MCM) are minehunting and minesweeping. In a research report by the RAND Corporation, minehunting is defined as the process of positively detecting, identifying, and engaging/neutralizing sea mines; minesweeping is the process of replicating a mine's target signature to cause mines to actuate. Minehunting is labor intensive and time consuming, while minesweeping is quick but less effective (Martin et al., 2019). Due to the higher certainty that mines are detected, classified, and neutralized, minehunting is the preferred tactic and is discussed in detail in this chapter.

1. Minehunting Kill Chain

Minehunting is best depicted as a sequential process—detect, identify, and neutralize (Figure 3). The steps of the process do not usually overlap, and they require different payloads to perform the functions. Each payload has to acquire the mine multiple times to positively track the mine before performing its main function. In a dynamic environment, the chances of sensors losing track of the mine increase with multiple iterations. In addition, neutralizing a mine can disrupt the environment, causing redundancy for remaining sensors to continue searching for the neutralized mine (Martin et al., 2019). Bradley Martin, Danielle Tarraf, Thomas Whitmore et al. also highlighted that inefficiency in the process is mainly a result of payloads not connected in a coherent way that enables them to share and process information.

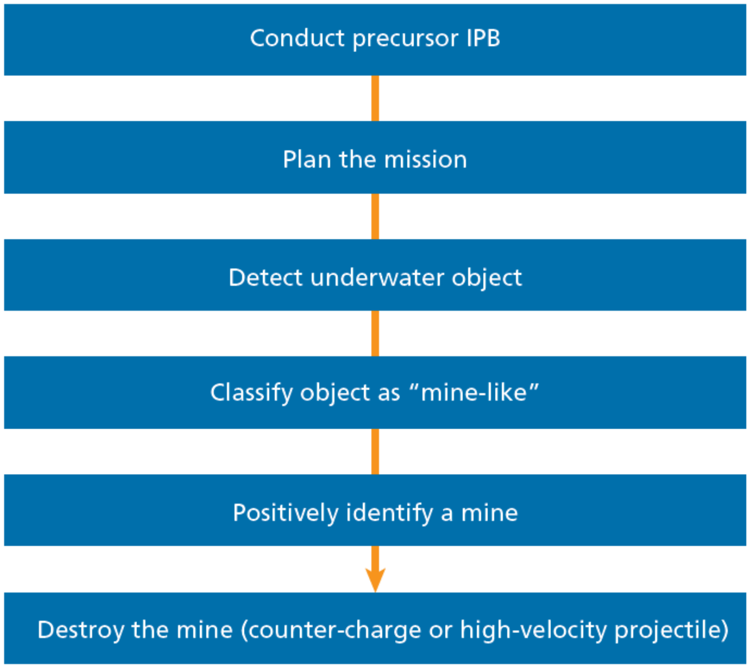

Figure 3. Minehunting sequence. Source: Martin et al. (2019).

2. Dedicated Mine Countermeasures Forces/Assets

Dedicated MCM forces are the units trained specifically for MCM operations (Ocean Studies Board et al., 2000). The Ocean Studies Board categorizes the forces into surface, airborne, and underwater (Ocean Studies Board et al., 2000). Currently, U.S. Navy MCM capabilities include Avenger class MCM ships, airborne MH-53E Sea Dragons, and MCM modules/systems fused into Littoral Combat Ships (LCS). The LCS MCM systems include the AN/AQS-20 minehunting sonar (Naval Sea Systems Command, 2019); AN/ASQ-235 Airborne Mine Neutralization System; Airborne Laser Mine Detection System; AN/DVS-1 Coastal Battlefield Reconnaissance and Analysis; Unmanned Influence Sweep System; Knifefish unmanned undersea vehicle (UUV); and Barracuda mine neutralization system (Miller, 2019). LCS MCM systems, however, are still not fully operational, but when they are, they can provide comprehensive, multidomain capability to mine hunt, sweep, and neutralize (Miller, 2019). Table 1 summarizes some MCM assets, but does not include LCS MCM systems.

Table 1. Dedicated mine countermeasures assets. Adapted from Ocean Studies Board et al. (2000).

Surface	USS Inchon	• Landing platform for MH-53E Sea Dragon • Repair and re-supply facility for Avenger and Osprey class coastal minehunters
	Avenger class	• Designed to find, classify, and destroy moored and bottom mines in both coastal and offshore areas • Employ sonar and video systems for minehunting and use remotely controlled mine detonating devices, cable cutters, and other more conventional minesweeping measures for mine removal
	Osprey class	• Operates in shallow coastal waters and harbors • Has minehunting capability only
Airborne	MH-53H Sea Dragon Helicopters	• Minehunting and sweeping capabilities • 24 HM-14/HM15 aircraft • 450 NM range • Five to seven person crew
Underwater	Explosive Ordnance Disposal (EOD)	• 17 mobile MCM detachments • A detachment consists of one officer and seven enlisted personnel • PQS-2A sonar • Mk 16 non-magnetic underwater breathing apparatus
	Marine Mammal System (MMS)	• 12 mammals, dolphins, and sea lions • Four systems available and one under development

3. Contribution of Autonomous/Unmanned Systems in Minehunting

According to the previously mentioned report by the RAND Corporation, the minehunting process is slow, perilous, and manpower intensive (Martin et al., 2019). In the report, Martin highlighted that depending on the CONOPS, minehunting is likely to be tedious and taxing on human endurance. Tasks of such nature are best exploited by autonomous systems. Martin further noted that autonomous systems currently being developed have two main functions, detection and neutralization. The functions are typically performed by different payloads which are not connected in a coherent way that enables them to share and process information. Sensor detection is achieved using sonars towed by manned helicopters or (autonomous) USV or (autonomous) UUV with sonars capable of detecting and classifying mines (Martin et al., 2019). Neutralization can be accomplished with expendable mine neutralizers. The expendable mine neutralizers require authorization due to their destructive operation and thus are semi-autonomous.

B. SEARCH PATTERNS OF MINEHUNTING SYSTEMS

This section introduces some of the search patterns that can be used by minehunters to search for naval mines. According to the training manual by Coastguard New Zealand (2013), the search patterns can be applied to different situations based on the size of the search area and knowledge of probable location of the target. Each search pattern may also result in a different probability of detection based on the coverage and coverage factors (Coastguard New Zealand, 2013).

1. Sector Search

Sector search is suitable when the probable location of the target is well established and the search area is small. Figure 4 illustrates a sector search pattern from a bird's eye view when two vessels are used. Probability of detection is very high for a sector search, but the search area is limited by the sweep width of the sensor. When the length of the search leg exceeds three times the sweep width, gaps start to occur and probability of detection falls (Coastguard New Zealand, 2013).

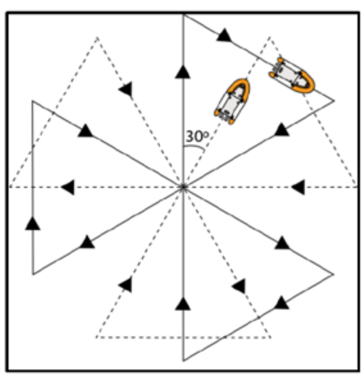

Figure 4. Sector search pattern with two vessels.
Source: Coastguard New Zealand (2013).

2. Expanding Square Search

An expanding square search is also suitable when the probable location of the target is reasonably well established and the search area is relatively small. Figure 5 illustrates what the search looks like from a bird's eye view. Probability of detection is not as high as it is for the sector search, but with this method the search area can be expanded, as required (Coastguard New Zealand, 2013).

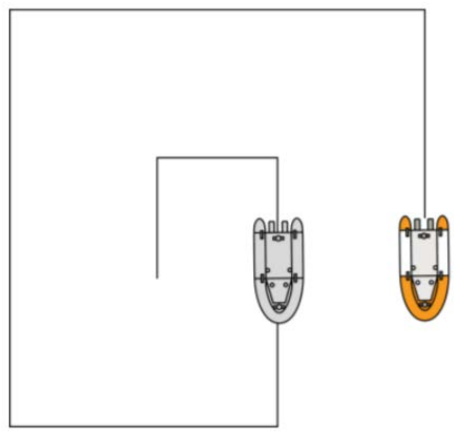

Figure 5. Expanding square search pattern.
Source: Coastguard New Zealand (2013).

3. Parallel Track Search

The parallel track search is suitable when there is no information on the location of the target and the search area is large. It is likely the most commonly used search method due to its flexibility and suitability to all sizes and shapes of search area (Coastguard New Zealand, 2013). Figure 6 illustrates what a parallel track search looks from a bird's eye view. A parallel search pattern is more efficient than the sector search and the expanded square search as it has less overlapping of coverage area.

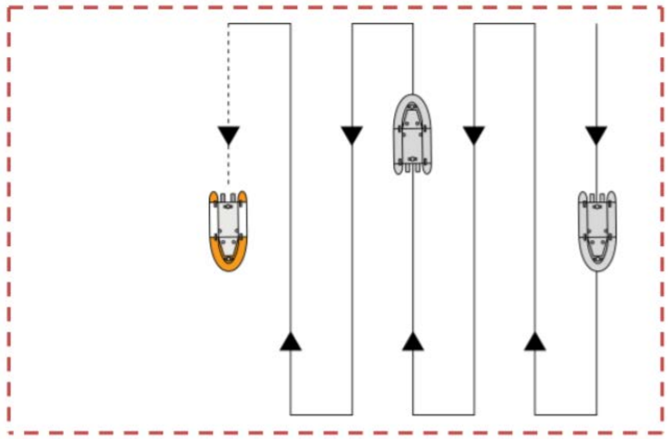

Figure 6. Parallel track search pattern.
Source: Coastguard New Zealand (2013).

4. Random Search

Random search is searching with no memory of previously searched history. Random search is important because it forms the lower limit on the effectiveness of searches that attempt to be systematic (J. Eagle, Class notes, April 20, 2020). A random search is mathematically simple, and the probability of detection can be obtained analytically based on the sensor and target conditions. One interesting result from analysis of random search is that the target has the highest probability of avoiding detection by not moving when a sensor is using the random search method (J. Eagle, Class notes, April 20, 2020).

C. UNMANNED VEHICLES IN MCM

This section introduces some of the unmanned vehicles used by Republic of Singapore Navy (RSN) and United States Navy (USN). These unmanned vehicles are either operational-ready or in their final development stage.

1. Mine Countermeasure USVs Developed for RSN

Two Mine Countermeasure USV have been developed for the enhancement of maritime security and homeland defense. On March 2, 2018, the Ministry of Defence (MINDEF) published a fact sheet highlighting the MCM USVs. The USVs can carry two different types of payload: Towed Synthetic Aperture Sonar (TSAS) and Expendable Mine Disposal System (EMDS) (refer to Table 2 for more details on their technical specifications). TSAS conducts underwater scans of the seabed to detect mines while EMDS neutralizes mines. The key features of the USVs include high speed coupled with better maneuverability, autonomous navigation with collision avoidance, and low manning (MINDEF, 2018).

Table 2. Technical specifications of MCM USVs. Adapted from MINDEF (2018).

Specification	**Mine Countermeasure USV with Towed Synthetic Aperture Sonar**	**Mine Countermeasure USV with Expendable Mine Disposal System**
		
Function	Detection of mines	Neutralization of mines
Length	16 meters	16 meters
Beam	5 meters	5 meters
Weight/ Displacement	30 tonnes	30 tonnes
Speed	> 25 knots	> 25 knots
Endurance	> 36 hours	> 36 hours
Operators (when operating remotely)	2	2
Equipment	Towed Synthetic Aperture Sonar Automatic Launch and Recovery System Navigation Radar Global Positioning System	Expendable Mine Disposable System Automatic Launch and Recovery System Navigation Radar Global Positioning System

a. Towed Synthetic Aperture Sonar

The USV with TSAS can be operated in semi-autonomous mode through an automatic launch and recovery system (LARS) to remotely launch and recover the sonar at the end of each operation. The TSAS is a high-resolution, towed side scan sonar for detection and classification of bottom and short tethered mines (refer to Table 3 for key technical specifications). The detection and classification system on board the USV can shorten the mine processing time by more than 50% (MINDEF, 2018).

Table 3. Key technical specifications for TSAS. Source: Thales (n.d.).

Speed	11 knots (max)
Max water depth	200m
Range	2*150m
Coverage rate	3km^2/h in SAS
Resolution	3.5cm
SAS cross resolution	5cm @150m

b. Expendable Mine Disposal System

An article from ECA Group (2017) claims that the USV with EMDS conducts mine disposal and can be operated with three people controlling the unmanned system. This greatly reduces the operational cost and human risks in the mine disposal process. The article also states that the USV is equipped with an inspection vehicle, K-STER I, and expendable vehicles, K-STER C (refer to Figure 7 for photograph of a K-STER C). It was further revealed that all the vehicles are launched remotely with automated LARS. The crew launches and pilots the K-STER I for inspection and, if mines are found, K-STER C will be deployed by a dedicated launching system (ECA Group, 2017).

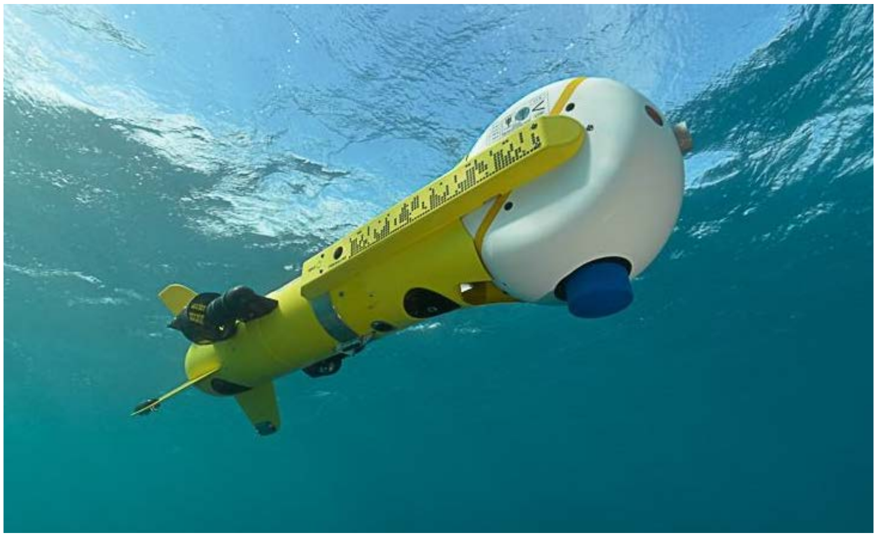

Figure 7. K-STER C, expendable mine disposal vehicle.
Source: ECA Group (n.d.).

2. Single Sortie Common Unmanned Surface Vehicle Developed for the United States Navy

The Common Unmanned Surface Vehicle (CUSV) developed for the U.S. Navy is a single sortie, mine hunting autonomous ship capable of detecting, classifying, and neutralizing a mine. David Larter (2019) highlighted that it is a significant achievement in MCM because the single sortie CUSV is scalable, safe, and fast. He further explained that no divers from the EOD team are required and the time to clear an area will be reduced by at least 30%. The CUSV itself was developed by Textron, while the detection and neutralization systems were developed by Raytheon. Based on the product video by Raytheon (2019), the CUSV tows an AQS-20 sonar system to detect and classify mines. The video clearly shows that upon successful classification, an operator will authorize the deployment of the Barracuda Expendable Mine Neutralizer. The Barracuda subsequently proceeds to autonomously reacquire the mine and neutralize the mine after confirmed authorization from the operator.

In a news article published by Raytheon in 2019, the Barracuda was described as "a semi-autonomous, unmanned underwater vehicle that identifies and destroys near-surface, volume and bottom sea mines. It can operate in shallow water, using an expendable, modular neutralizer with a kill mechanism, propulsion, sensors and communications buoy, which transmits wirelessly back to the host ship" (Raytheon, 2019).

3. Unmanned Underwater Vehicle, Knifefish, Developed for the United States Navy

Knifefish is a self-propelled, unmanned vehicle designed to detect and classify mines. It can be deployed from the LCS, any suitable surface ship, or from shore. The key benefits of Knifefish are that it "detects, classifies and identifies buried mines in high-clutter underwater environments; allows 'plug and play' integration with ship systems and mission modules; integrates into multiple ship types; provides intelligence support for other mine warfare systems; and enables rapid mission turnaround time" (Montferret, n.d.). The Knifefish system, which was developed for the U.S. Navy, has two UUVs and support systems, low-frequency broadband sonar, and automated target-recognition software to allow autonomy to the sensor while the host ship stations outside of the suspected minefield (Keller, 2019). The Knifefish is not a complete MCM solution on its own, as it has to cooperate with another mine neutralization system to dispose of any classified mines. One possible system for Knifefish to work with is the Airborne Mine Neutralization System developed by Raytheon.

