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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**A CAPABILITY-BASED APPROACH TO ANALYZING
THE EFFECTIVENESS AND ROBUSTNESS OF AN
OFFSHORE PATROL VESSEL IN THE SEARCH AND
RESCUE MISSION**

by

Mohammad J. Ashpari

December 2012

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AND ROBUSTNESS OF AN OFFSHORE PATROL VESSEL IN THE SEARCH
AND RESCUE MISSION**

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ABSTRACT

In this thesis, a model of effectiveness for an offshore patrol vessel conducting search and rescue missions is developed and described. Beginning with a brief overview of work done by colleagues from the University of Genoa, Italy, as well as documents currently in use by the United States Navy and Coast Guard for search and rescue, this thesis provides a link between physical ship design factors and the operational effectiveness of a search and rescue mission.

The methodology involved developing a search model, then using an enhanced experimental design to explore how operational noise factors, along with physical ship characteristics, impact the effectiveness of search and rescue. Those characteristics include the ship's maximum speed, the number of helicopters onboard, and the number of unmanned aerial vehicles onboard. Operational noise factors include the visibility, the direction of the wind, the maximum speeds as well as the search speeds of the other search entities, the distance to the last known datum, the uncertainty radius of the last known datum, and other environmental factors. Four metamodels are then developed to express which factors have the greatest impact on the performance of the ship as a function of cumulative probability detection threshold in a search and rescue mission.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	BACKGROUND	1
	1. Model-Based Ship Design.....	2
	2. Search and Rescue	3
B.	THESIS OBJECTIVES AND ORGANIZATION.....	4
II.	MODELING THE OPV IN SAR OPERATIONS	5
A.	INTRODUCTION.....	5
B.	ITALIAN MODEL	5
	1. Overview and Assumptions.....	5
	2. Italian Model Experiments.....	9
	3. Italian Study Findings	10
	4. Limitations of the Italian Model and Study	10
C.	ALTERNATIVE SEARCH MODELS	11
	1. Cooperative Search Model	11
	2. National SAR Supplement	13
D.	NPSS MODEL DEVELOPMENT	14
	1. Overall Approach.....	14
	2. OPV	15
	3. Helicopter.....	15
	4. Use of Multiple Detectors	16
	5. Use of Unmanned Aerial Vehicles	16
	6. Target, Visibility, Environmental Conditions, and Air Speed.....	16
	7. Variable Search Speeds	17
	8. Search Box Generation.....	19
	9. Wind Speed Correction	20
	10. Coverage Factor	21
	11. Search Pattern and Detection Probability	22
	12. Number of Helicopters/UAVS	25
	13. DOE–NOLH	26
	14. Measure of Effectiveness	27
III.	ANALYSIS	29
A.	ANALYSIS 1: THE FULL FACTOR METAMODEL.....	30
	1. Analysis 1 Rough Regression	31
	2. Partition Tree Analysis.....	35
	a. MOE 1a: Average Time to Achieve Cumulative Pd of 0.95..	36
	b. MOE 2a: Average Time to Achieve Cumulative Pd of 0.75..	37
	c. MOE 3a: Average Time to Achieve Cumulative Pd of 0.5....	40
	d. MOE 4a: Average Time to Achieve Cumulative Pd of 0.25..	42
	e. Comparing all Four MOEs	44
	3. Number of Splits versus Rsquare	45

B.	ANALYSIS 2: THE METAMODEL FOR THE CONTROLLABLE FACTORS	46
1.	Partition Tree Analysis: Comparing MOE 1b, 2b, 3b, 4b	46
2.	Number of Splits versus Rsquare	51
C.	COMPARISON: NPSS MODEL WITH ITALIAN MODEL	51
IV.	CONCLUSIONS AND RECOMMENDATIONS.....	57
A.	CONCLUSIONS	57
B.	RECOMMENDATIONS AND FUTURE WORK	58
1.	Italian Model Recommendations.....	58
2.	NPSS Model Future Work	59
a.	<i>Non-Rectangular Search Box</i>	59
b.	<i>“Rescue” Aspect of Mission</i>	60
c.	<i>SAR Hazards</i>	60
d.	<i>Helicopter/UAV Refueling/Maintenance</i>	60
e.	<i>Additional Noise Variables</i>	61
C.	SUMMARY	61
	LIST OF REFERENCES	63
	INITIAL DISTRIBUTION LIST	65

LIST OF FIGURES

Figure 1.	Italian model OPV and datum initial positions (From Anghinolfi et al., 2011)	6
Figure 2.	Italian model fishing boat directional bounds (From Anghinolfi et al., 2011)	6
Figure 3.	Italian model determination of the exploration area (From Anghinolfi et al., 2011)	7
Figure 4.	Coordinated creeping line—single unit (From Office of the Chief of Naval Operations, 1997).....	8
Figure 5.	Time to complete parallel-path search (From Vincent & Rubin, 2004)	12
Figure 6.	Inputs in search area generation.....	20
Figure 7.	Italian model search pattern (From Anghinolfi et al., 2011)	22
Figure 8.	Four parallel searchers (From Washburn, 2002)	23
Figure 9.	Distributions of MOEs - Analysis 1.....	30
Figure 10.	Regression summary (MOE 1a).....	31
Figure 11.	First few significant factors (MOE 1a)	32
Figure 12.	Regression summary (MOE 2a).....	32
Figure 13.	First few significant factors (MOE 2a)	33
Figure 14.	Regression summary (MOE 3a).....	33
Figure 15.	First few significant factors (MOE 3a)	34
Figure 16.	Regression summary (MOE 4a).....	34
Figure 17.	First few significant factors (MOE 4a)	35
Figure 18.	Partition summary (MOE 1a).....	36
Figure 19.	Partition tree (MOE 1a)	37
Figure 20.	Contributing factors (MOE 1.a)	37
Figure 21.	Partition summary (MOE 2a).....	39
Figure 22.	Partition tree (MOE 2a)	39
Figure 23.	Contributing factors (MOE 2a).....	40
Figure 24.	Partition summary (MOE 3a).....	40
Figure 25.	Partition tree (MOE 3a – left branch)	41
Figure 26.	Partition tree (MOE 3a – right branch)	42
Figure 27.	Contributing factors (MOE 3a).....	42
Figure 28.	Partition summary (MOE 4a threshold).....	43
Figure 29.	Partition tree (MOE 4a – left branch)	43
Figure 30.	Partition tree (MOE 4a – right branch)	44
Figure 31.	Contributing factors (MOE 4a).....	44
Figure 32.	Contributing factors (MOEs 1a, 2a, 3a, 4a)	45
Figure 33.	Partition summary (MOE 1b)	47
Figure 34.	Partition tree (MOE 1b)	47
Figure 35.	Partition summary (MOE 2b)	48
Figure 36.	Partition tree (MOE 2b)	48
Figure 37.	Partition summary (MOE 3b)	49
Figure 38.	Partition tree (MOE 3b)	49