D. MAP AWARE NON-UNIFORM AUTOMATA

The MANA software is an agent-based distillation environment that has been developed by New Zealand's Defence Technology Agency (DTA). MANA is used in a large variety of domestic and international defense science studies (McIntosh et al., 2007). MANA was developed based on two key ideas: (1) behavior of the entities plays a critical role in possible outcomes, and (2) detailed physics-based calculations are useless in determining force mixes and combat effectiveness (McIntosh et al., 2007). MANA has stochastic elements and is a time-step simulation.

The key features in MANA that differ from many other agent-based modeling environments are MANA's capability to explore intelligence, communications, terrain map, locations, and event-driven behaviors. These features allow MANA to construct a complex adaptive system emulating real-world factors during combat, such as a change of strategy as the battle unfolds; the influence of intelligence during decision making; and effective use of sensors (McIntosh et al., 2007). A limitation of MANA is that it is not designed to examine detailed military operations, and imperfect entity behaviors may lead to disastrous consequences. This limitation is intentional and has the potential to help users discover valuable insights from the simulation model (McIntosh et al., 2007).

Parameters in MANA can be categorized into four basic types: personality weightings, move constraints, intrinsic capabilities, and external factors influencing movement. These simple parameters give rise to an enormous possibility of behaviors (McIntosh et al., 2007). MANA receives input on the parameters from extensible markup language (XML) files. Outputs from MANA are in comma separated value (CSV) files that can be easily post processed to obtain defined metrics.

Useful features for running large experiments in MANA include multi-runs, data farming, genetic algorithm, and data analysis. Multi-run is critical as it introduces randomness into the scenario as specified by a seed number. Although useful, data farming within MANA is limited to varying up to two parameters. To overcome this limitation, the Simulation Experiments and Efficient Designs (SEED) Center at the Naval Postgraduate School (see https://harvest.nps.edu) has a program capable of running MANA simulations based on a chosen design of experiment. The genetic algorithm emulates the natural selection process by selecting desirable inputs, which improve performance metric(s), and propagates them in subsequent runs. There involves randomness in each iteration to allow exploration of the complete solution space, increasing the chance of finding a global optimal solution (Gulosh, 2018). Data analysis in MANA generates a pre-determined set of time-dependent metrics, such as “average casualty rates, Loss Exchange Ratios, fractal dimensions, detection rates, and clustering statistics” (McIntosh et al., 2007, p. 97). In most cases, where different metrics are required, another data analysis tool is used in processing the output results files.

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III. MODEL DEVELOPMENT

A. INTRODUCING THE SCENARIO

Scenario selection was based on defensive mine countermeasures (MCM) to protect the vital waterways of the Singapore Straits from hostile forces. Hostile forces are in the form of small terrorist boats planting moored or bottom mines. There is no effective way to prevent all terrorist boats from transiting through the Singapore Straits; thus, the mission is detecting, classifying, and neutralizing the mines after they are deployed.

1. Region

The Straits of Malacca and Singapore compose one of the busiest Sea Lines of Communication (SLOC) connecting the East and the West. More than 200 vessels transit the waterways daily, resulting in highly congested waters (Qu & Meng, 2012). The entire length of the Singapore Straits is approximately 113 kilometers and the average width is about 19 kilometers (Vernon, 2015). Figure 8 is a map of the operational areas segmented by the reporting system.

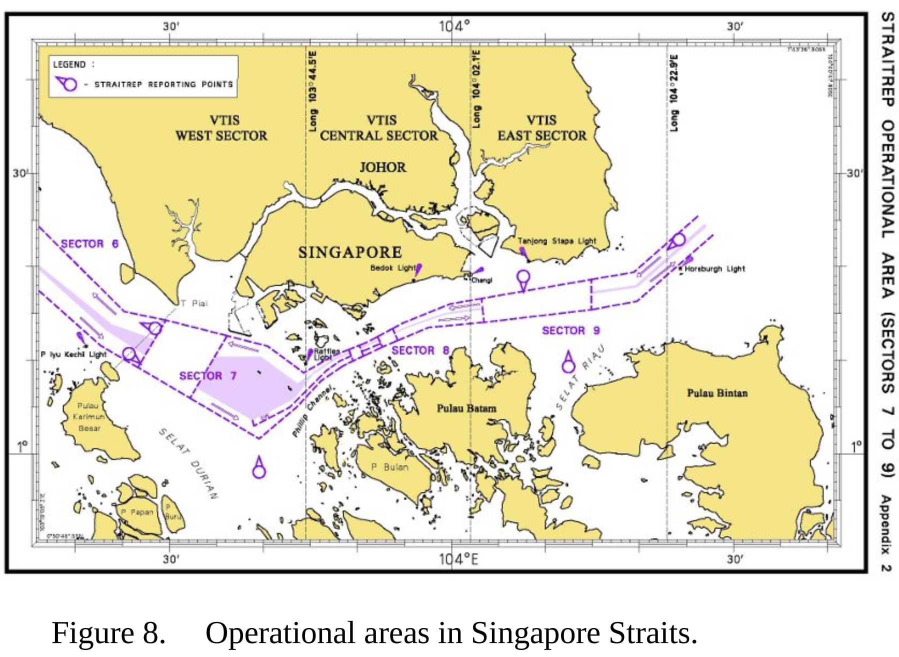

Figure 8. Operational areas in Singapore Straits.
Source: Maritime and Port Authority of Singapore (n.d.).

2. Units Involved

This section introduces the forces involved in the MCM mission. The forces are broadly categorized into enemy forces, friendly forces, and neutral forces.

a. Enemy Forces

Terrorist boats with the intention to plant naval mines in Singapore's waters are a source of threat to peaceful voyagers. As terrorist boats are small, fast, and inconspicuous, they are hard to detect and track. The focus of this study is to detect and neutralize stationary naval mines instead of detecting and capturing mobile terrorist boats. Therefore, the enemy in the scenario is naval mines that can be planted anywhere along accessible waters. Although there are many different types of naval mines, there is no distinction as to what type of naval mine is planted. These naval mines do not move after they are planted; thus, they are generally moored mines or bottomed mines.

b. Friendly Forces

The minehunting unit consists of a detector, a classifier, and a neutralizer. They are deployed from a manned host ship that stays out of the search area. The detector and classifier are typically integrated into one system (which will be referred to as detectors for the subsequent part of this thesis), while the neutralizer is a separate system. Three types of friendly units are studied. The USV with TSAS is an unmanned detector; USV with EMDS is an unmanned neutralizer, and CUSV is an unmanned single-sortie USV capable of detecting and neutralizing mines. The mission is to neutralize as many mines as possible within a specified time frame.

c. Neutral Forces

During the search process, commercial vessels are transiting in the sea lanes as per normal operations. These vessels vary in size from small crafts less than five meters in width to large cargo ships as wide as 60 meters. These vessels may obstruct the intended search path of the detectors and prevent them from covering the entire search area. The high flow of commercial ships along the waterway poses an additional challenge to the minehunting mission.

B. MEASURE OF EFFECTIVENESS

The United States Air Force defines MOE as “a criterion used to assess changes in system behavior, capability, or operational environment that is tied to measuring the attainment of the end state, achievement of an objective, or creation of an effect” (Curtis E. Lemay Center, 2016). A good MOE has to be quantifiable, measurable, related to the objective (effect), and tracks progress or assists decision making (J. Kline, Class notes, July 8, 2020). In this thesis, MCM vehicles seek to detect and eliminate as many naval mines as possible within the allocated time frame. As the operation is a perpetual search for naval mines, any active naval mine will pose a risk to vessels transiting within the area.

1. MOE1: Percentage of Mines Neutralized

Percentage of Mines Neutralized is the primary MOE; it is computed using the number of mines neutralized divided by the number of mines planted in the simulation runs. The number of mines neutralized will be the same as the number of mines classified when there are sufficient neutralization units in the simulations. For all the simulation runs, the author has provided sufficient neutralization units such that all mines detected will be neutralized.

2. MOE2: Average Mine Active Time

Average mine active time is computed by subtracting the time the mine was deployed from time the mine was neutralized and only applies to mines that were neutralized. It is a measure of the average time interval of active mines remaining in the search area and thus is an indicator of the risk to transiting vessels. This is a secondary MOE to gain more insights on the risk given that the mines are neutralized.

C. MODEL ASSUMPTIONS

Models seldom mirror actual situations perfectly. Therefore, assumptions are made to scope the problem and simplify complex scenarios. The assumptions help remove unnecessary features and direct the focus of the study scenarios. The following are the critical assumptions formulated with the corresponding the model design or agent development. These modeling assumptions will result in optimistic values for both our measures of effectiveness; however, we seek insight on relative performance due to our design factors, not attempting to predict actual performance.

- The objective of the study is to detect and neutralize mines. Therefore, naval mines will not detonate to destroy or damage commercial or military vessels. Naval mines are simulated as idle agents with no weapons.

- All USVs are cooperative and share information within the agents. Detectors are capable of sending the exact location of classified mines to neutralizers with an insignificant time delay. Neutralizers do not need to spend time to redetect and reclassify the mines in order to detonate them.

- Naval mines are either moored or bottom mines that are deployed by terrorist ships. The naval mines are thus stationary and armed once deployed.

- Detection and classification are simplified to detection with a probability of success as a function of range. Detection in MANA is modeled by how often the sonar scans while classification determines target confirmation with a probability of success. Therefore, classification is used to represent the probability of detection.

- Reliability of USVs is not considered in this study, and thus, endurance, maintenance, and breakdowns are not simulated.

- The revisit rate to be studied is at every eight hours or every 24 hours. With search pattern, area, and runtime fixed, three or one detector is modeled to search the battlefield to represent the revisit rate, respectively.

- There are no false positive detections of naval mines. Therefore, all expendable neutralizers deployed are consumed without retrieval.

D. BUILDING THE MODEL

This section documents the model setup in MANA-V. Details of the model include the battlefield, squads' characteristics, and model workarounds. The model assumptions in the previous section are critical inputs to the construction of the MANA model.

1. Battlefield

The simulation area is simplified to a 10 kilometer by 10 kilometer open sea with no restriction on movement. This simplification allows results to be scalable to larger area and avoids unsubstantiated claims to terrain details. The maximum run time for the simulation is set to 24 hours to ensure that it is within the endurance of all the unmanned systems. Longer hours are not explored because sustainability is not a study criterion and there would be trade-offs in the number of replications the author can simulate with time and space constraints. Figure 9 is a screenshot of a sample scenario in MANA. Red addition symbols represent naval mines, blue ship symbols represent detectors, and pink ship symbols represent neutralizers. Details of the agents are explained next, under "Squad Characteristics and Workarounds."

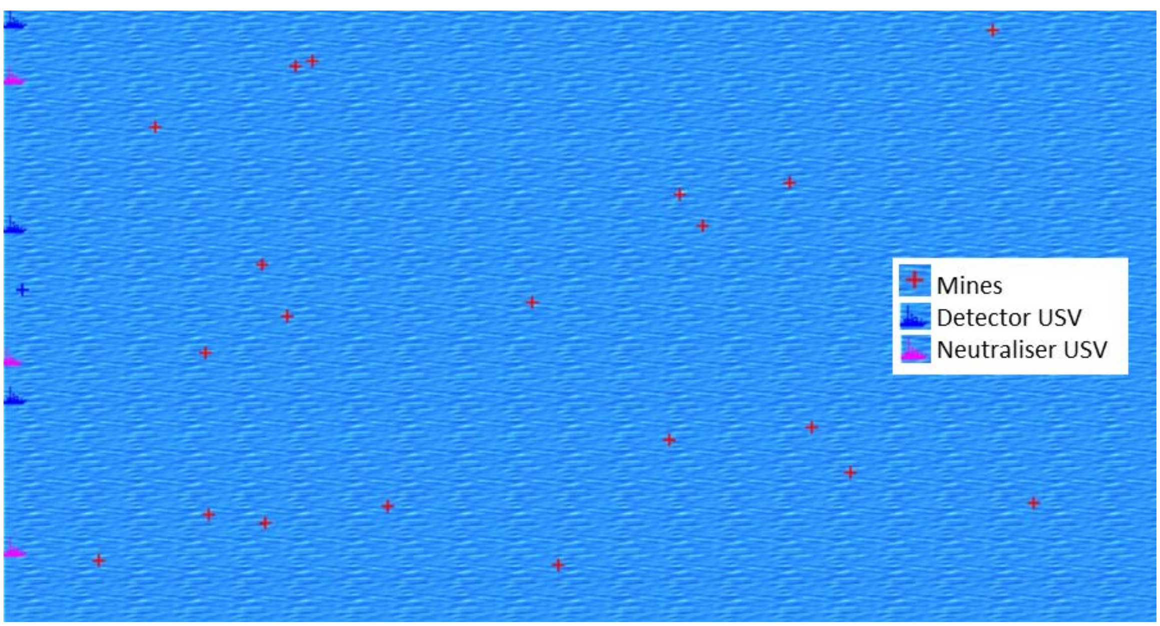

Figure 9. Screenshot of sample scenario in MANA

2. Squads Characteristics and Workarounds

This section documents the detailed descriptions of the five squad types modeled in the different scenarios as well as critical workarounds to achieve desired behaviors. Note that a squad in MANA is a set of agents that begins the scenario with identical capabilities and behaviors. The author used assumptions, open access publications, product specifications from manufacturers, and inputs from subject matter experts to build the squads' characteristics. Fixed parameter values used in squad behaviors represent an estimated value that is not critical as the study draws conclusions by comparing between simulation runs rather than providing specific values on detailed operations parameters. Workarounds used are based on consultation with subject matter experts and experimentation with MANA-V.

a. Enemy Forces: Red Mines

This agent squad represents the naval mines that can be planted anywhere within the map with equal probability. The naval mines are the red addition symbols shown in Figure 9. Once planted by terrorist boats, the naval mines are stationary. As the simulation represents ongoing operations where naval mines can be planted anytime, mines appear in the map randomly at different times. With the constraint of 24 hours runtime, mines must appear before the map is searched. For example, mines are activated within the first 16 hours in the base case scenario to ensure that the whole map can be searched at least once by the detectors after the mines are planted. In the experiment where there is only one detector, mines are activated at the start of the simulation to ensure all mines have a chance of being detected.

b. Friendly Forces: USV with TSAS

This agent squad represents the unmanned surface vehicle towing the synthetic aperture sonar. The USVs with TSAS are the blue ship symbols shown in Figure 9. Their role is to detect and classify naval mines where the information can be shared with the neutralizers. The author obtained speed, range, and coverage rate from the product specifications of the manufacturer while the probability of detection is based on input from subject matter experts. The USVs follow a parallel track search pattern, which is the recommended search pattern when there is no information on the location of the mines. Figure 10 illustrates the path taken by the USVs to search the area in MANA. In the scenarios where there are three USVs with TSAS, the revisit rate is approximately eight hours. In the scenario where there is only one USV with TSAS, the revisit rate is approximately 24 hours.