Figure 39.	Partition summary (MOE 4b)	50
Figure 40.	Partition tree (MOE 4b)	50
Figure 41.	Regression summary (Italian results).....	53
Figure 42.	Regression fit (Italian results).....	53
Figure 43.	Regression summary (NPSS model).....	54
Figure 44.	Regression fit (NPSS model)	54
Figure 45.	More efficient search box (After Anghinolfi et al., 2011).....	59
Figure 46.	Water chill without anti-exposure suit (From Office of the Chief of Naval Operations, 1997).....	60

LIST OF TABLES

Table 1.	Italian model SAR scenario factors (From Anghinolfi et al., 2011).....	10
Table 2.	Uncorrected visual sweep-width for fixed-wing aircraft (From National Search and Rescue Committee, 2000)	13
Table 3.	Uncorrected visual sweep-width for vessels and boats (From National Search and Rescue Committee, 2000)	14
Table 4.	Search aircraft speed correction (From National Search and Rescue Committee, 2000)	18
Table 5.	Input factor ranges and levels	27
Table 6.	Rsquare for MOE “a” series	46
Table 7.	Rsquare for MOE “b” series	51
Table 8.	NPSS model changes	52
Table 9.	Metamodel comparison.....	55

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LIST OF ACRONYMS AND ABBREVIATIONS

<i>A</i>	Search Box Area
AAW	Anti-Air Warfare
ASR	Air-Sea Rescue
ASuW	Anti-Surface Warfare
BIC	Bayesian Information Criterion
CDP	Cumulative Probability of Detection
CVN	Nuclear-powered Aircraft Carrier
<i>d</i>	Distance from the OPV to the center of last known target datum (Italian Model)
DatumCDR	Distance from ship to the center of the last known target datum
DD	Destroyer
DOE	Design of Experiments
EEZ	Exclusive Economic Zone
FB	Fishing Boat
FF	Fast Frigate
<i>h</i>	Timestep
HeloMax	Maximum Helicopter Speed
HeloSS	Helicopter's Search Speed
ICL	Inverse Cube Law
LHA	Landing Helicopter Assault
LHD	Landing Helicopter Dock
LRC	Lateral Range Curve
MIO	Maritime Interdiction Operation
MOE	Measure of Effectiveness
NOLHC	Nearly-Orthogonal Latin Hypercube
NPS	Naval Postgraduate School
NPSS	Naval Postgraduate School Search
NumHelo	Number of Helicopters
NumUAV	Number of UAVs
OEM	Operational Effectiveness Model
ONR	Office of Naval Research
OPV	Offshore Patrol Vessel
ϕ	Wind Direction relative to x-axis (Italian Model)
Pd	Probability of Detection
<i>r</i>	Uncertainty Radius (Italian Model)
RCC	Rescue Coordination Center

Rsquare	Coefficient of Determination
SAR	Search and Rescue
ShipMax	Maximum Ship Speed
SSM	Ship Synthesis Model
SSS	Ship's Search Speed
t	Time
Target	Target Type
UAV	Unmanned Aerial Vehicle
UAVSS	UAV's Search Speed
USCG	United States Coast Guard
USN	United States Navy
V^D	Target Velocity (Italian Model)
Vis	Visibility
W	Corrected Sweep Width
W^H	Corrected Sweep Width of Helicopter (Italian Model)
WHEC	High Endurance Cutter
WindBounds	Directional Bound offset from wind direction
WindD	Wind Direction relative to x-axis
WindSR	Wind Speed Ratio
WMEC	Medium Endurance Cutter
W^{OPV+H}	Corrected Sweep Width of Helicopter and Ship (Italian Model)
WPB	Patrol Boat
δ	Directional Bound offset from wind direction (Italian Model)
$Y(t)$	Detection Rate as a function of time (Italian Model)

EXECUTIVE SUMMARY

Historically, ship builders have designed ships to optimize the performance of their primary missions. Search and rescue (SAR), has traditionally been a secondary mission in design.

Beginning with a brief overview of work done by colleagues from the University of Genoa, Italy, as well as documents currently in use by the United States Navy and Coast Guard for search and rescue, this thesis explores the link between physical ship characteristics and operational effectiveness by building and exploring the Naval Postgraduate School Search (NPSS) model. In this effort, the impact of carrying more helicopters, unmanned aerial vehicles, and/or increasing the ship's maximum speed can be clearly seen in the measure of effectiveness for the SAR mission.

Additionally, this thesis incorporates operational noise factors such as visibility, wind direction, the maximum speeds as well as the search speeds of the other search entities, distance to the last known datum, the uncertainty radius of the last known datum, and other environmental factors, in an attempt to determine if these ship designs perform robustly across the myriad of noise factors.

Four metamodels are then developed to express which factors have the greatest impact on the performance of the ship for four different cumulative probability detection thresholds in the SAR mission. The NPSS results show that the operational effectiveness varies substantially for different ship configurations, but that there is still a great deal of variability that the metamodels cannot capture. The maximum ship speed is the dominant factor for thresholds of 25%, 50%, and 75%, but that the availability of at least one unmanned aerial vehicle is the most important if a 95% threshold is required.

The results from the NPSS model are compared to and contrasted with those of the Italian model for the restricted set of circumstances explored in the earlier Italian study. Although the two models have different measures of effectiveness and therefore cannot be directly compared, the metamodels show that the factors have similar

importance in the two models. For the restricted set of search operations examined in the Italian study, the output of both the Italian model and the NPSS model are very predictable.

These results contribute to a larger project that aims at developing a methodology for evaluating the operational effectiveness of offshore patrol vessels for a variety of missions before proceeding to the detailed design of these units.