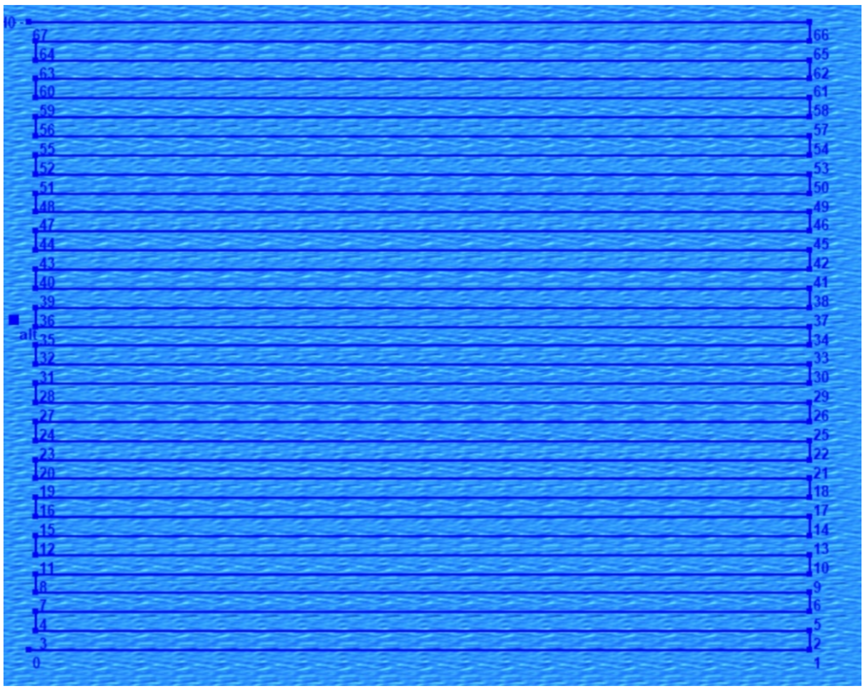

Figure 10. Parallel track search pattern for detectors in MANA

c. *Friendly Forces: USV with EMDS*

This agent squad represents the unmanned surface vehicles loaded with KSTER-I and KSTER-C. The USVs with EMDS are the pink ship symbols shown in Figure 9. Their role is to neutralize the classified naval mines with a 100% success rate. With a sufficient number of USVs with EMDS, all classified mines will be neutralized within the simulation run time. The agent has six KSTER-C loaded and requires reloading at a host ship when all the KSTER-C are expended. In all the scenarios, there are three USVs with EMDS to ensure sufficient neutralization units. The mode of operations of the three USVs is one of the CONOPS to be studied. In the base case scenario, all three USVs with EMDS are unrestricted in the area and will move to neutralize the closest mine classified. In the second experiment, each USV with EMDS is tagged to a unique detector. In another experiment, each USV with EMDS is responsible for a search area.

d. Friendly Forces: CUSV

This agent squad represents the single sortie Common Unmanned Surface Vehicle (CUSV) carrying AN/AQS-20 sonar and the Barracudas. The single sortie CUSV reduces the number of USVs to be deployed on the field and thus streamlines the minehunting process. The role of this agent includes identifying, classifying, and neutralizing the naval mines. As there was no information on the specifications on AN/AQS-20, it was assumed to have specifications similar to TSAS as both are synthetic aperture sonars. Based on the product video by the manufacturer, each CUSV has six Barracudas loaded, and once a Barracuda is deployed, the CUSV will continue with the search (Raytheon, 2020). Similar to a USV with TSAS, CUSV uses a parallel track search pattern, and three CUSVs are deployed in the scenario to achieve a revisit rate of approximately eight hours.

e. Neutral Forces: Commercial Vessels

This agent squad represents commercial vessels transiting through the Singapore Straits. The vessels can be big or small, but there is no distinction of size within the model. The role of this agent is to artificially direct the searchers away from their original planned parallel tracks. In the small area of 100 square kilometers, there are 50 neutral agents to emulate congested waters. A literature review indicated that within a constricted narrow passage, the recommended safety distance between two ships is approximately 1200 meters (Horteborn, 2019). This would imply that a fully congested waterway will have approximately 70 ships in the area. For the USV to be able to transit, it requires gaps and thus an estimated value of 50 neutral ships was used.

f. Workaround 1: Cooperative Systems Share Information

Detection and neutralization are performed by two different agent squads, and there can be multiple agents in each agent squad. Each agent functions as an individual unit and makes its own decisions based on its given personality. There are parameters to emulate sharing of information within squads and between squads. The sharing of situational awareness without updates on mines status, however, resulted in several undesirable behaviors of the neutralizer agents. Thus, to emulate timely sharing of information between detectors and neutralizers, the naval mines are modeled to change their agent class after they have been successfully classified by the detectors. Once the agent class is changed, neutralizer agents are able to detonate the naval mines. This simplifies the complicated sharing of information with all neutralizers, and allows all neutralizers to be updated on the status and locations of classified naval mines. This workaround did not explicitly model sharing of information, but simulates the effect of information being transmitted to the neutralizer agents.

g. Workaround 2: Deviation from Planned Route

The detectors are planned to follow a parallel track search pattern while scanning through the search area. However, there are at least two known reasons for detectors to deviate from their planned route. The presence of other vessels in the area will force detectors to deviate from their course to avoid collision. Inaccurate positioning and navigation systems will also result in vessels sailing off-course. A built-in MANA feature, random patrol, is normally used to emulate this behavior. With the lowest setting for random patrol, however, the movement is overly erratic and all deviations have the same fixed magnitude. In order for the deviations to be less erratic and with random magnitudes, the deviation from the planned route is modeled using a high number of random moving neutral agents in the map. These neutral agents will randomly direct the detectors to sail off-course to a threshold magnitude (based on the setting) before returning to the original course. This workaround can be used to emulate any situation that causes detectors to deviate from their original course. The frequency and threshold of the deviation can be controlled by the number of neutral units and personality of the detectors.

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IV. DESIGN OF EXPERIMENT

Designing an experiment is an important part in experimental studies. Experiments need to be carefully designed in order to efficiently use resources. There are many different ways of designing experiments, such as full-factorial, fractional factorials, Nearly Orthogonal Latin Hypercube (NOLH) and, Nearly Orthogonal/Balanced (NO/B) designs. Selection of experiment design depends on the number of factors, the variable type, and computational capability. In this thesis, the author employed the use of Second Order NO/B design based on a Naval Postgraduate School dissertation by Alexander D. MacCalman (2013) to help run the experiments (MacCalman, 2013).

A. FACTORS AND LEVELS

Several factors were identified to be varied in the experiments and for sensitivity analysis. Each of the factors was varied over a range based on input from subject matter experts, open access publications, and product specifications from manufacturers. The values are estimates in rough order of magnitude and should not be viewed as actual operational parameters. Table 4 summarizes the factors and levels used for the experiments.

Table 4. Factors with range and variable type

Factor / Description	Range	Type of Variable
1. Number of mines	4–20	Discrete (9 levels)
2. Detector path deviation (m)	0–100	Discrete (11 levels)
3. Overlapping sensor range (m)	(-)50–50	Discrete (11 levels)
4. Detector movement speed (knots)	7–11	Discrete (9 levels)

Based on communication with this research's sponsors, each terrorist boat can carry approximately three naval mines per trip and the endurance of their boat is approximately 12 hours. Therefore, naval mines were planted with an average time of one every four hours for each terrorist boat. The author also assumed that a maximum of five terrorist boats is used for an area of 100 square kilometers. This translates to a maximum of 20 mines deployed in 16 hours.

Detector path deviation is the maximum distance the detector will travel away from its planned search path. The deviation could be due to inaccurate navigation or the presence of obstacles or vessels within the search area. Range of detector path deviation is estimated based on the width of vessels transiting the waterways. The width of large cargo ships is approximately 50 meters; thus, the range of path deviation was set to be between zero to 100 meters. Zero path deviation would imply detectors are traveling exactly the planned search path, without other vessels in the area and with 100% accurate navigation/ positioning.

Overlapping sensor range refers to the length of search width that overlaps in the parallel track search pattern. When the overlapping length is higher, the parallel track search pattern is more compact and more time is required to search the same area. When the overlapping length is negative, there will be gaps in the search path and less time is required to search the same area. The range of the overlapping length is based on communication with sponsors and estimation from the probability of detection of the sensor. At negative 50 meters overlapping length, with zero path deviation, all mines will have an opportunity to be classified in the simulation. As the search path of the detectors is manually input into the model, changing the overlapping length is tedious and prone to errors. The author has provided an alternative by modifying the range of the sensor instead of changing the search path. The detailed range for probability of detection for each discrete level sensor setting can be found in Table 5.

Table 5. Sensor settings for range at fixed probability of detection

Probability of Detection		1.0	0.9	0.8	0
Range (m) Example: In Base Case, first 100 m has 100% detection, next 25 m has 90% detection, next 25 m has 80% detection.	**-50**	75	100	125	-
	-40	80	105	130	-
	-30	85	110	135	-
	-20	90	115	140	-
	-10	95	120	145	-
	0 (Base Case)	100	125	150	-
	10	105	130	155	-
	20	110	135	160	-
	30	115	140	165	-
	40	120	145	170	-
	50	125	150	175	-

Detector speed is limited by the sensor and USV capabilities. Based on product specifications for the sensor and the USV, the maximum operating speed is 11 knots. Detector speed directly influences the time taken to finish searching a given area, and the minimum speed to clear the simulated area is approximately nine knots. Detector speed was varied from 7 to 11 knots to include the required speed and within the maximum speed.

B. SECOND ORDER NEARLY ORTHOGONAL/BALANCED DESIGN

A full-factorial design is often the first option to consider when there are only a few factors, as it is the most exhaustive design that can show all main effects and all interactions of the factors. Based on the number of factors, levels, and scenarios, the design space for a full-factorial design would comprise 49,005 design points. However, on average, the time required to complete one simulation run is approximately one minute and the size of the output files is approximately 130 MB. With only one replication for all design points in a full-factorial, 34 days on a single processor and 6.37 TB of space would be required. Given the limited time and space for the experiment, a more efficient design is necessary.

In 2013, MacCalman developed a genetic algorithm that constructs a design with excellent space-filling properties and is ideal to fit second order models with a mixture of continuous and discrete factor types. The Second Order NO/B design has minimal correlations between all main, quadratic, and two-way interaction factors (MacCalman, 2013). The main advantages of a Second Order NO/B design are that it is able to estimate all second order terms with minimal confounding and also fit potentially higher order terms if they are significant. The custom design builder used to construct our design is available publicly for download at http://harvest.nps.edu. In addition, a peer reviewed paper by MacCalman et al. (2017) contains a concise explanation of the evolutionary algorithm used to construct these designs with an emphasis on continuous factors.

C. EXPERIMENT ONE: BASE CASE SCENARIO

This thesis describes a total of five experiments, each exploring a different configuration. In this first experiment, also called the base case scenario, the author is studying the use of two sorties in the minehunting mission. Detector USVs will be searching for naval mines using a parallel track search pattern, and when a naval mine is detected, the next available neutralizer USV will engage the naval mine with no restrictions. There are three detector USVs and three neutralizer USVs, resulting in a revisit rate of approximately eight hours for the 100 square kilometer area. The author has selected a Second Order NO/B design with 300 design points (DP). Each DP has 40 replications, for a total of 1,200 simulated minehunting missions.

D. EXPERIMENT TWO: DEDICATED NEUTRALIZER TO DETECTOR

In Experiment Two, the author explores the configuration where the detector and neutralizer are paired. This implies that the neutralizer is stationed close to its assigned detector. The motivation of this configuration is to deploy two sorties as close as possible to one sortie operation. In this configuration, a specific neutralizer might be overwhelmed if all the naval mines are detected by the same detector. All other setup follows the setup used in Experiment One.

E. EXPERIMENT THREE: DEDICATED NEUTRALIZATION AREA

In Experiment Three, the author explores the configuration where each neutralizer has a dedicated neutralization area. This implies that the neutralizer is stationed in an area and it will only neutralize naval mines found in its designated area. The motivation for this configuration is to improve the response time of neutralizers when the search area is large.

If all the naval mines are concentrated in one area, however, the neutralizer might be overwhelmed. All other setup follows the setup used in Experiment One.

F. EXPERIMENT FOUR: REDUCED REVISIT RATE

In Experiment Four, the author explores the configuration where the revisit rate is reduced from once every eight hours to once every 24 hours. This is achieved by deploying one detector as compared to three detectors in the base case scenario. The motivation of this configuration is to test the impact to MOEs when there are fewer USVs deployed. All other setup follows the setup used in Experiment One.

G. EXPERIMENT FIVE: SINGLE SORTIE

In Experiment Five, the author explores the configuration with a single sortie as compared to two sorties. A single sortie greatly reduces the number of USVs required for the operation, with a more significant reduction when the search area is large and the revisit rate is high. This configuration models the single sortie CUSV used by the U.S. Navy.

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V. DATA ANALYSIS AND EXPERIMENT RESULTS

A. JMP PRO 15 AND ANALYTIC METHODS

JMP PRO 15 is a commercially available statistical discovery software used by scientists, engineers, and data explorers. The capabilities of JMP PRO 15 include, but are not limited to, data cleanup, data visualization, data analysis, statistical modeling, predictive modeling and cross-validation, and model comparison (SAS, n.d.). The author used the software to perform some data analytical tasks, including data processing, statistics summary, regression analysis, and partition tree analysis. Regression and partition tree analysis tend to complement each other, and thus, both are performed on the experimental results.

1. Stepwise Regression

In JMP, stepwise regression is a method of selecting a subset of predictor effects for a regression model. JMP searches through the list of predictors and identifies the predictors that best represent the regression model based on the selected criterion. SAS has suggested that stepwise regression is beneficial in the following circumstances (SAS, 2020b):

- Insufficient knowledge to guide selection of predictors for the model
- Desire to interactively search for predictors to fit the model
- Desire to reduce the variance caused by unnecessary terms in the model

These conditions apply to most generic situations when building regression models. With limited knowledge of the effects of each predictor, the author has depended on stepwise regression to identify statistically significant predictors and interactions. Stepwise regression also allows a certain level of judgement in trading-off a higher R-squared value for a parsimonious and more explainable model.

2. Partition Tree Analysis

In JMP, a partition tree is a technique that recursively splits the data based on the effects of the predictors on response values, creating a decision tree (SAS, 2020a). The splits will go on until a satisfactory tree is obtained (SAS, 2020a). Partition trees are easy to interpret and provide a broad level understanding of the data. Nonetheless, when there are too many splits, the tree becomes complex and less useful. Judgment is required to decide the suitability of each split. For this thesis, the author used partition trees to detect thresholds and interactions.

B. STOCHASTIC VARIABILITY OF REPRESENTATIVE SCENARIO

In all stochastic simulations, there will be a certain level of variability of the MOEs due to pure randomness. It is not practical to study the variability of all the design points unless the objective of the study is to determine a robust design with a clear target MOE. The author quantifies the variability within a design point by completing 1,000 replications of one design point in the base case scenario. The parameters used in this design point are shown in Table 6. These input parameters are set to their mean to obtain a representative scenario.

Table 6. Input parameters for representative scenario

Factor / Description	Value
1. Number of mines	12
2. Detector path deviation (m)	50
3. Overlapping sensor range (m)	0
4. Detector movement speed (knots)	9

The histogram for percentage of mines neutralized in Figure 11 shows that the mean percentage of mines neutralized is 99.43%, with a standard deviation of 2.16%. There are 934 runs out of the 1,000 runs where all mines were neutralized, 64 runs out of 1,000 runs where one mine was missed, and two runs out of 1,000 runs where two mines were missed. Runs with two mines missed are rare occurrences, but are still possible with 1,000 replications. Variability is considered low as the 95% confidence interval on the mean percentage of mines neutralized is narrow, with a range from 0.9930 to 0.9957.

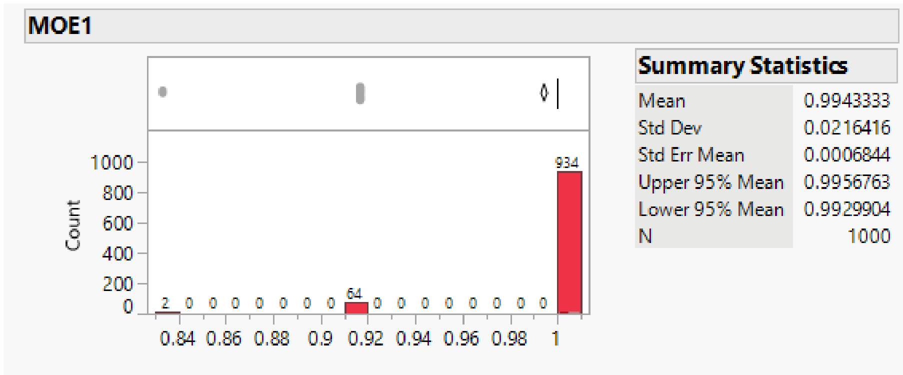


Figure 11. Summary statistics for MOE1 (percentage of mines neutralized)

The histogram for MOE2 in Figure 12 (average mine active time) shows that the mean is 236.2 minutes, the standard deviation is 42.3 minutes, the minimum is 112.3 minutes, and the maximum is 396.0 minutes. The histogram resembles that of a normal distribution with a slight positive skewness of 0.158. This suggests that there is a degree of variability in the results due to randomness. Assuming a normal distribution, a 5% level of significance, 40 replications, and a desired power of at least 90%, the effect size the model is able to catch is a difference of 21.6 minutes.

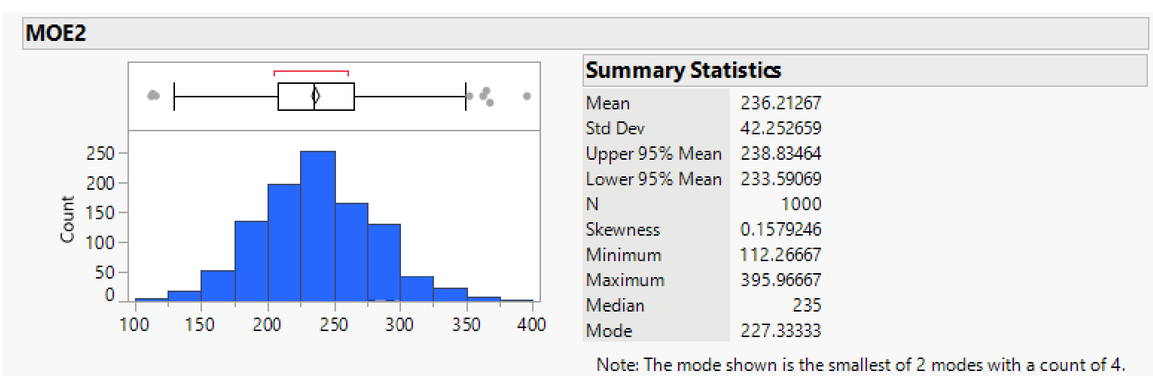


Figure 12. Summary statistics for MOE2 (average mine active time)

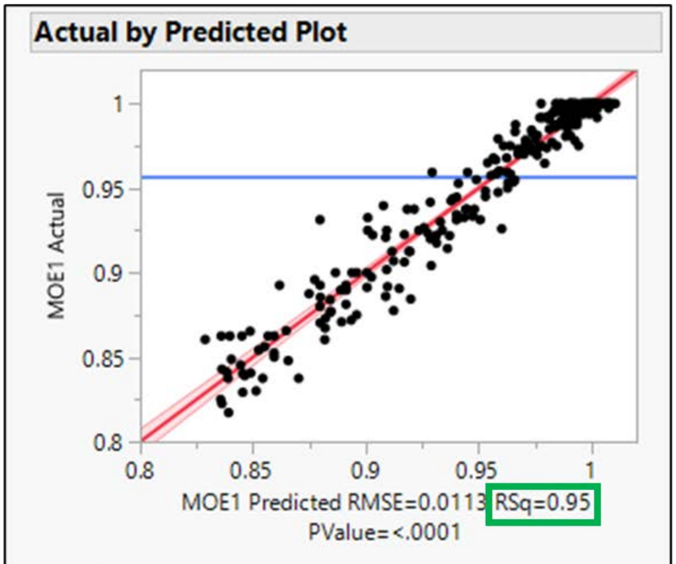
C. ANALYSIS AND RESULTS OF EXPERIMENT ONE

Experiment One is the base case scenario where two sorties are used and the next available neutralizer is deployed to clear the naval mine regardless of the location. In this experiment, 300 design points were generated using a Second Order NO/B design, with 40 replications for each design point. Within each design point, the mean value of the MOEs was computed to represent the average MOE at each design point. This computation helps to reduce variability due to randomness within a design point and produces a more statistically reliable MOE value. Forty replications was selected based on resource constraints and the rule of thumb to apply the central limit theorem (Devore, 2008). All the experiments were conducted using the same procedures, unless otherwise stated.

1. MOE1: Percentage of Mines Neutralized

MOE1 is the primary metric, reflecting the effectiveness of the CONOPS. The summary statistics show that the mean is 0.957, with a standard deviation of 0.052. The 95% confidence interval for the mean is [0.951, 0.963]. The results suggest that the USVs will detect and neutralize 95.7% of the mines deployed in the search area over the range of study variables. Note that the regression and partition tree fits provide a proportion of mines neutralized (i.e., a number between zero and one). These are converted to percentages in our exposition for ease of understanding.

Stepwise regression was conducted for the four variables, their interactions up to third order, and their cubic functions. The author used the Bayesian information criterion (BIC) and personal judgment to obtain a predictive and explainable model. First of all, the linear model is not accurate when it is near to the extremes, as the maximum actual value is bounded by one, while the fitted linear model can exceed one. Secondly, the important takeaways are the effects and interactions of the variables. A regression model with six terms was constructed with an R-squared of 0.95 (Figure 13). That is, 95% of the variance of the simulation averages is explained by this parsimonious regression model. The parameter estimates clearly highlight that the most significant contributor is overlapping sensor range followed by detector speed and the interaction term between overlapping sensor range and path deviation. It is inferred that the number of mines has no significant impact on MOE1, as it was not included as a factor. This implies that the base case CONOPS is capable of handling the range of the mines studied in this research, with no impact on the effectiveness.



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
(OverlapSensRng+0.53333)*(OverlapSensRng+0.53333)	-0.000025	7.385e-7	-33.98	<.0001*
OverlapSensRng	0.0013014	5.35e-5	24.32	<.0001*
DetectorMoveSpd	0.0047595	0.0005	9.51	<.0001*
(PathDev-50.5667)*(OverlapSensRng+0.53333)	-3.509e-6	6.568e-7	-5.34	<.0001*
PathDev	9.3228e-5	2.076e-5	4.49	<.0001*
(OverlapSensRng+0.53333)*(OverlapSensRng+0.53333)*(OverlapSensRng+0.53333)	7.9743e-8	2.773e-8	2.88	0.0043*

Figure 13. Regression model of MOE1 (percentage of mines neutralized) in Experiment One

The prediction profiler in Figure 14 offers a visual and interactive display of the relationship of the main factors with the response. First and foremost, we see that overlapping sensor range is by far the most important factor in the percentage of mines neutralized. Evidently, overlapping sensor range has a negative quadratic relationship with MOE1, yielding a maximum value at approximately 25 meters. One interpretation is that there are diminishing returns to overlapping sensor range and eventually a decrease in performance. Detector speed has a linearly positive effect on percentage of mines neutralized. In addition, the interaction profiles in Figure 15 display the interaction between overlapping sensor range and path deviation. The interaction makes sense as it shows that when there are gaps in the search pattern, increasing path deviation helps to detect mines, and with overlaps in the search pattern, increasing path deviation results in missing mines. This result is interesting because we can use path deviation to our advantage when there are gaps in the search pattern.

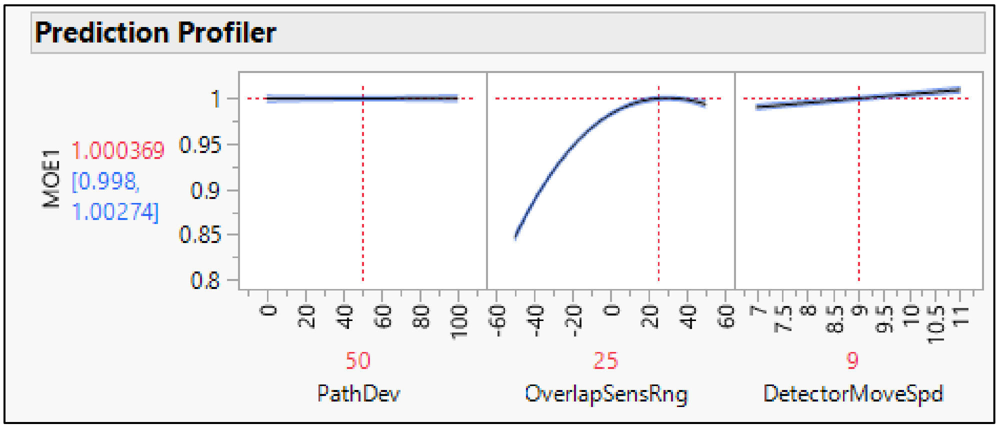


Figure 14. Prediction profiler of MOE1 (percentage of mines neutralized) in Experiment One

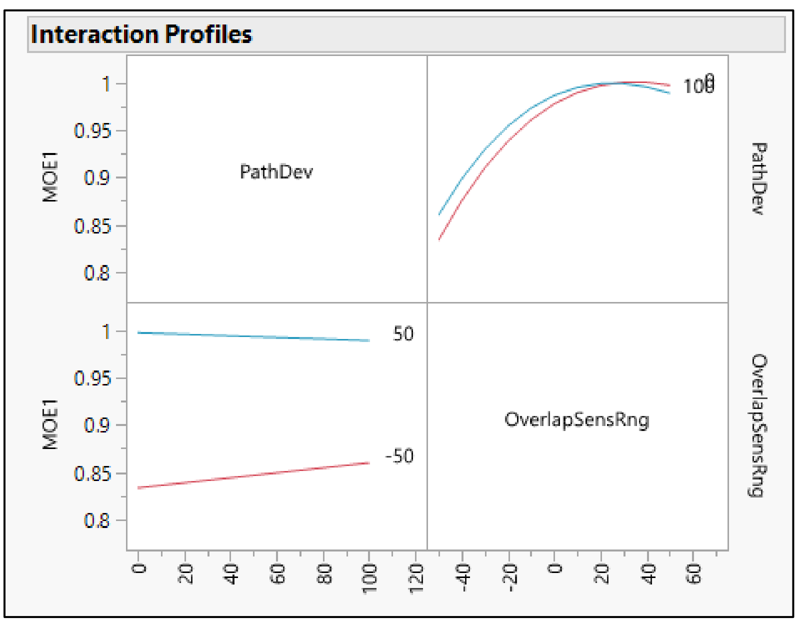


Figure 15. Interaction profiles of MOE1 (percentage of mines neutralized) in Experiment One

Figure 16 shows the partition tree obtained on percentage of mines neutralized. The green boxes indicate the better option from each split. Based on just three splits, the R-squared value is 0.859. Two of the splits are on overlapping sensor range and one split is on detector speed. The splits indicated that having gaps greater than 20 meters is detrimental to percentage of mines neutralized. No gap and no overlap of the sensor range would produce reasonably good performance, as the mean of percentage of mines neutralized reaches 0.995. Detector speed at 8 knots was used as a threshold value for the third split to obtain a mean value of 0.998. The threshold values obtained at the splits indicate that decision makers need to ensure no gaps and the detector speed should be above 8 knots. The results make sense as gaps guarantee some areas will not be searched and the detector speed required to cover the whole map is between 8 to 9 knots.

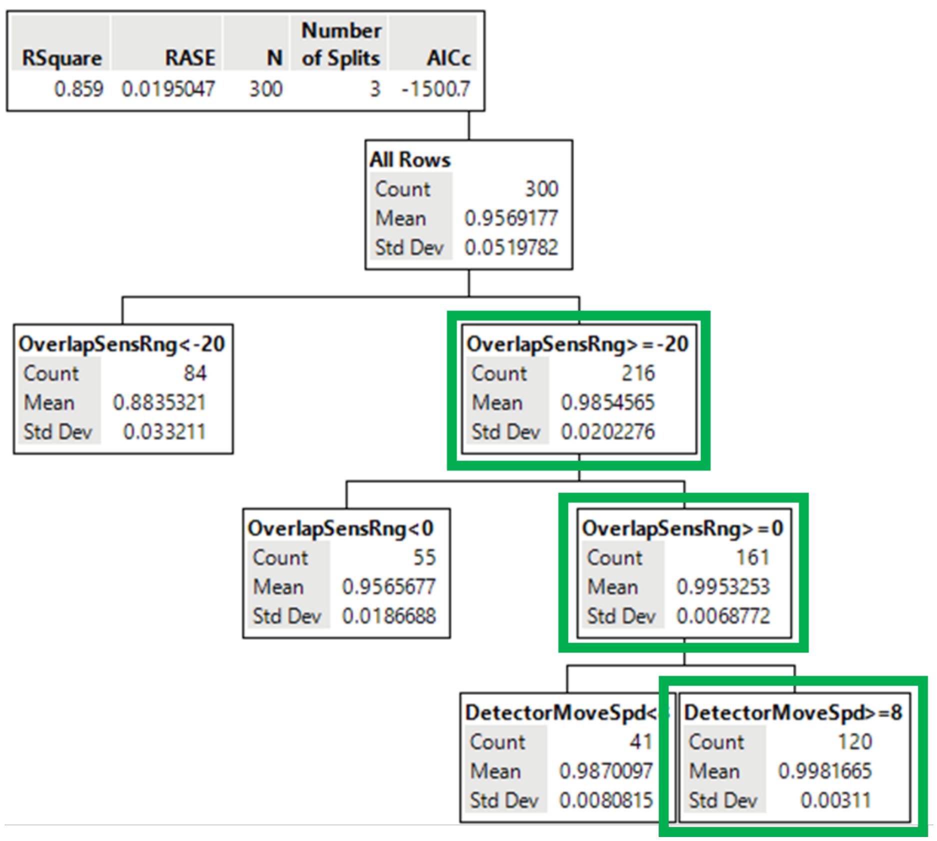


Figure 16. Partition tree of MOE1 (percentage of mines neutralized) in Experiment One

2. MOE2: Average Mine Active Time

MOE2 is the secondary metric used to quantify the risk vessels are exposed to when transiting along the waterway. The summary statistics in Figure 17 show that the mean is 242 minutes, with a standard deviation of 35 minutes. The 95% confidence interval for the mean is [238 minutes, 246 minutes]. The minimum and maximum values are 178 minutes and 320 minutes, respectively. The results indicated high variability in the 300 design points, with vessels at risk from a range of 3 hours to 5.5 hours.

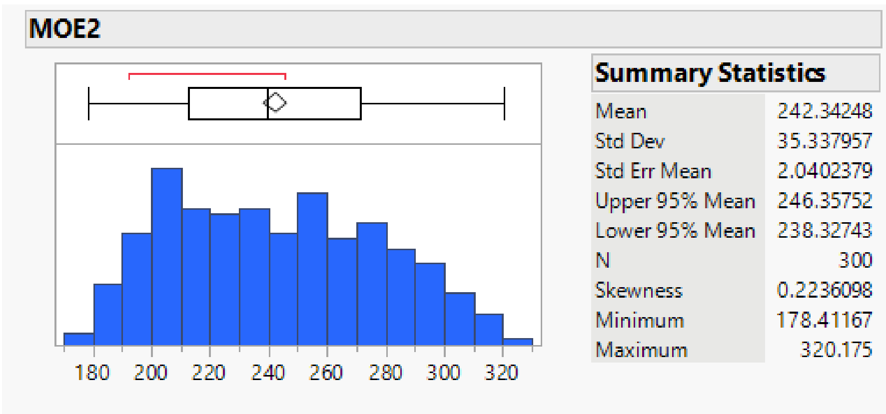
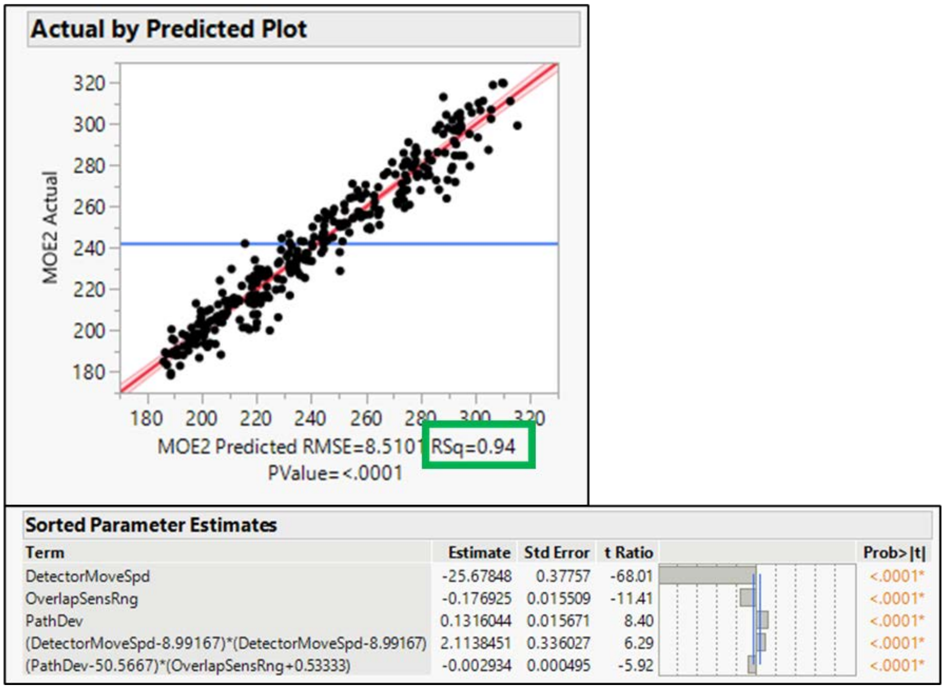


Figure 17. Summary statistics of MOE2 (average mine active time) in Experiment One

A regression model with five terms was constructed with an R-squared of 0.94 (Figure 18). The parameter estimates in Figure 18 highlight detector speed as the most influential factor, followed by overlapping sensor range and path deviation. Again, the number of mines has no significant impact on average mine active time. The prediction profiler in Figure 19 indicates detector speed has a generally negative linear relationship with average mine active time, as one would expect. Overlapping senor range has a linearly positive effect on average mine active time. In addition, the interaction profiles in Figure 20 display the interaction between overlapping sensor range and path deviation. The interaction indicates that when there are gaps in the search pattern, increasing path deviation increases average mine active time; and with overlaps in the search pattern, increasing path deviation has little impact on the mine active time. The results suggest that mines will take longer to be detected with path deviation and gaps in the search pattern.