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I. INTRODUCTION

A. BACKGROUND

Throughout history, the great nations have been those which controlled the seas. From the ancient times of Persia to the World War II days of Japan, loss of sea power has caused many nations to fail (NAVEDTRA, 2012). “Control of the seas means security. Control of the seas can mean peace. Control of the seas can mean victory. The United States must control the seas if it is to protect your security” (Kennedy, 1963). The United States Navy has been traditionally identified with the operation of iconic capital ships such as battleships and aircraft carriers. These blue water vessels provide the sustainable logistic reach, allowing a persistent presence all around the world. Although these ships have been predominantly used in power projection and deterrence to maintain security, these capital ships have also been the primary means for the U.S. to accomplish all of its secondary missions as well. Even though these large ships were not initially designed with some secondary missions as a requirement, in an attempt to compensate, ships are retrofitted to accommodate these missions. The U.S. Landing Helicopter Dock (LHD) and Landing Helicopter Assault (LHA) types of ships for example, were not configured to conduct the Search and Rescue (SAR) mission. Crew berthing, work spaces, even deck parking for the SAR helicopters, were not initially incorporated in the design of these ships, and currently are accommodated via means of retrofitting. If smaller, cheaper ships could be designed with these secondary naval duties as their primary requirement, clearly they would perform better than the current blue water vessels for their respective missions. This concept has been the objective of not only the U.S., but many countries worldwide.

For most countries, naval duties consist of SAR, Maritime Interdiction Operation (MIO), fishery protection, pollution control, fire-fighting, salvage operations, anti-surface warfare (ASuW), anti-air warfare (AAW), counter-narcotics, humanitarian operations and exclusive economic zone (EEZ) patrol. To perform these duties, many different designs for Offshore Patrol Vessels (OPVs) have been created, each to conduct specific

tasks, with the designs being based on the experience of the naval architect. At least 30 countries are known to have a total of 89 OPVs currently on order, while planning for another 98 at a value of over \$15 billion (Offshore Patrol Vessel Sector Report, 2010).

The OPV type chosen depends on that country's specific naval requirements. These requirements can form based on the country's geographic location, political aspirations and/or intended role of its naval force in the world. However, the majority of OPV programs are of a cheaper basic patrol vessel that can be used in a variety of roles.

1. Model-Based Ship Design

The Office of Naval Research (ONR) is working with Naval Postgraduate School (NPS) to support a group of Italian research colleagues in assessing their operational effectiveness models (OEMs) representing the OPV's performance capabilities in a set of different naval operational scenarios. These scenarios of interest include missions such as ASuW, AAW, MIO, and SAR.

The overall project aims at developing a methodology for evaluating the operational effectiveness of OPVs before proceeding to the detailed design of these units. In particular, this methodology should be the basis for the development of the OEM, for quickly analyzing the impact of different choices in unit requirements, quantified in terms of Measure of Effectiveness (MOE). The OEMs will work jointly with another module, the Ship Synthesis Model (SSM), in order to properly evaluate the features that units must show before releasing them to the successive detailed design phase. As part of this overall project, this thesis will specifically focus on the SAR mission, which is a well-known naval operation. While there is a breadth of possible SAR operations and scenarios, this thesis focuses on a ship responding to a distress signal.

2. Search and Rescue

The United States Defense Department defines SAR as an operation normally coordinated by a Rescue Coordination Center (RCC) or rescue sub-center, using available personnel and facilities to locate persons in distress and deliver them to a place of safety (England, 2006).

There are various forms of SAR: ground SAR is traditionally associated with wilderness zones, and urban/suburban environments (Urban Search and Rescue [US&R] 2009); combat SAR occurs when SAR operations are carried out during war or near combat zones (About.com U.S. Military, 2009). Lastly, air-sea rescue (ASR), which refers to the combined use of aircraft (helicopters, and fixed-wing unmanned aerial vehicles (UAVs)) and surface vessels to search for and recover survivors of aircraft downed at sea as well as passengers of vessels in distress, are the form of SAR that is mostly discussed in this paper.

The main purpose of SAR operations for the U.S. Navy is to save lives, the most expensive component of the Navy. U.S. maritime SAR is conducted predominantly by the U.S. Coast Guard (USCG), and the U.S. Navy.

The USCG maintains a wide variety of SAR resources, specifically dedicated to conduct maritime SAR throughout the U.S. Medium-range SAR involves fixed-wing aircraft such as the HU-25, and rotary-wing aircraft such as the HH-60 and HH-65. In addition to aircraft, the USCG utilizes 378 foot high endurance cutters (WHECs), 180-270 foot medium endurance cutters (WMECs) and 80-110 foot patrol boats (WPB) (United States National Search and Rescue Supplement 2000).

The United States Navy (USN) maintains extensive numbers and types of aircraft, including both fixed and rotary wing. The P-3 is used for long range missions, the S-3 and E-2 are carrier based fixed-wing aircraft, and the H-60 rotary wing type is utilized onboard various different vessels. The vessels most often utilized by the USN include destroyers (DD) and fast frigates (FF) for surface search, nuclear-powered aircraft carriers (CVNs), landing helicopter docks (LHDs) and landing helicopter assaults (LHAs) for air search, and submarines for subsurface search.

Currently, the USN conducts SAR operations in accordance with the Navy Search and Rescue Tactical Information Document (Office of the Chief of Naval Operations, 1997) which consists of lookup tables, charts, graphs, and step-by-step instructions on how to conduct SAR. The information used to build this document stems from the United States National Search and Rescue Supplement (National Search and Rescue Committee, 2000), which has been constructed through actual search scenario experiments.

As far as modeling SAR, there are different approaches that can be taken. Simulation is an approach that can be used to mimic movement, patterns, and visual detection ranges of a typical search scenario. Another approach is to make use of the tables that populate the SAR supplement, to calculate estimates for a given SAR scenario directly.

B. THESIS OBJECTIVES AND ORGANIZATION

In this thesis, a model of SAR operations is developed using a Microsoft Excel-based approach to calculate estimates for the SAR scenario directly. Once the model is developed, a state-of-the-art experimental design is used to explore variants of this model in an efficient, systematic process. The primary goal is to answer the primary and secondary questions for ONR:

Can a model of SAR Operations be developed using Microsoft Excel to show potential mission effectiveness of a ship design concept with results comparable to the Italian research team's simulation results?

Can this new model be improved through more realistic operational representation and explored using enhanced experimental design techniques in order to provide broader insights than the results from the original Italian model?

While there is a breadth of possible SAR operations and scenarios, this thesis focuses on a ship responding to a distress signal.

II. MODELING THE OPV IN SAR OPERATIONS

A. INTRODUCTION

To develop a basic SAR model, there must be at least three entities: an OPV, a helicopter, and a search target. In order to ensure the model helps analyze the same scenario analyzed by the Italian group, at the bare minimum, the same key assumptions need to be considered as a starting point. From there, the idea is to explore different avenues to add realism while at the same time ensuring the objective of the model is continuously being met, namely measuring the effectiveness of different ship configurations in the SAR mission.

B. ITALIAN MODEL

1. Overview and Assumptions

Our Italian research colleagues from the University of Genoa, Italy as mentioned in Chapter I created a SAR scenario (shown in Figure 1) in which an OPV (Offshore Patrol Vessel Sector Report, 2010) is searching for a fishing boat labeled “FB”. Throughout this thesis, this model is referred to as “the Italian model”. In this scenario, the OPV receives a distress signal, in which the fishing boat relays that it will imminently be losing propulsion as well as communication capabilities. The OPV also has the information on a last known datum of the fishing boat to be a distance d away. This location of the fishing boat at the time of the distress signal is not known exactly, but it is assumed to be uniformly distributed within a circle of radius r (called the uncertainty radius) around the datum.

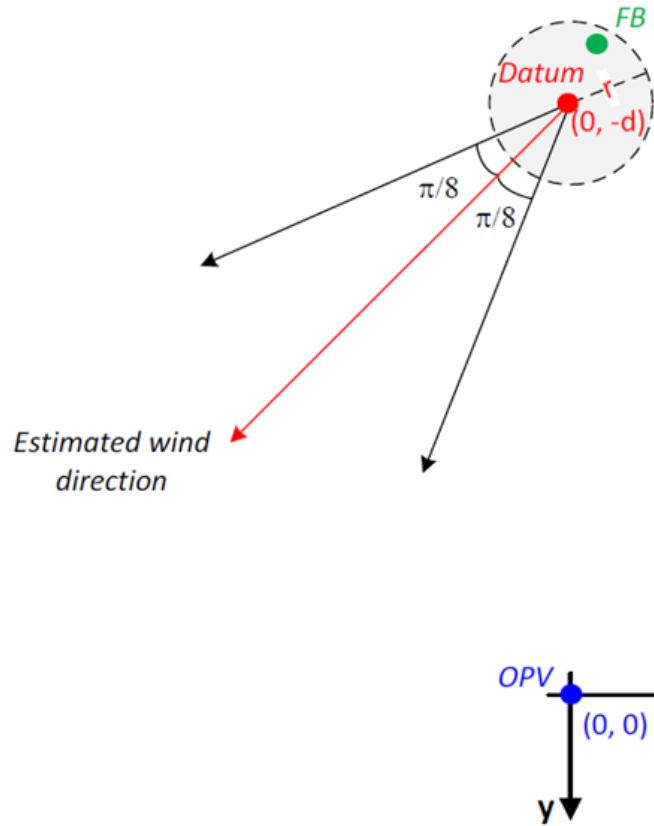


Figure 1. Italian model OPV and datum initial positions (From Anghinolfi et al., 2011)

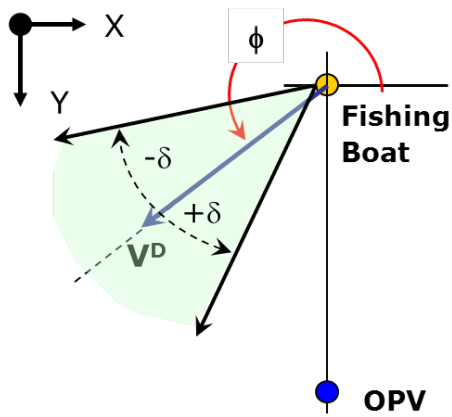


Figure 2. Italian model fishing boat directional bounds (From Anghinolfi et al., 2011)

Figure 2 shows that additional uncertainty arises because the target can move. The model assumes the target/FB movement velocity (represented as V^D) remains fixed, and this movement will be limited to being a direct function of the wind velocity:

$$V^D = EstimatedWindSpeed \cdot \left(\frac{1.5}{2.0}\right) \quad (\text{Equation 1})$$

According to the Italian group, this relationship between the wind speed and target speed is an estimate that comes from the Italian SAR manual. The model also assumes target movement directional bounds δ with fixed values equal to $\pm\pi/8$ radians in the direction of the wind. Additionally, the direction of the wind with respect to the x-axis is represented by the variable ϕ (shown in Figure 2). Using the known maximum wind velocity, the outer-most coordinates of the three intercept data are computed (shown in equations 2 through 5) using Cartesian motion equations (equations 6 through 9). Then by including the original datum location, a search box is constructed to encapsulate all four data plus each of their respective uncertainty buffers (shown in Figure 3).

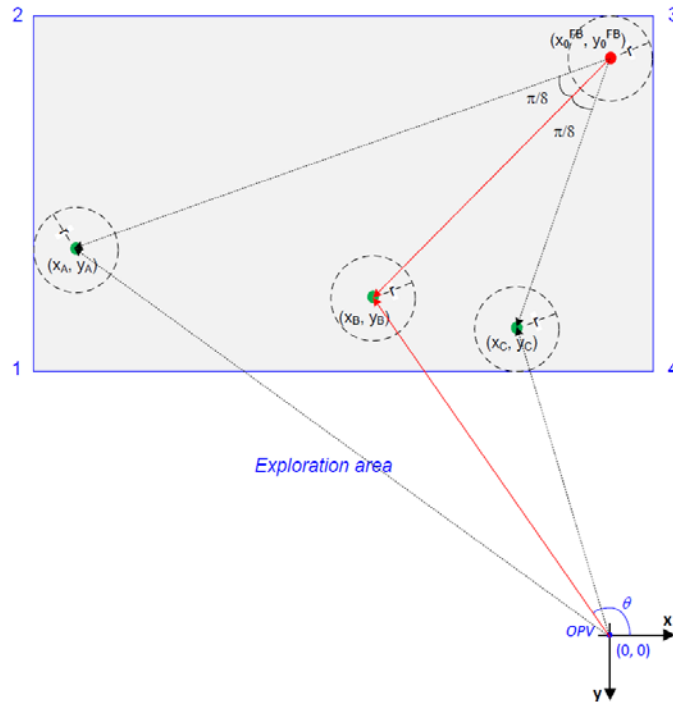


Figure 3. Italian model determination of the exploration area (From Anghinolfi et al., 2011)