Term	Estimate	Std Error	t Ratio	Prob>|t|
DetectorMoveSpd	-25.67848	0.37757	-68.01	<.0001*
OverlapSensRng	-0.176925	0.015509	-11.41	<.0001*
PathDev	0.1316044	0.015671	8.40	<.0001*
(DetectorMoveSpd-8.99167)*(DetectorMoveSpd-8.99167)	2.1138451	0.336027	6.29	<.0001*
(PathDev-50.5667)*(OverlapSensRng+0.53333)	-0.002934	0.000495	-5.92	<.0001*

Figure 18. Regression model of MOE2 (average mine active time) in Experiment One

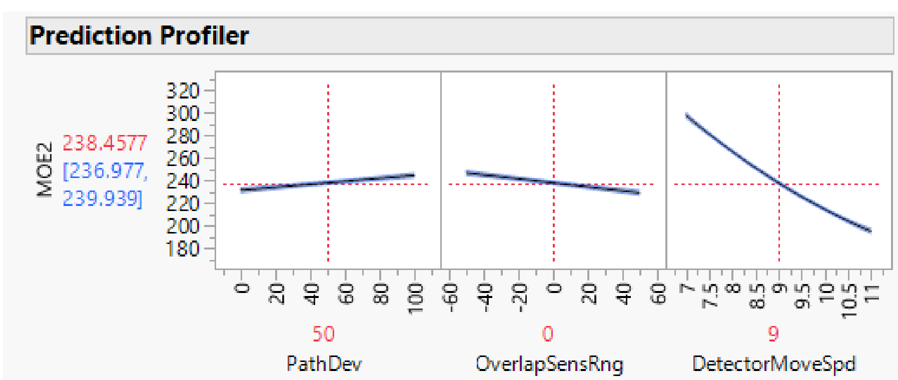


Figure 19. Prediction profiler of MOE2 (average mine active time) in Experiment One

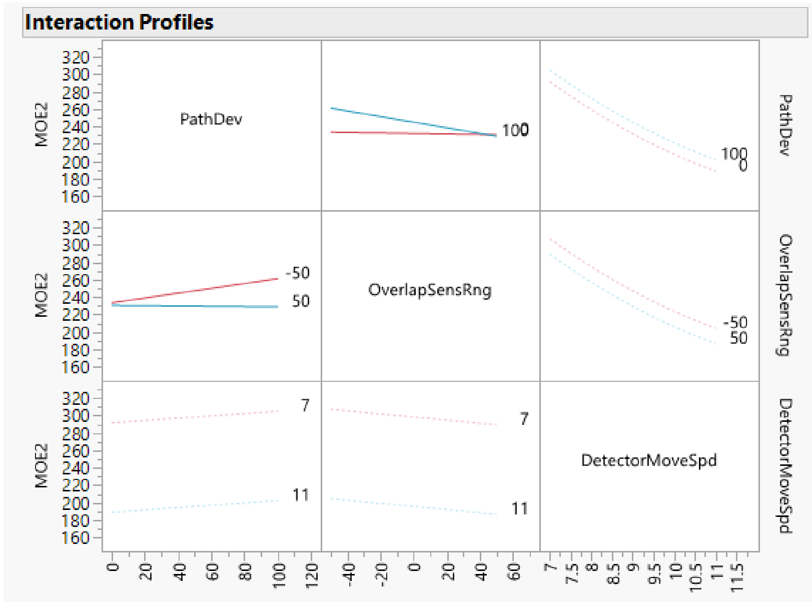


Figure 20. Interaction profiles of MOE2 (average mine active time) in Experiment One

Figure 21 shows the partition tree obtained for average mine active time. The green boxes indicate the better option from each split. Based on just three splits, the R-squared value is 0.863. All the three splits are on detector speed. The splits indicate that detector speed is clearly the dominant factor influencing average mine active time. The threshold value for each split is at the middle point of the detector speed range, suggesting that the relationship is very close to a linear line. Therefore, it can be inferred that average mine active time will likely continue to improve with higher detector speed.

D. ANALYSIS AND RESULTS OF EXPERIMENT TWO

Experiment Two is the scenario where each neutralizer is paired with one detector. The experiment is conducted using the same procedures and the results are analyzed using the same techniques as Experiment One.

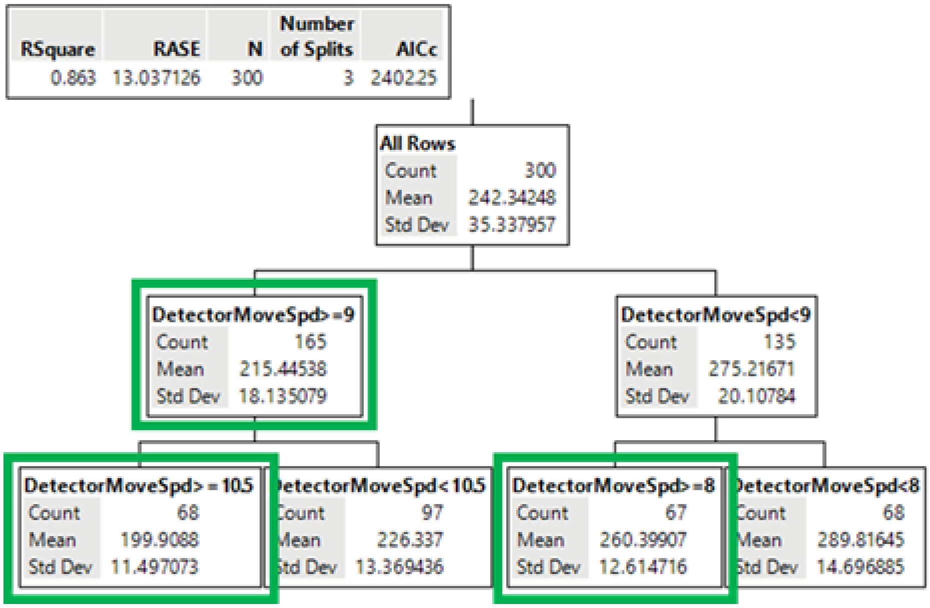


Figure 21. Partition tree for MOE2 (average mine active time) in Experiment One

1. MOE1: Percentage of Mines Neutralized

The results and analysis obtained for Experiment Two are very similar to those for Experiment One. This is not surprising as the relationships between factors and MOE1 should not be affected greatly by pairing neutralizers with detectors. The summary statistics show that the mean is 0.957, with a standard deviation of 0.051. The 95% confidence interval for the mean is [0.951, 0.963]. The results suggest that the USVs will detect and neutralize 95.7% of the mines deployed in the search area over the range of study variables.

A regression model with five terms was constructed with an R-squared of 0.94 (Figure 22). The parameter estimates clearly highlight the most significant contributor is overlapping sensor range, followed by detector speed and the interaction term between overlapping sensor range and path deviation. The relationships of the factors to the response are similar to the observations in Experiment One. The partition tree shown in Figure 23 splits at the exact same thresholds as the tree obtained from Experiment One and thus reinforces the importance of overlapping sensor range in influencing percentage of mines neutralized.

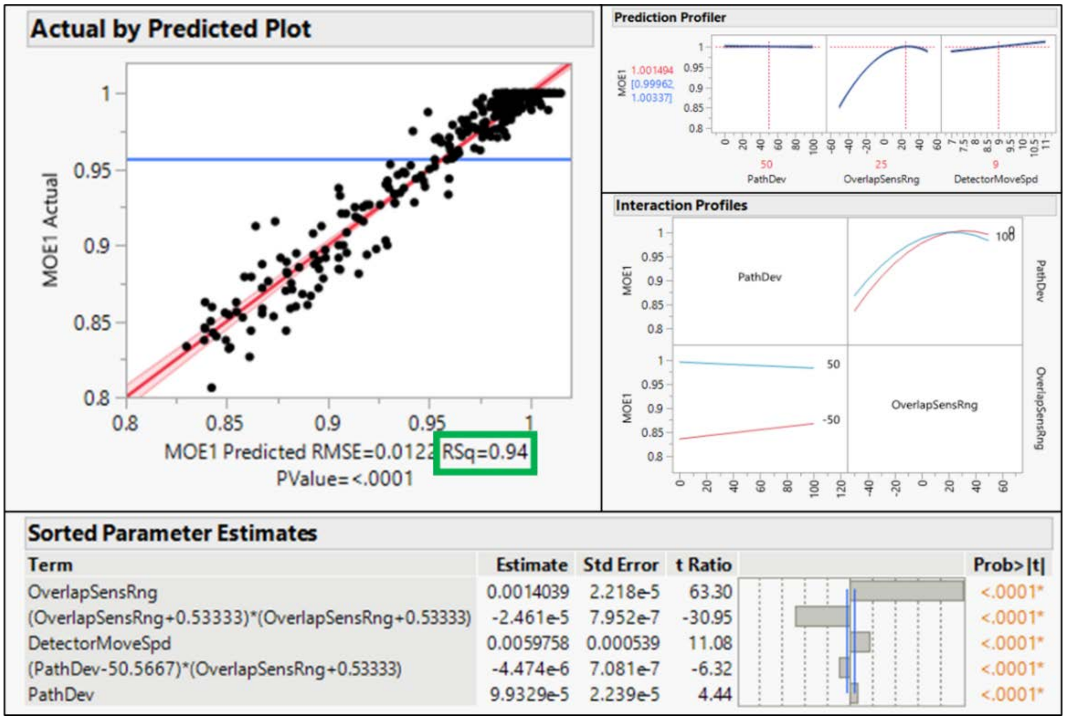


Figure 22. Regression model of MOE1 (percentage of mines neutralized) in Experiment Two

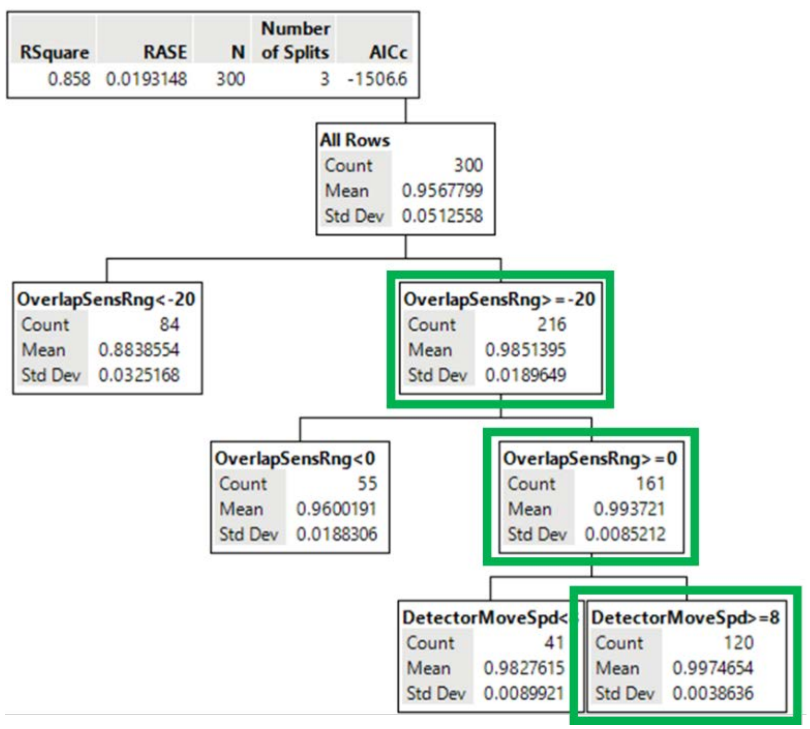


Figure 23. Partition tree of MOE1 (percentage of mines neutralized) in Experiment Two

2. MOE2: Average Mine Active Time

The summary statistics in Figure 24 show that the mean is 253 minutes, with a standard deviation of 34 minutes. The 95% confidence interval for the mean is [249 minutes, 257 minutes]. The minimum and maximum values are 186 minutes and 330 minutes, respectively. The results indicate high variability in the 300 design points, with vessels at risk from a range of 3 hours to 5.5 hours.

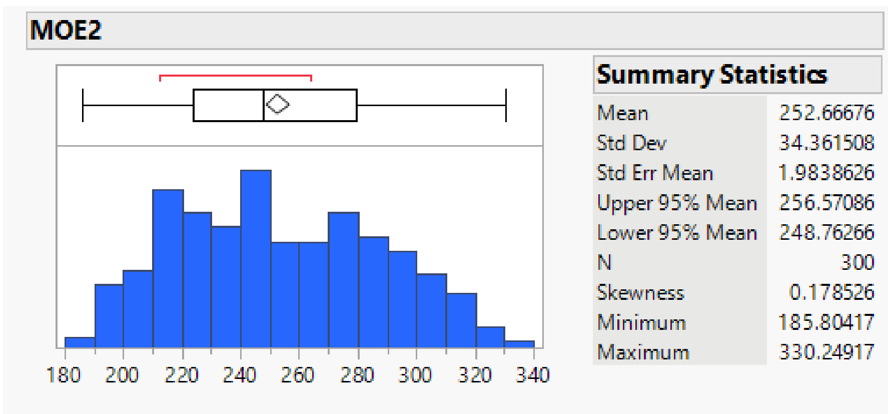


Figure 24. Summary statistics of MOE2 (average mine active time) in Experiment Two

A regression model with six terms was constructed with an R-squared of 0.94 (Figure 25). The parameter estimates in Figure 25 indicate detector speed as the most influential factor followed by mines and path deviation. Number of mines was included as a factor due to the fact that more mines detected by the same detector have to wait for the dedicated neutralizer to detonate the mines. The interaction profiles display similar interaction as observed in Experiment One. The interaction indicates that when there are gaps in the search pattern, increasing path deviation increases average mine active time; and with overlaps in the search pattern, increasing path deviation has little impact on the average mine active time. The results suggest that mines will take longer to be detected with path deviation and gaps in the search pattern. The partition tree of average mine active time in Figure 26 highlights that detector speed is the dominant factor influencing average mine active time, yielding the same threshold values as Experiment One.

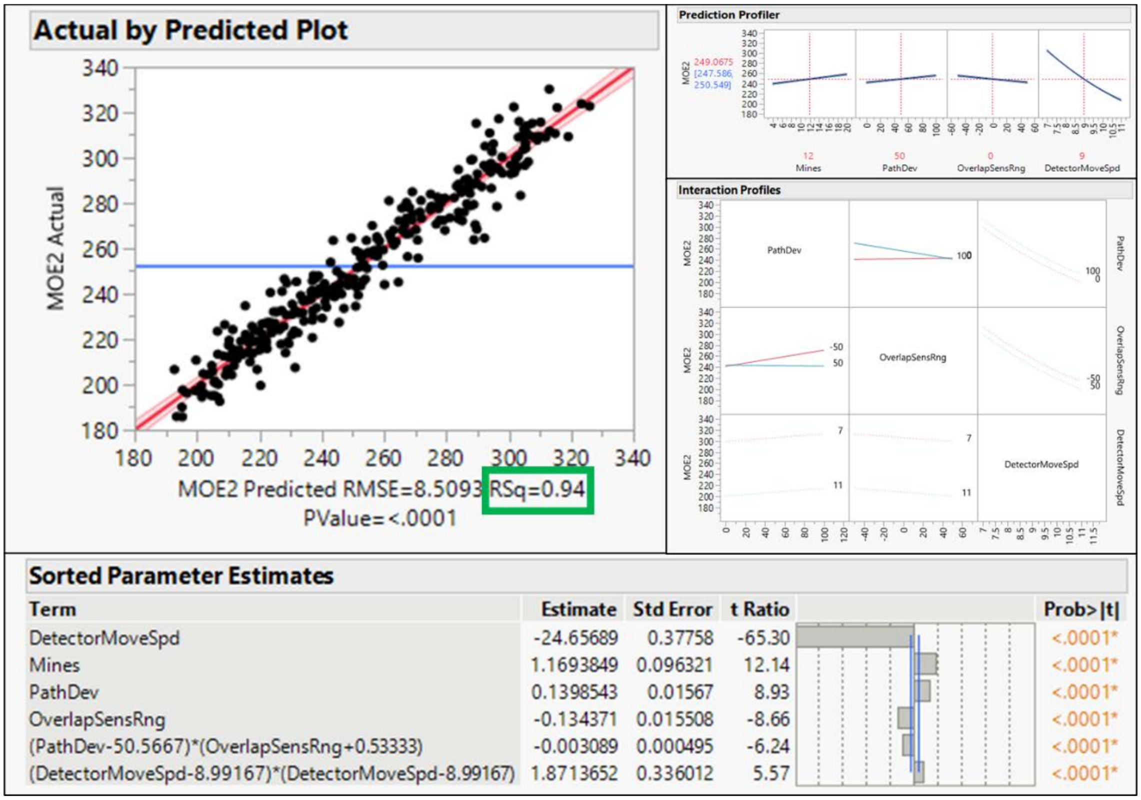


Figure 25. Regression model of MOE2 (average mine active time) in Experiment Two

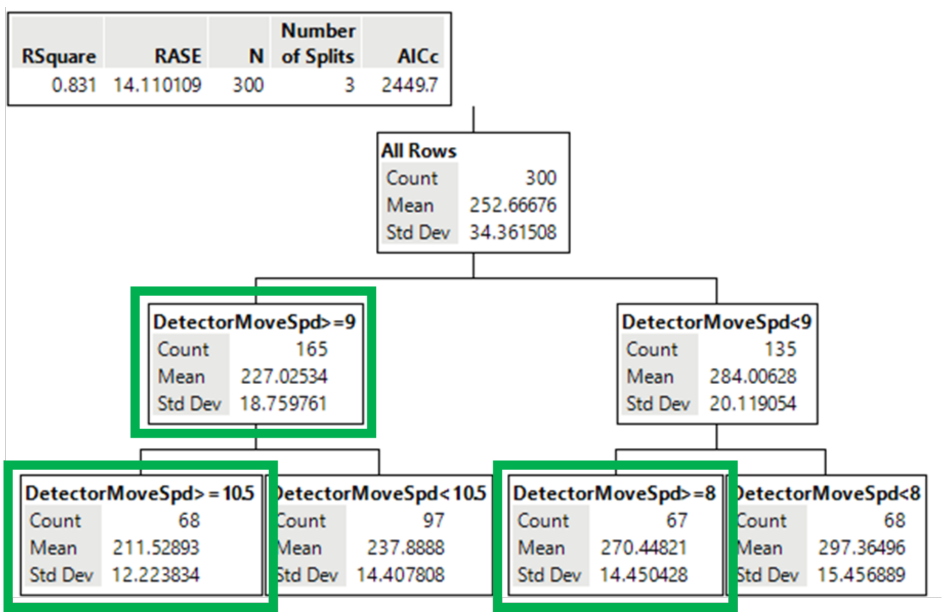


Figure 26. Partition tree of MOE2 (average mine active time) in Experiment Two

E. ANALYSIS AND RESULTS OF EXPERIMENT THREE

Experiment Three is the scenario where each neutralizer has a dedicated neutralization area. The experiment is conducted using the same procedures and the results are analyzed using the same techniques as all previous experiments.