$$x = x_0^{FB} + t \cdot V_x^{FB} \quad (\text{Equation 2})$$

$$y = y_0^{FB} + t \cdot V_y^{FB} \quad (\text{Equation 3})$$

$$x = x_0^{OPV} + t \cdot V_{max}^{OPV} \cdot \cos \theta \quad (\text{Equation 4})$$

$$y = y_0^{OPV} + t \cdot V_{max}^{OPV} \cdot \sin \theta \quad (\text{Equation 5})$$

$$x_1 = x_2 = \min\{x_0^{FB}, x_A, x_B, x_C\} - r \quad (\text{Equation 6})$$

$$x_3 = x_4 = \max\{x_0^{FB}, x_A, x_B, x_C\} + r \quad (\text{Equation 7})$$

$$y_1 = y_4 = \min\{y_0^{FB}, y_A, y_B, y_C\} - r \quad (\text{Equation 8})$$

$$y_2 = y_3 = \max\{y_0^{FB}, y_A, y_B, y_C\} + r \quad (\text{Equation 9})$$

Once the search box is defined, the OPV moves at maximum ship velocity to the closest corner of the search box, and then begins searching for the target.

The ship is designed to follow a coordinated creeping line search pattern with a single helicopter overhead, once the ship has reached the interior of the search box. A portion of the search path is shown in Figure 4. Similarly, the ship itself will follow a larger creeping line search pattern if the search box is large.

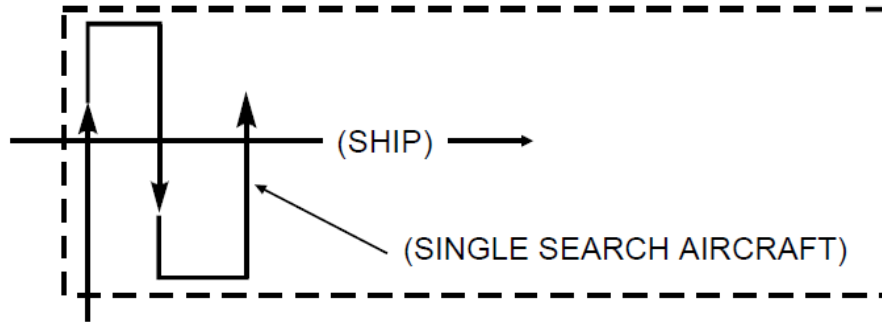


Figure 4. Coordinated creeping line—single unit (From Office of the Chief of Naval Operations, 1997)

In this model, even if the ship or helicopter comes close to the target, detection is not guaranteed. The detection depends on the cumulative probability of detection (CDP) of the ship and helicopter using a detection rate model. Daniel Wagner in his book “Naval Operations Analysis” describes how a detection rate model can be used to obtain a CDP:

For the time $t \geq 0$, the CDP at time t , is defined to be the probability that detection occurs at least once during $[0, t]$:

$CDP(t) = \Pr\{\text{at least one detection occurs no later than time } t\}$

$CDP(t) = \Pr\{\text{time-to-initial-detection} \leq t\}$

Search models can consist of a sequence of discrete glimpses, or they may be continuous looking model. In the Italian model's case, the simulation uses a continuous looking model to obtain a cumulative probability of detection.

With the assumption that the detection rate of the search entity occurs at a detection rate, $\Upsilon(t)$ at time t , the notion of independence can be extended to a continuous looking model. Detections, (not necessarily the initial detections), can now occur as a Poisson process, with a variable rate parameter, $\Upsilon(t)$. This would imply:

For any time t , for a small $h > 0$, where h is a timestep,

$\Pr\{\text{AtLeastOneDetectionOccursIn}[t, t + h]\} \approx h \cdot \Upsilon(t)$, and

$\Pr\{\text{MoreThanOneDetectionOccursIn}[t, t + h]\}$ is negligible compared to $h \cdot \Upsilon(t)$

Occurrences of detections in nonoverlapping time intervals are independent.

With this modification, the CDP can be expressed in terms of $\Upsilon(t)$, during the time interval $[0, t]$:

$$p(t) = 1 - e^{-\int_0^t \gamma(u) du} \quad (\text{Equation 10})$$

(Wagner, Sanders & Mylander, 1999)

The SAR operation ends once the ship has either located the target, or completed a single search of the box without finding the target. By simulating this operation over 10,000 runs with target initial positions uniformly distributed over the datum uncertainty radius, the Italian model can estimate the probability of success for a specific set of initial conditions.

2. Italian Model Experiments

The Italian model is run using ten fixed parameters and varying three discrete factors shown in Table 1.

Fixed parameter	Value
Datum Uncertainty r	2 nm
Wind maximum speed	20 kn
OPV patrolling speed	15 kn
OPV acceleration	0.1 m/s ²
W value of OPV	2 nm
W value of Helicopter	5.8 nm
Helicopter speed	70 kn
Helicopter maximum flight time	150 min
Helicopter setup time	30 min
Helicopter-OPV maximum distance	20 nm

Table 3 – Fixed parameters of the SAR scenario

DOE factor	Range
Initial distance d	[50 nm, 200 nm]
OPV maximum speed	[22 kn, 40 kn]
Helicopter presence	[0, 1] (binary value)

Table 1. Italian model SAR scenario factors (From Anghinolfi et al., 2011)

3. Italian Study Findings

After running the model with experiments, the Italian study concludes that of the three variable factors, the presence of the helicopter has the largest impact on the output of the model's measure of effectiveness, followed by the OPV's maximum speed, and lastly by the initial distance. More results on the Italian study can be found in Chapter III.C.

4. Limitations of the Italian Model and Study

The Italian model uses the CDP of a ship to represent SAR performance; however it does not seem to put any emphasis on limiting time. The maximum amount of time required to finish a scenario varies with different ship configurations. Some scenarios end relatively quickly, while others take a much larger amount of time to complete.

If a ship is able to conduct SAR with a CDP of 0.95 would seem close to optimal, however if it requires the ship two months of searching to attain that cumulative

probability, then in reality the fishing boat crew may not have survived the search effort. This may mean that time should also be included as a measure of effectiveness for SAR.

Additionally, the Italian model solely accounts for the effect of a single SAR helicopter. Expanding the ship design to include the possibility of accommodating multiple helicopters may allow the ship to achieve a higher probability of detection for area search (Pd). Along the same lines, having UAVs may prove to be a more cost effective way to achieve the same capabilities as having additional helicopters attached to the ship.