1. MOE1: Percentage of Mines Neutralized

The results and analysis obtained for Experiment Three are very similar to those for Experiment One and Experiment Two. There is little difference in sectorizing the neutralizers to dedicated detector or dedicated neutralization areas. The summary statistics show that the mean is 0.956, with a standard deviation of 0.053. The 95% confidence interval for the mean is [0.950, 0.962]. The results suggest that the USVs will detect and neutralize 95.6% of the mines deployed in the search area over the range of study variables.

A regression model with six terms was constructed with an R-squared of 0.96 (Figure 27). The parameter estimates clearly highlight the most significant contributor is overlapping sensor range, followed by detector speed and the interaction term between overlapping sensor range and path deviation. The relationships of the factors to percentage of mines neutralized are similar to the observations in Experiment One and Experiment Two. The partition tree shown in Figure 28 splits at the exact same thresholds as the tree obtained from Experiment One and Experiment Two and thus reinforces the importance of overlapping sensor range in influencing percentage of mines neutralized.

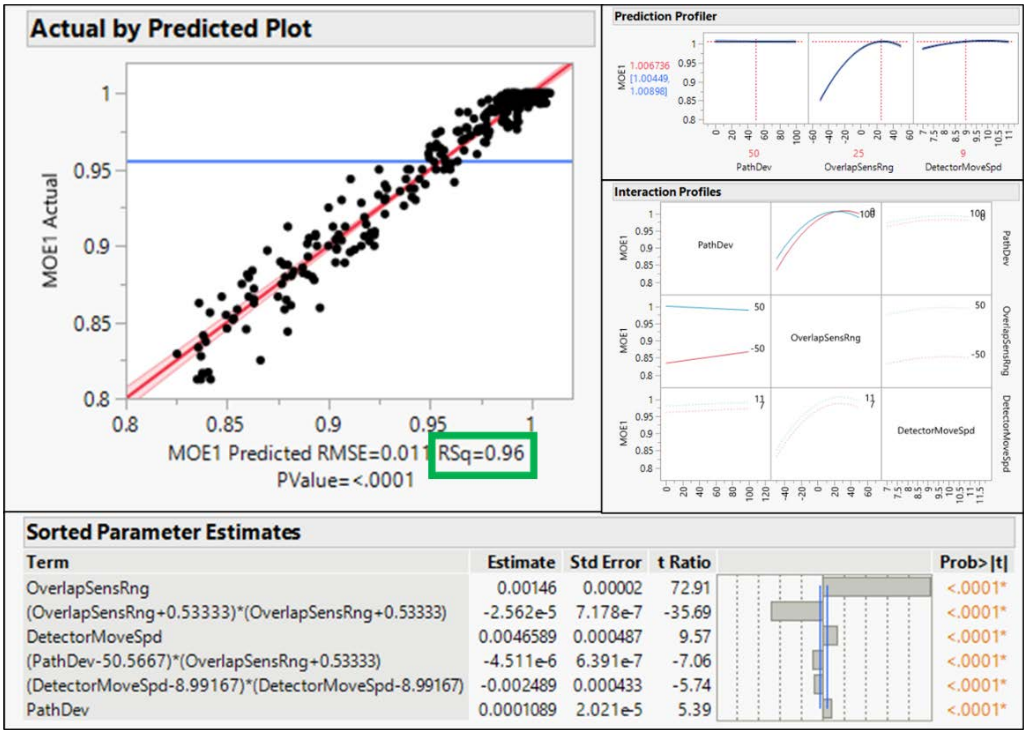


Figure 27. Regression model of MOE1 (percentage of mines neutralized) in Experiment Three

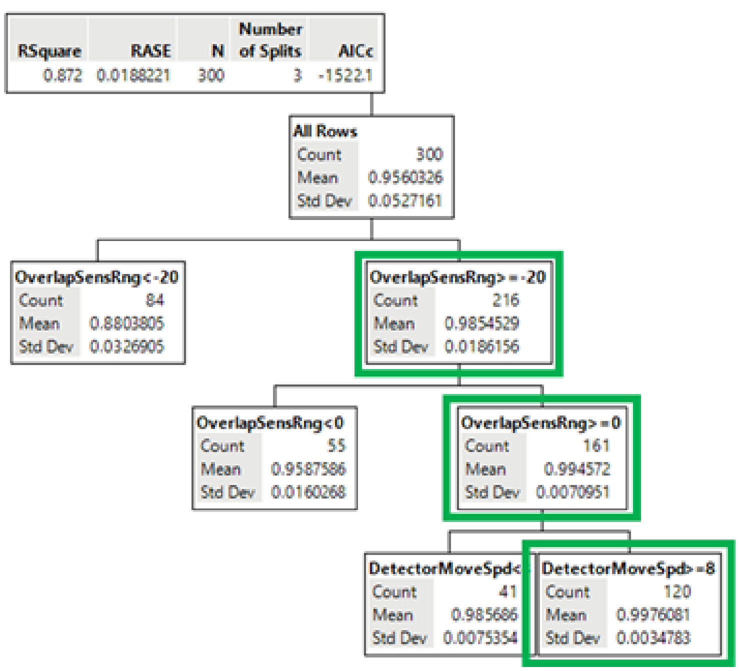


Figure 28. Partition tree of MOE1 (percentage of mines neutralized) in Experiment Three

2. MOE2: Average Mine Active Time

The summary statistics in Figure 24 show that the mean is 250 minutes, with a standard deviation of 34 minutes. The 95% confidence interval for the mean is [247 minutes, 254 minutes]. The minimum and maximum values are 182 minutes and 326 minutes, respectively. The results indicate high variability in the 300 design points, with vessels at risk from a range of 3 hours to 5.5 hours.

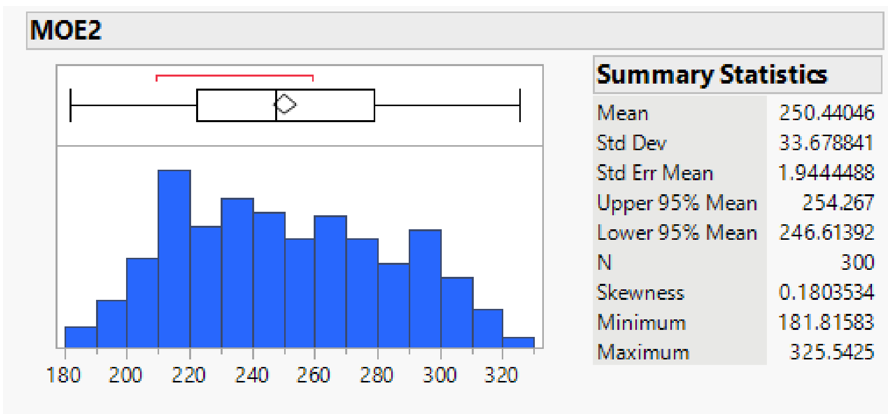


Figure 29. Summary statistics of MOE2 (average mine active time) in Experiment Three

A regression model with six terms was constructed with an R-squared of 0.95 (Figure 30). The parameter estimates in Figure 30 highlight detector speed as the most influential factor, followed by overlapping sensor range and mines. Mines were included as a factor due to the fact that a higher concentration of mines in an area requires waiting for the dedicated neutralizer to detonate the mines. The interaction profiles display similar interactions to those observed in Experiment One and Experiment Two. The results suggest that mines will take longer to be detected with path deviation and gaps in the search pattern. The partition tree of average mine active time in Figure 26 highlights that detector speed is the dominant factor influencing average mine active time yielding the same threshold value as in Experiment One and Experiment Two.

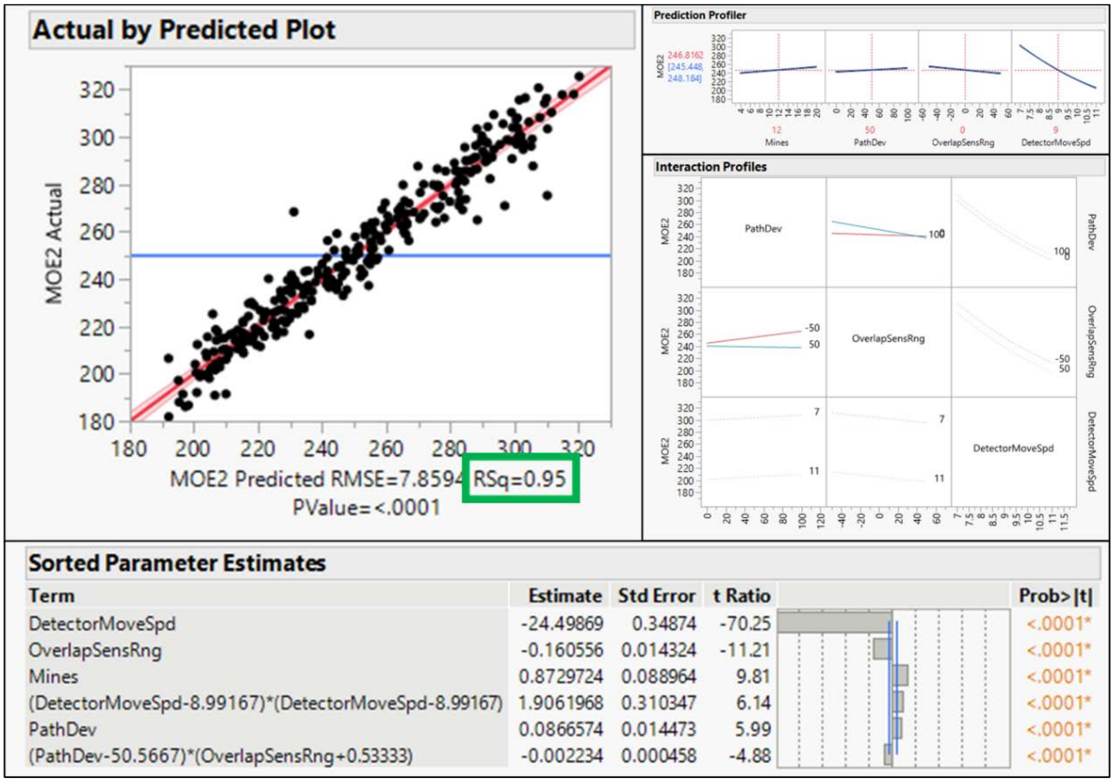


Figure 30. Regression model of MOE2 (average mine active time) in Experiment Three

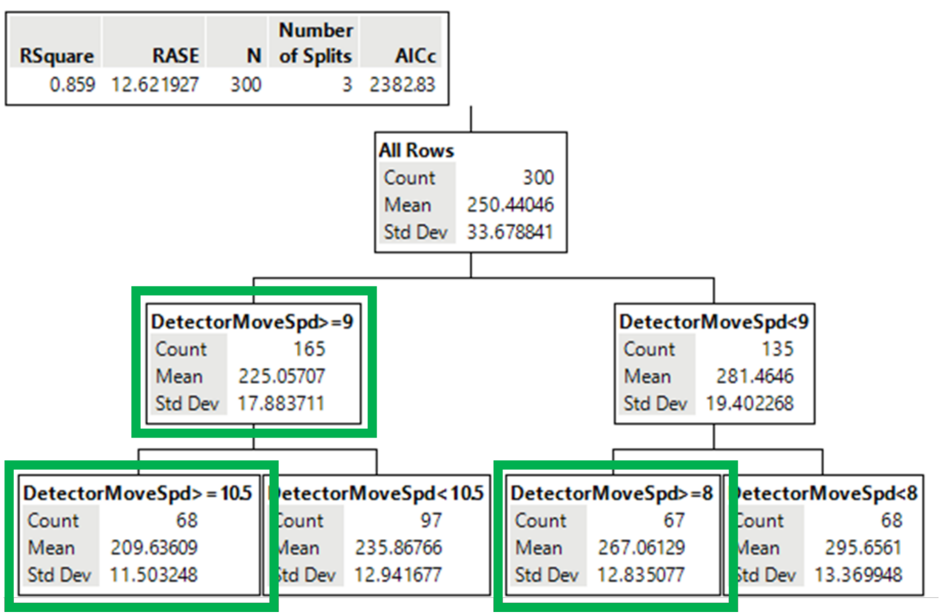


Figure 31. Partition tree of MOE2 (average mine active time) in Experiment Three

F. ANALYSIS AND RESULTS OF EXPERIMENT FOUR

Experiment Four is the scenario where revisit rate is reduced from once every 8 hours to once every 24 hours. The experiment is conducted using the same procedures and the results are analyzed using the same techniques as all previous experiments.

1. MOE1: Percentage of Mines Neutralized

The summary statistics show that the mean is 0.921, with a standard deviation of 0.075. The 95% confidence interval for the mean is [0.912, 0.929]. The results suggest that the USVs will detect and neutralize 92.1% of the mines deployed in the search area over the range of study variables. The key reason for the lower percentage of mines neutralized as compared to the previous three experiments is that the area was only searched once in the 24 hours as compared to thrice in the 24 hours for Experiment One, Experiment Two, and Experiment Three.

A regression model with six terms was constructed with an R-squared of 0.96 (Figure 32). The parameter estimates clearly highlight that the most significant contributor is overlapping sensor range followed by detector speed. Similar to Experiment One, the number of mines was not included as a significant factor, which implies that the CONOPS is capable of handling the range of the mines studied with no impact on the effectiveness. The prediction profiler in Figure 32 shows that overlapping sensor range has a negative quadratic relationship with percentage of mines neutralized, yielding a maximum value at approximately 25 meters. Detector speed has a cubic relationship with percentage of mines neutralized, indicating trivial increase when the speed goes beyond 9 knots. The fact that there is no interaction term suggests path deviation only interacts with overlapping sensor range when the revisit rate is higher.

Figure 33 shows the partition tree obtained on percentage of mines neutralized. The green boxes indicate the better option from each split. Based on three splits, the R-squared value is 0.784. Although the regression model differs greatly between Experiment Four and Experiment One, the thresholds obtained from the partition tree are the same. Therefore, the results also demonstrate that decision makers need to ensure no gaps in the search route, and the detector speed should be above 8 knots.