Lastly, the Italian model seems overly constrained. Many model parameters that would vary in actual SAR missions are fixed for the study; these parameters will be labeled the noise factors. For example, the search itself was hardcoded to find one specific target, namely a single survivor in the water, when SAR in general encompasses wide ranges for number of personnel, as well as the length of the ship to be rescued. Because some of the noise factors in the Italian model are fixed, it is difficult to determine how the model behaves if those fixed parameters have a different set of values.

The questions then arise, “How does having more search assets affect the SAR mission given a search box? Is it worth having more than two search assets (a helicopter and a ship)?”

C. ALTERNATIVE SEARCH MODELS

Before the NPSS model is presented, a brief discussion of other search models and methods are provided below.

1. Cooperative Search Model

An analysis conducted by Vincent and Rubin (2004) sought to analyze the effects of cooperative search using UAV. The analysis assumed that each search unit performed the search in a “cooperative manner,” meaning that each search unit was able to communicate and coordinate with every other search unit in the execution of their search effort. The cookie cutter detection rule was used (otherwise known as the definite range law of detection); specifically, it was assumed the search units always detect targets within a specified radial distance. Under these assumptions, it was found that the time

required to complete the search decreased exponentially, as more and more search units were added to the task (Figure 5). After a certain number of search units, diminishing returns are noted in the time required to complete the search. This paper provides the insight that having more search assets allows you to complete the searching of your search box in a shorter period of time, but only up to a point. Although it would not be as efficient if the search was conducted by independent search units rather than “cooperative” search units, it can be deduced that when adding additional search units with respective probabilities of detection greater than zero, the cumulative probability of detection can only increase in a similar fashion.

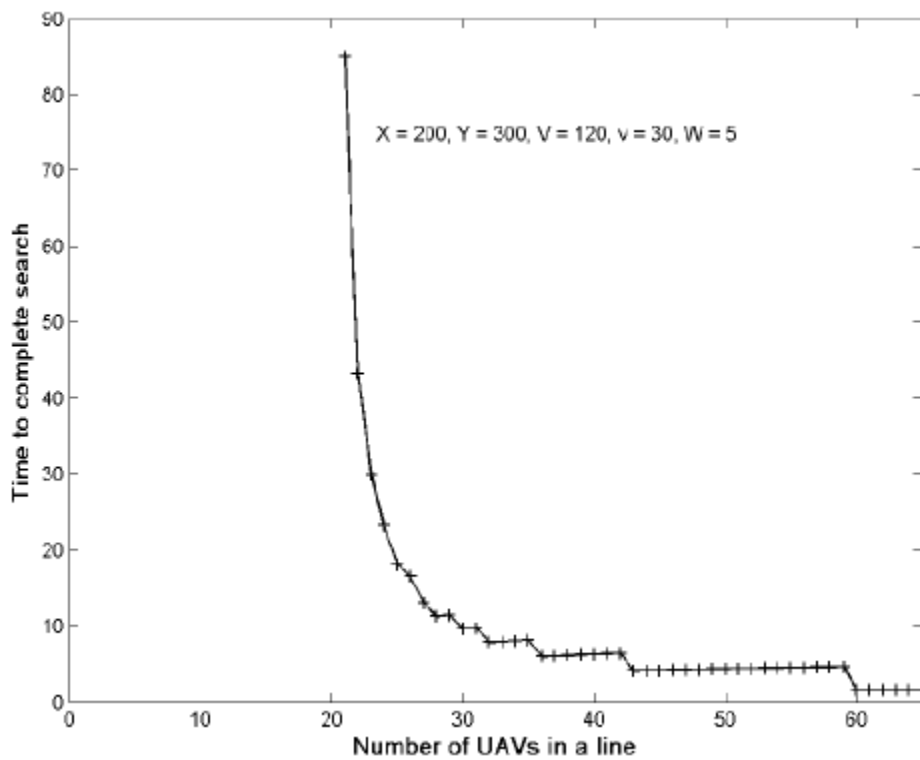


Figure 5. Time to complete parallel-path search (From Vincent & Rubin, 2004)

Although the cooperative search model utilized a cookie cutter detection rule, sensors, detectors, and even observer’s conducting visual search can come in a wide variety of detection capabilities. Some are near-sighted, some are far-sighted, and some see better with the left eye than the right. An observer’s detection of a target depends on many variables.

2. National SAR Supplement

To avoid specific assumptions concerning the visual detection function, such as the cookie cutter (definite range law) assumption used in the Cooperative Search Model, actual data can be used. The National SAR Supplement contains empirical data on effective sweep width for various search platforms and various search objects under differing conditions, obtained from actual search experiments. A portion of one such table is shown in Table 2 as Uncorrected Visual Sweep Width. Given a target for search, SAR aircraft altitude, and the visibility present, these tables provide an estimate of an uncorrected visual sweep width for the given SAR asset.