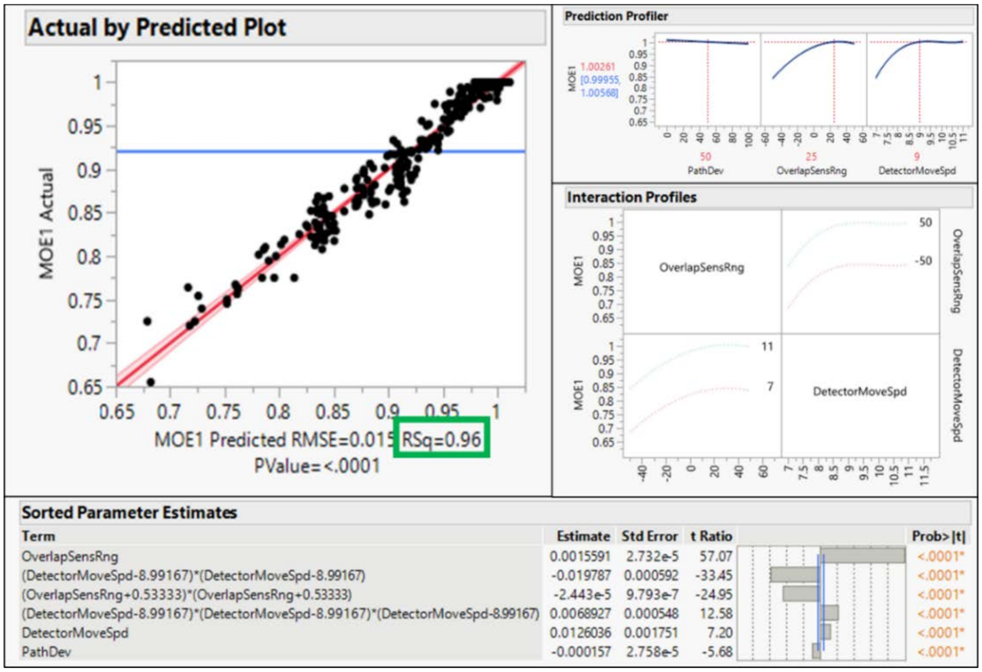


Figure 32. Regression model of MOE1 (percentage of mines neutralized) in Experiment Four

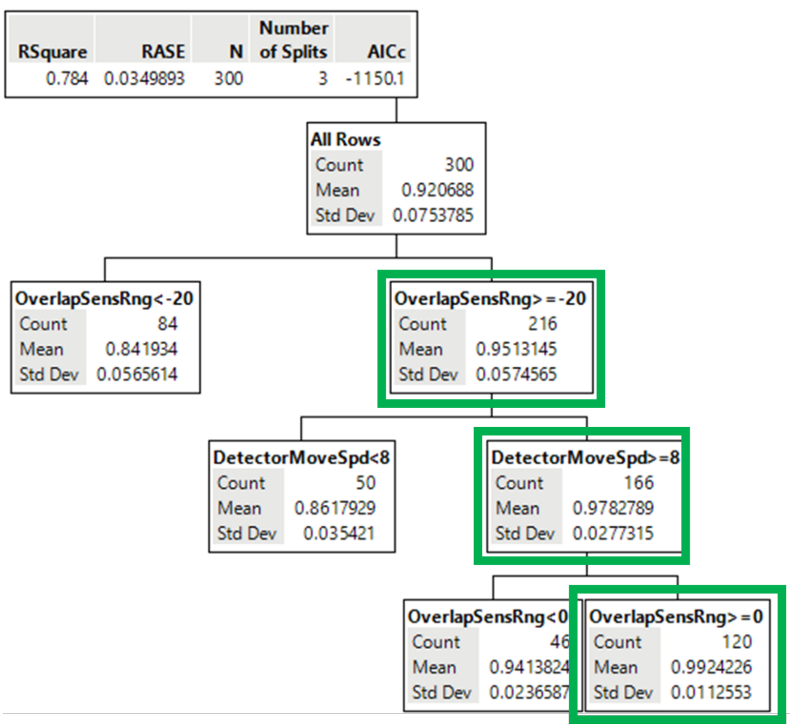


Figure 33. Partition tree of MOE1 (percentage of mines neutralized) in Experiment Four

2. MOE2: Average Mine Active Time

The summary statistics in Figure 34 show that the mean is 655 minutes, with a standard deviation of 69 minutes. The 95% confidence interval for the mean is [647 minutes, 662 minutes]. The minimum and maximum values are 505 minutes and 781 minutes, respectively. The results indicate high variability in the 300 design points, with vessels at risk from a range of 8 hours to 13 hours. The average mine active time increased significantly as the area is not searched as frequently with reduced revisit rate.

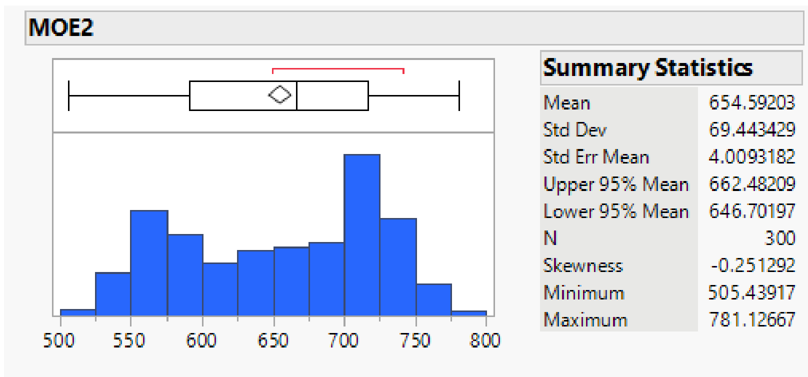


Figure 34. Summary statistics of MOE2 (average mine active time) in Experiment Four

A regression model with three terms was constructed with an R-squared of 0.92 (Figure 18). Only detector speed entered the regression model, indicating none of the other factors affect average mine active time. The prediction profiler in Figure 35 indicates detector speed has a generally negative quadratic relationship with average mine active time. There appear to be diminishing returns to average mine active time and it will eventually reach zero returns as detector speed increases. This is reasonable because with increasing detector speed, mines will get detected faster, but the improvement will be lesser and lesser. The performance improved at lower speed could be due to mines not being detected at all. At speeds less than 8.5 knots, the full area is not searched within 24 hours. When mines are not detected, they are not included in the computation of average mine active time. The partition tree of average mine active time in Figure 36 indicates that with just three splits, an R-squared value of 0.894 is achieved.

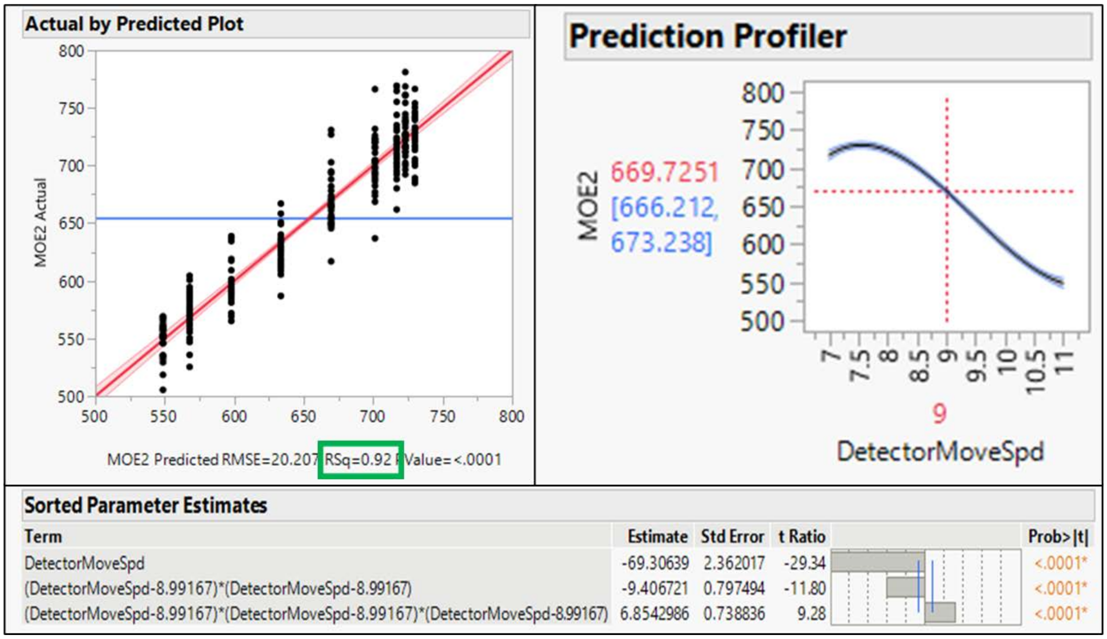


Figure 35. Regression model of MOE2 (average mine active time) in Experiment Four

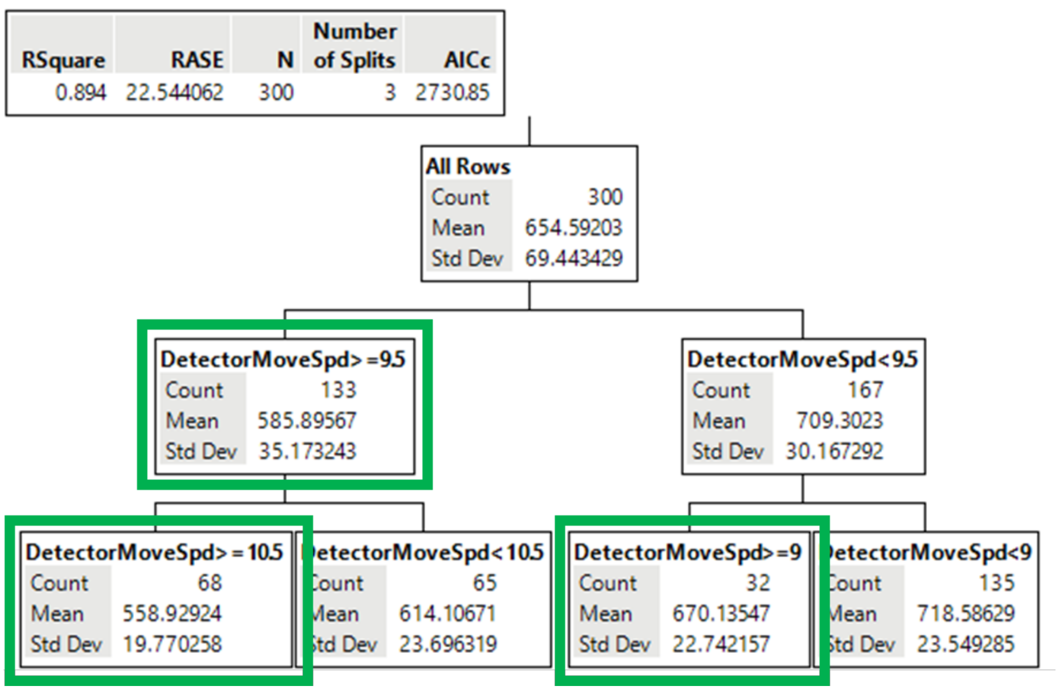


Figure 36. Partition tree for MOE2 (average mine active time) in Experiment Four

G. ANALYSIS AND RESULTS OF EXPERIMENT FIVE

Experiment Five is the scenario where single sortie CUSV is used for MCM missions. The experiment is conducted using the same procedures and the results are analyzed using the same techniques as all previous experiments.

1. MOE1: Percentage of Mines Neutralized

The results and analysis obtained for Experiment Five are very similar to those for Experiment One, Experiment Two, and Experiment Three. This implies that both the single sortie operation and the two sortie operations produce similar performance in terms of percentage of mines neutralized. The summary statistics show that the mean is 0.953, with a standard deviation of 0.052. The 95% confidence interval for the mean is [0.947, 0.959]. The results suggest that the USVs will detect and neutralize 95.3% of the mines deployed in the search area over the range of study variables.

A regression model with six terms was constructed with an R-squared of 0.94 (Figure 37). The parameter estimates clearly highlight that the most significant contributor is overlapping sensor range, followed by detector speed and the interaction term between overlapping sensor range and path deviation. The relationships of the factors to the response are similar to the observations in Experiment One, Experiment Two, and Experiment Three. The partition tree shown in Figure 38 splits at the exact same thresholds as the tree obtained from Experiment One, Experiment Two, and Experiment Three, and thus reinforces the importance of overlapping sensor range in influencing percentage of mines neutralized.

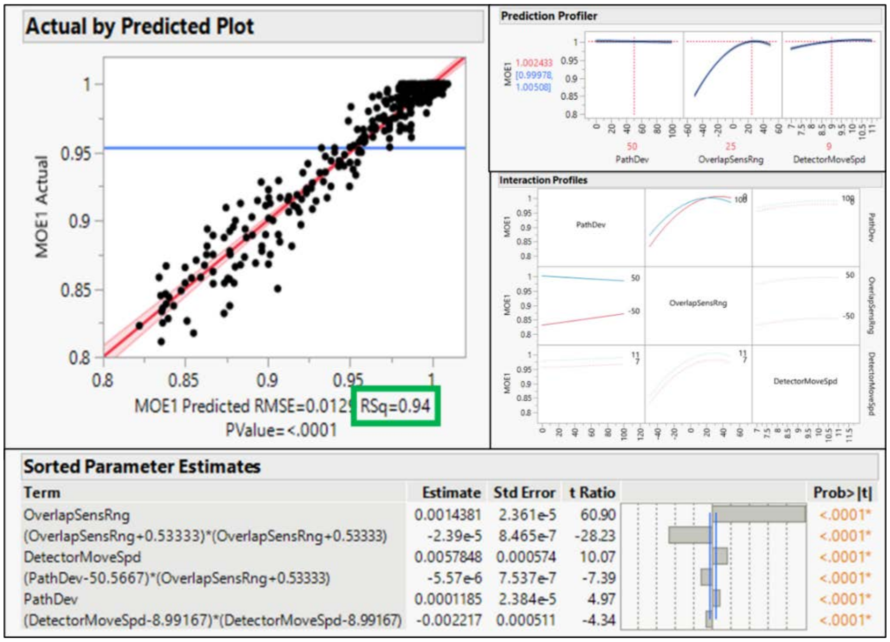


Figure 37. Regression model of MOE1 (percentage of mines neutralized) in Experiment Five

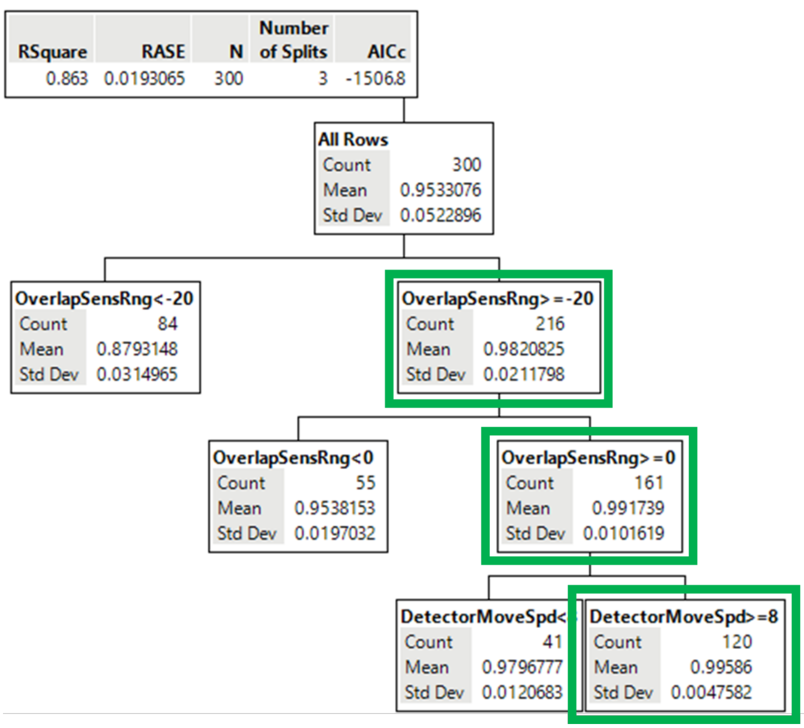


Figure 38. Partition tree of MOE1 (percentage of mines neutralized) in Experiment Five

2. MOE2: Average Mine Active Time

The summary statistics in Figure 39 show that the mean is 244 minutes, with a standard deviation of 34 minutes. The 95% confidence interval for the mean is [240 minutes, 248 minutes]. The minimum and maximum values are 176 minutes and 334 minutes, respectively. The results indicate high variability in the 300 design points, with vessels at risk from a range of 3 hours to 5.5 hours.

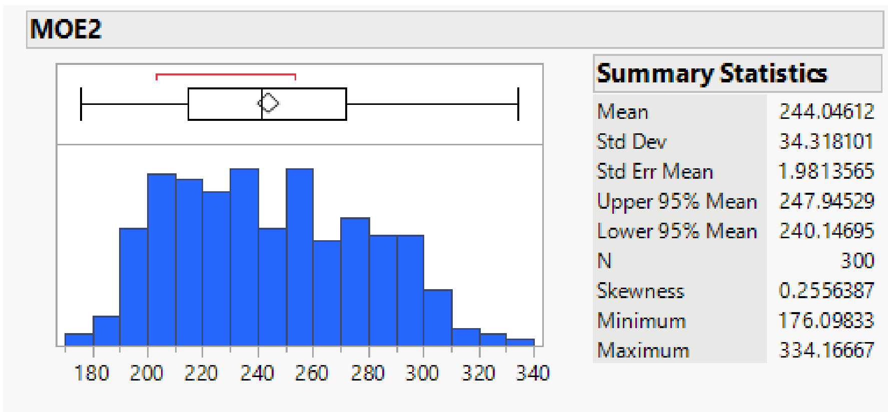


Figure 39. Summary statistics of MOE2 (average mine active time) in Experiment Five

A regression model with six terms was constructed with an R-squared of 0.94 (Figure 40). The parameter estimates in Figure 25 indicate detector speed as the most influential factor, followed by mines and path deviation. Number of mines was included as a factor due to the fact that each mine detected will cause the CUSV to stop and deploy the expendable neutralizer, increasing the average mine active time. The interaction profiles display similar interactions as those observed in Experiment One, Experiment Two, and Experiment Three. The results suggest that mines will take longer to be detected with path deviation and gaps in the search pattern. The partition tree of average mine active time in Figure 41 highlights that detector speed is the dominant factor influencing average mine active time, yielding the same threshold values as Experiment One, Experiment Two, and Experiment Three.

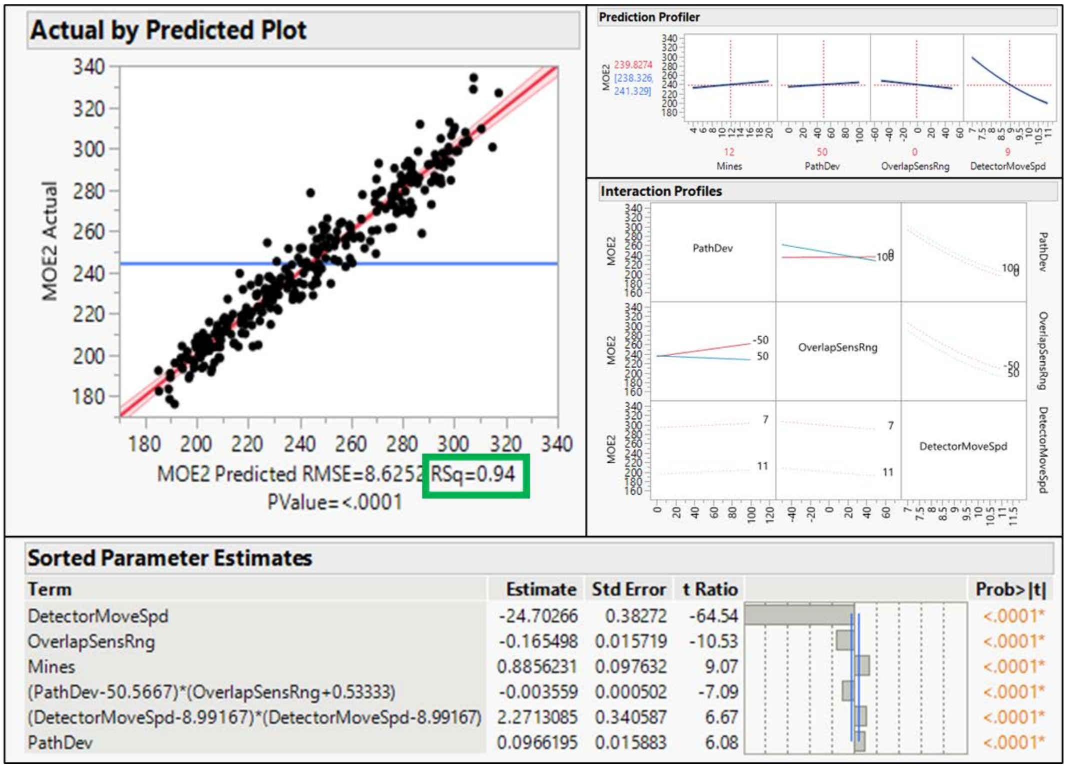


Figure 40. Regression model of MOE2 (average mine active time) in Experiment Five

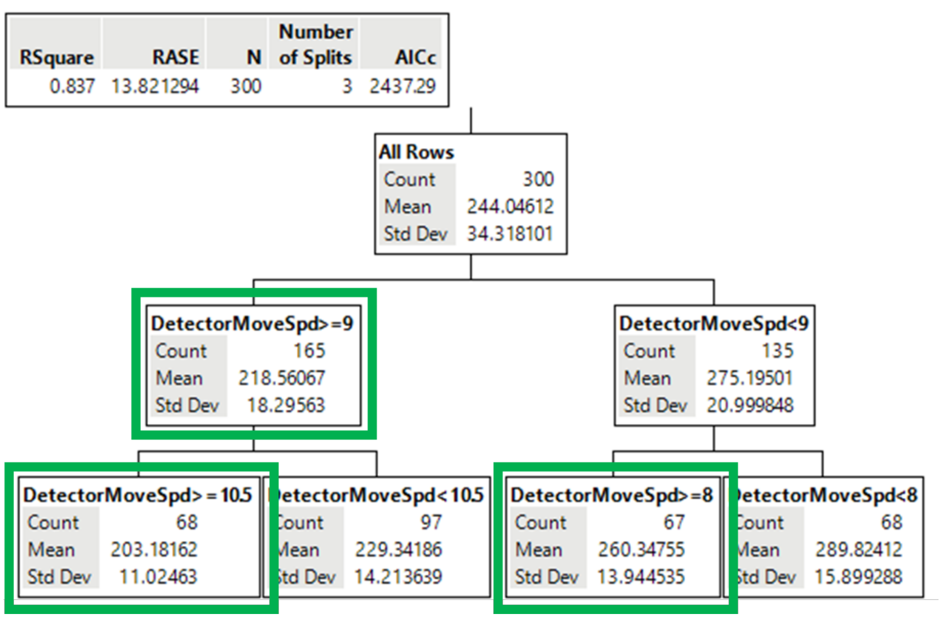


Figure 41. Partition tree of MOE2 (average mine active time) in Experiment Five

H. ANALYSIS AND RESULTS OF SECTORIZING NEUTRALIZERS, REVISIT RATE, AND DIFFERENT PLATFORMS USED

The results from all five experiments were combined and analyzed using a nonparametric test and random forest. Pairwise non-parametric testing was used to determine whether the scenarios in each experiment are statistically different from the other scenarios. Random forest was performed to obtain the columns contribution chart through a large number of randomized individual trees.

1. MOE1: Percentage of Mines Neutralized

A nonparametric comparison, using the Wilcoxon Method, for each pair of scenarios as shown in Figure 42 indicates that there is no statistical difference between Experiment One, Experiment Two, Experiment Three, and Experiment Five. The p-values for each test pair are greater than 0.05. This is in agreement with the analysis of individual experiments where similar regression models and partition trees were produced. Experiment Four is significantly different from all the other experiments due to the reduction of the revisit rate resulting in only one scan to the area. This is clearly a disadvantage because once the detector fails to find the mine, there is no second chance to find it in Experiment Four. In the other experiments where the revisit rate is once every 8 hours, there may be a possibility that a mine missed by one detector can be detected by another detector, which will search the area subsequently. In this situation, the mine active time for the mine found will be higher than the average value.

Nonparametric Comparisons For Each Pair Using Wilcoxon Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
5_1Sortie	4_ReducedRevisit	60.3533	14.11439	4.27602	<.0001*	0.018750	0.006563	0.030000
3_Area	2_Paired	-0.0533	14.06507	-0.00379	0.9970	0.000000	-0.002083	0.002083
2_Paired	1_BaseCase	-6.1167	14.04029	-0.43565	0.6631	0.000000	-0.002500	0.000694
3_Area	1_BaseCase	-6.9400	14.05105	-0.49391	0.6214	0.000000	-0.003125	0.000694
5_1Sortie	3_Area	-17.7000	14.10563	-1.25482	0.2095	-0.001250	-0.004687	0.000000
5_1Sortie	2_Paired	-18.5333	14.09932	-1.31448	0.1887	-0.001389	-0.004722	0.000000
5_1Sortie	1_BaseCase	-25.1867	14.08917	-1.78766	0.0738	-0.002083	-0.005357	0.000000
4_ReducedRevisit	3_Area	-72.8633	14.08627	-5.17265	<.0001*	-0.020536	-0.033214	-0.009444
4_ReducedRevisit	2_Paired	-74.9900	14.07812	-5.32671	<.0001*	-0.020833	-0.033333	-0.010000
4_ReducedRevisit	1_BaseCase	-78.0133	14.06543	-5.54646	<.0001*	-0.021119	-0.033333	-0.010417

Difference Plot

Figure 42. Pairwise comparison of MOE1 (percentage of mines neutralized)

The random forest test with 1,000 trees was performed on percentage of mines neutralized, and the results are shown in Figure 43. The column contributions chart clearly identifies that the most influential factor is overlapping sensor range, followed by detector speed, and scenario. Overlapping sensor range alone accounted for 76% of splits and thus is clearly the dominating factor, while scenario only accounts for 9% of the splits.

Column Contributions

Term	Number of Splits	SS	Portion
OverlapSensRng	6223	1.17836104	0.7591
DetectorMoveSpd	6081	0.15950001	0.1028
Scenario	6215	0.13693973	0.0882
PathDev	6137	0.04081307	0.0263
Mines	6220	0.0366563	0.0236

Figure 43. Columns contribution of MOE1 (percentage of mines neutralized) in bootstrap forest

2. MOE2: Average Mine Active Time

A nonparametric comparison, using the Wilcoxon Method, for each pair of scenarios as shown in Figure 44 indicates there is statistical differences between most experiments. The exceptions are Experiment One with Experiment Five and Experiment Two with Experiment Three are not statistically different from each other. The p-values for these test pairs are 0.51 and 0.45, respectively, while the rest are less than 0.05. This result complements the analysis of the individual experiments, which is not able to produce comparisons to this level of detail. The results suggest that the single sortie and two sortie operations perform equally well in terms of average mine active time, and dedicated neutralizer to detector or area does not affect the average mine active time.

The random forest analysis with 1,000 trees was performed on average mine active time, and the results are shown in Figure 45. The column contributions chart clearly demonstrates the most influential factor is scenario, followed by detector speed. Scenario is the overwhelming influential factor, accounting for 95% of the splits. Since scenario is the most critical factor, it would be reasonable to compare the means within the scenarios.

Figure 46 is the boxplot for average mine active time, and it indicates that Experiment One and Experiment Five perform slightly better than Experiment Two and Experiment Three.

Nonparametric Comparisons For Each Pair Using Wilcoxon Method

q*	Alpha
1.95996	0.05

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL	Difference Plot
4_ReducedRevisit	1_BaseCase	299.997	14.15392	21.1953	<.0001*	418.978	406.859	429.920	
4_ReducedRevisit	2_Paired	299.997	14.15392	21.1953	<.0001*	408.931	396.935	419.931	
4_ReducedRevisit	3_Area	299.997	14.15392	21.1953	<.0001*	411.465	399.536	422.308	
2_Paired	1_BaseCase	49.577	14.15392	3.5027	0.0005*	10.678	4.793	16.443	
3_Area	1_BaseCase	40.377	14.15392	2.8527	0.0043*	8.601	2.662	14.267	
5_1Sortie	1_BaseCase	9.317	14.15392	0.6582	0.5104	1.871	-3.899	7.589	
3_Area	2_Paired	-10.600	14.15392	-0.7489	0.4539	-2.199	-7.839	3.494	
5_1Sortie	3_Area	-32.750	14.15392	-2.3138	0.0207*	-6.730	-12.287	-1.037	
5_1Sortie	2_Paired	-42.387	14.15392	-2.9947	0.0027*	-8.867	-14.561	-3.053	
5_1Sortie	4_ReducedRevisit	-299.997	14.15392	-21.1953	<.0001*	-417.651	-428.846	-405.617	

Figure 44. Pairwise comparison of MOE2 (average mine active time)

Column Contributions

Term	Number of Splits	SS		Portion
Scenario	3278	11852278.2		0.9453
DetectorMoveSpd	3452	570197.463		0.0455
OverlapSensRng	3559	40151.3405		0.0032
Mines	3645	38536.2909		0.0031
PathDev	3613	36945.0738		0.0029

Figure 45. Columns contribution of MOE2 (average mine active time) in bootstrap forest

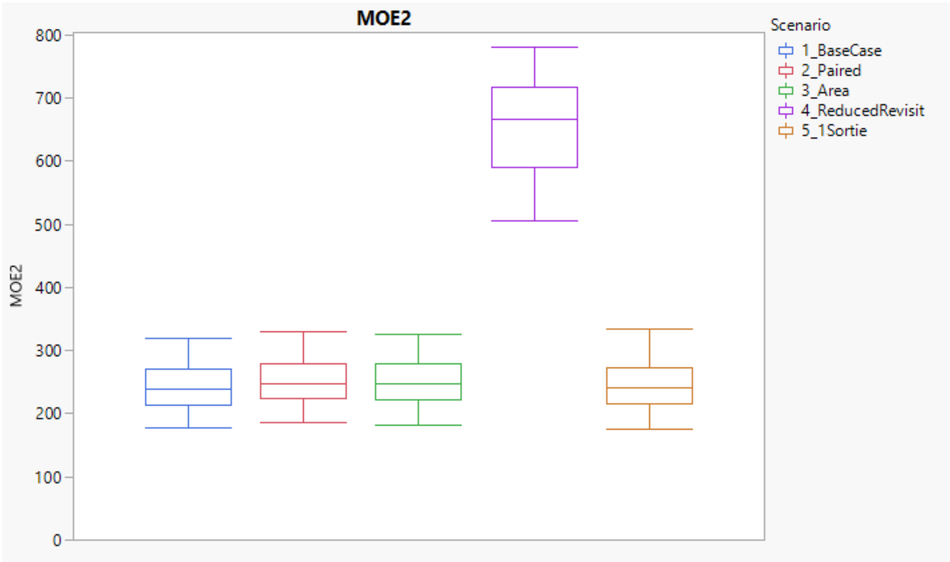


Figure 46. Box plot of MOE2 (average mine active time)

VI. THESIS CONCLUSION AND FUTURE WORK

A. RESEARCH SUMMARY

This thesis explored different concept of operations (CONOPS) using a variety of unmanned systems in mine countermeasure (MCM) missions. Unmanned systems studied include unmanned surface vehicles (USV), and unmanned underwater vehicles (UUV) used by the Republic of Singapore Navy and the United States Navy. CONOPS studied included sectorization of neutralizers, type of platforms, and search patterns. The thesis scenarios depicted the different CONOPS in simple and concise MANA models to achieve high-level scenarios. Cutting-edge design of experiment and a precise analysis process produced important insights to help steer the direction of further research.

B. RESEARCH FINDINGS

The thesis findings focused on how CONOPS can affect performance and risk to transiting vessels. Performance refers to the percentage of mines neutralized while risk to transiting vessels refers to the average mine active time in the search area. It is important to note that while the findings may apply well beyond Singapore, the findings are made with reference to the scenarios studied and only apply when similar conditions are met.

- Single sortie and two sortie operations perform equally well in terms of performance and risk to the transiting commercial vessels.
- Sectorizing neutralizers by either detectors or areas has no impact on their performance, but it increases the risk to the transiting commercial vessels.
- Reducing revisit rate is detrimental to both performance and risk to transiting commercial vessels.
- All the CONOPS studied in this thesis are capable of handling the number of mines looked at with no impact to performance.
- Planning overlaps in sensor range is the most critical factor in improving the performance of MCM missions.

- Detector speed is the most critical factor in reducing the risk of transiting commercial vessels.

- Interactions between path deviation and overlapping sensor range show that when there are gaps in the sensor range, increasing path deviation leads to better detection; when there are overlaps in the sensor range, increasing path deviation leads to missing mines.

C. FUTURE RESEARCH

The author recommends several opportunities for follow-on research, including:

- Expand the scenarios to include other unmanned systems, such as unmanned aerial vehicles and autonomous underwater vehicles in the CONOPS.

- Incorporate endurance, maintenance, and breakdowns for the unmanned systems to gauge the number of platforms required to ensure round-the-clock scanning and clearing efforts.

- Introduce terrain details into the model, such as access points, high traffic area, low traffic area, and radar scanning area.

- Include transiting commercial vessels which can be damaged by mines that are deployed. This will allow simulations to generate an MOE on the number of ships damaged by mines and assess the actual physical loss.

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