Search Object	Altitude 300 Feet Visibility (NM)						Altitude 500 Feet Visibility (NM)							
	1	3	5	10	15	20	30	1	3	5	10	15	20	30
Person in Water*	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1
Raft 1 person	0.3	0.7	0.9	1.2	1.3	1.3	1.3	0.3	0.7	0.9	1.2	1.4	1.4	1.4
Raft 4 person	0.4	0.9	1.3	1.7	2.0	2.2	2.2	0.4	1.0	1.3	1.8	2.0	2.2	2.2
Raft 6 person	0.1	1.1	1.5	2.1	2.5	2.7	2.7	0.4	1.1	1.5	2.2	2.5	2.8	2.8
Raft 8 person	0.4	1.2	1.6	2.3	2.6	2.9	2.9	0.4	1.2	1.6	2.3	2.7	2.9	2.9
Raft 10 person	0.4	1.2	1.7	2.4	2.9	3.2	3.2	0.4	1.2	1.7	2.5	2.9	3.2	3.2
Raft 15 person	0.5	1.3	1.9	2.7	3.2	3.5	4.0	0.5	1.3	1.9	2.7	3.3	3.6	4.0
Raft 20 person	0.5	1.4	2.1	3.1	3.7	4.2	4.8	0.5	1.5	2.1	3.2	3.8	4.2	4.8
Raft 25 person	0.5	1.5	2.2	3.4	4.1	4.6	5.2	0.5	1.6	2.3	3.4	4.1	4.6	5.3
Power Boat < 15 ft	0.4	0.8	1.1	1.4	1.6	1.7	1.7	0.4	0.9	1.2	1.5	1.7	1.8	1.8
Power Boat 16-25 ft	0.5	1.6	2.4	3.5	4.3	4.8	4.8	0.5	1.7	2.4	3.6	4.3	4.8	4.8
Power Boat 26-40 ft	0.6	2.1	3.3	5.3	6.6	7.6	9.1	0.6	2.1	3.3	5.3	6.7	7.7	9.1
Power Boat 41-65 ft	0.6	2.6	4.5	8.1	10.9	13.1	16.4	0.6	2.7	4.5	8.1	10.9	13.1	16.5
Power Boat 66-90 ft	0.6	2.8	5.0	9.7	13.5	16.6	21.6	0.6	2.8	5.0	9.8	13.5	16.7	21.7
Sail Boat 15 ft	0.5	1.5	2.2	3.2	3.8	4.3	4.3	0.5	1.6	2.2	3.2	3.9	4.3	4.3
Sail Boat 20 ft	0.6	1.8	2.6	4.0	4.9	5.6	5.6	0.6	1.8	2.7	4.0	5.0	5.6	5.6
Sail Boat 25 ft	0.6	2.0	3.1	4.8	6.0	6.9	6.9	0.6	2.0	3.1	4.9	6.1	7.0	7.0
Sail Boat 30 ft	0.6	2.3	3.6	5.9	7.5	8.8	10.6	0.6	2.3	3.6	5.9	7.6	8.8	10.6
Sail Boat 40 ft	0.6	2.6	4.3	7.5	10.0	11.9	14.8	0.6	2.6	4.3	7.6	10.0	11.9	14.8
Sail Boat 50 ft	0.6	2.7	4.6	8.4	11.3	13.6	17.3	0.6	2.7	4.6	8.4	11.3	13.7	17.3
Sail Boat 65-75 ft	0.6	2.8	4.9	9.3	12.7	15.5	20.0	0.6	2.8	4.9	9.3	12.7	15.5	20.0
Sail Boat 76-90 ft	0.6	2.8	5.1	9.9	13.7	16.9	22.1	0.6	2.8	5.1	9.9	13.7	17.0	22.1
Ship 90-150 ft	0.6	2.9	5.4	11.1	15.9	20.0	26.9	0.6	2.9	5.4	11.1	15.9	20.1	26.9
Ship 150-300 ft	0.6	3.0	5.7	12.5	18.8	24.7	34.8	0.6	3.0	5.7	12.5	18.9	24.7	34.8
Ship > 300 ft	0.7	3.0	5.8	13.2	20.6	27.9	41.4	0.7	3.0	5.8	13.2	20.6	27.9	41.4

Table 2. Uncorrected visual sweep-width for fixed-wing aircraft (From National Search and Rescue Committee, 2000)

Similarly, tables for ships conducting SAR are also available in the supplement; given a target to search, the length of the ship conducting SAR, and the visibility, the sweep width can be estimated (Table 3).

Search Object	Vessel SRU (90° WPB) Visibility (NM)						Small Boat SRU (41° UTB) Visibility (NM)					
	1	3	5	10	15	20	1	3	5	10	15	20
Person in Water*	0.3	0.4	0.5	0.5	0.5	0.5	0.2	0.2	0.3	0.3	0.3	0.3
Raft 1 person	0.9	1.8	2.3	3.1	3.4	3.7	0.7	1.3	1.7	2.3	2.6	2.7
Raft 4 person	1.0	2.2	3.0	4.0	4.6	5.0	0.7	1.7	2.2	3.1	3.5	3.9
Raft 6 person	1.1	2.5	3.4	4.7	5.5	6.0	0.8	1.9	2.6	3.6	4.3	4.7
Raft 8 person	1.1	2.5	3.5	4.8	5.7	6.2	0.8	2.0	2.7	3.8	4.4	4.9
Raft 10 person	1.1	2.6	3.6	5.1	6.1	6.7	0.8	2.0	2.8	4.0	4.8	5.3
Raft 15 person	1.1	2.8	3.8	5.5	6.5	7.2	0.9	2.2	3.0	4.3	5.1	5.7
Raft 20 person	1.2	3.0	4.1	6.1	7.3	8.1	0.9	2.3	3.3	4.9	5.8	6.5
Raft 25 person	1.2	3.1	4.3	6.4	7.8	8.7	0.9	2.4	3.5	5.2	6.3	7.0
Power Boat < 15 ft	0.5	1.1	1.4	1.9	2.1	2.3	0.4	0.8	1.1	1.5	1.6	1.8
Power Boat 16-25 ft	1.0	2.0	2.9	4.3	5.2	5.8	0.8	1.5	2.2	3.3	4.0	4.5
Power Boat 26-40 ft	1.1	2.5	3.8	6.1	7.7	8.8	0.8	1.9	2.9	4.7	5.9	6.8
Power Boat 41-65 ft	1.2	3.1	5.1	9.1	12.1	14.4	0.9	2.4	3.9	7.0	9.3	11.1
Power Boat 66-90 ft	1.2	3.2	5.6	10.7	14.7	18.1	0.9	2.5	4.3	8.3	11.4	14.0
Sail Boat 15 ft	1.0	1.9	2.7	3.9	4.7	5.2	0.8	1.5	2.1	3.0	3.6	4.0
Sail Boat 20 ft	1.0	2.2	3.2	4.8	5.9	6.6	0.8	1.7	2.5	3.7	4.6	5.1
Sail Boat 25 ft	1.1	2.4	3.6	5.7	7.0	8.1	0.9	1.9	2.8	4.4	5.4	6.3
Sail Boat 30 ft	1.1	2.7	4.1	6.8	8.6	10.0	0.9	2.1	3.2	5.3	6.6	7.7
Sail Boat 40 ft	1.2	3.0	4.9	8.5	11.2	13.3	0.9	2.3	3.8	6.6	8.6	10.3
Sail Boat 50 ft	1.2	3.1	5.2	9.4	12.5	15.0	0.9	2.4	4.0	7.3	9.7	11.6
Sail Boat 65-75 ft	1.2	3.2	5.5	10.2	13.9	16.9	0.9	2.5	4.2	7.9	10.7	13.1
Sail Boat 76-90 ft	1.2	3.3	5.7	10.8	15.0	18.4	0.9	2.5	4.4	8.3	11.6	14.2
Ship 90-150 ft	1.8	3.3	6.0	12.0	17.1	21.5	1.4	2.5	4.6	9.3	13.2	16.6
Ship 150-300 ft	1.8	3.4	6.3	13.4	20.1	26.0	1.4	2.6	4.9	10.3	15.5	20.2
Ship > 300 ft	1.8	3.4	6.4	14.1	21.8	29.2	1.4	2.6	4.9	10.9	16.8	22.5

Table 3. Uncorrected visual sweep-width for vessels and boats (From National Search and Rescue Committee, 2000)

From Table 2 and 3, it is apparent that visibility (Vis) and the target type (Target) are factors that affect the overall sweep width of the vessel/fixed-wing aircraft. If visibility is poor, it is more difficult to locate a target than if visibility is good. Tables 2 and 3 show that as the visibility decreases, so does the uncorrected sweep width.

D. NPSS MODEL DEVELOPMENT

1. Overall Approach

The interest of this thesis is to build an Excel model called the Naval Postgraduate School Search (NPSS) model to address some of the limitations identified in section B, to incorporate the option of having multiple aerial search entities of rotary and fixed-wing configurations, to ensure noise factors and other physical ship factors are included and varied efficiently in the model using a state-of-the-art experimental design, again with the goal to answer the primary and secondary questions. The benefit of incorporating additional noise factors could potentially lead to a more robust model and in turn, ship design.

The NPSS model delineates between two types of modeling factors; decision factors and noise factors. Decision factors refer to physical ship design characteristics

that a ship builder can “decide” on, to include or exclude in the construction of a ship. Noise factors are factors in a realistic search scenario over which there is no control; environmental conditions, visibility, and target are examples of noise factors. A complete list of the decision factors and noise factors can be found in Table 5 in Chapter II.

2. OPV

Like the Italian experiment, the NPSS has a single OPV. The maximum speed of the ship is a factor labeled ShipMax. The experiment explores a large number of values, as well as a larger range of speeds, which includes the Italian experiment’s range as a subset of itself. Additionally, the NPSS experiment incorporates a factor the ship’s search speed (SSS). This is the speed at which the ship will search once it is within the search box. The search speed can be less than the maximum speed.

3. Helicopter

The Italian model has incorporated a hardcoded distance requirement that restrains a helicopter from flying farther than a given maximum distance from the ship. The reason for this constraint is to model the necessity for communication and directional guidance with the OPV.

With cheap modern global positioning guidance systems and satellite radios/receivers, and assuming the helicopter has these systems installed, the need for this distance constraint can be eliminated. Although this is a deviation from the Italian model, such an assumption has tremendous simplifying effects for modeling purposes.

In the NPSS model, the helicopter may fly its flight path once the ship has entered the search box, regardless of how far the ship may be from the helicopter. With this assumption, and given the only ship-to-helicopter interaction occurs when the target is found, the search pattern of the helicopter and the search pattern of the ship can be assumed to be independent of one another. Search patterns are discussed in further detail in Section C.11.

4. Use of Multiple Detectors

Using the ideas from the Cooperative Search model discussed in Chapter I, it would seem that adding multiple detectors to the NPSS model may reveal the possibility of tradeoffs in the MOE. It is trivial that with the addition of search detectors, each with a probability of detection greater than zero, the aggregate detection rate will increase. Since there is nothing constraining a ship configuration from having the maximum number of detectors, it is also trivial that the best performance will come from the ship configuration with the maximum number of detectors. What will be interesting to analyze however, is “how much of an effect” this aggregate detection rate increase has on the overall MOE.

5. Use of Unmanned Aerial Vehicles

Stemming from the idea that having multiple detectors would offer an interesting trade-study, UAVs can be looked at as the cheaper alternative or complement to the helicopter. UAVs in general, tend to be smaller than helicopters, which in turn can mean less manpower necessary to operate and maintain the aircraft, smaller requirement for storage of aircraft and equipment onboard the ship, and a lower fuel expenditure for the aircraft. These considerations could directly influence the ship design. However, the greatest advantage is that the aircraft is unmanned so the human risk is removed from the search aspect of the mission.

6. Target, Visibility, Environmental Conditions, and Air Speed

In the Italian model, the search target is assumed to be a fishing boat that sends out a final distress signal to the search entities, and loses all future communication capabilities. Although only one type of target is used in the Italian model, results obtained from the NPSS model may prove to be more robust if the NPSS model is able to incorporate and account for an array of possible targets, which may provide better insights as to what set of targets a given ship would be ideal to conduct SAR.

In the Italian study, these environmental factors were all fixed at specific values. By varying these factors in the NPSS experiment, it will present insights on how sensitive the relationships amongst the factors in the MOE are to the presence of variable environmental conditions.

Conveniently, the effects factors such as visibility, altitude, and target type have on a searcher's visual sweep width have been tabularized in the National SAR Supplement as the "Uncorrected Sweep Width". These uncorrected sweep width values are then "corrected" by a correction factor that allows the sweep width to account for environmental weather conditions, as well as the air speed the searcher is traveling at, and is known as the Corrected Sweep Width W .

The use of sweep width in the search and detection problem was established by B. O. Koopman while working for the U.S. Navy during WWII. Koopman called this measure of detectability *effective sweep width*. The idea is that since no sensor is perfect, a detection experiment must consider all detection opportunities to establish how "detectable" a specific target is, with a given sensor, within a given environment. Koopman's methodology was incorporated in the first edition of the U.S. National Search and Rescue Manual in 1959, became accepted by SAR organizations worldwide shortly afterwards, and has been included ever since.

In 1978, using Koopman's methodology, the USCG research and development center ran extensive experiments to gather more accurate and realistic SAR data in actual search scenarios. The data collected from these efforts form the basis of the National SAR Manuals/Supplements used today.

7. Variable Search Speeds

In their conclusion, the Italian group found that a ship's maximum speed does affect the ship's performance in conducting SAR, so it is clear that ShipMax should be examined in the NPSS model. What may be unclear is whether or not varying a searching entity's search speed will have any effect on the performance of SAR. Although it may be intuitive that traveling at a larger speed allows for more area to be searched, this does not necessarily mean the cumulative probability of detection increases. Table 4, which is

from the National Search and Rescue Supplement, indicates that as search speed increases, the correction factor decreases. This decreases the estimate for the search entity’s corrected sweep width, and in turn can mean a lower cumulative probability of detection. In other words, there may be a knee in the curve between the cumulative probability of detection and the entity search speed.

<i>Search Object</i>	<i>Fixed Wing Speed (Knots)</i>			<i>Helicopter Speed (Knots)</i>			
	<i>150 or less</i>	<i>180</i>	<i>210</i>	<i>60 or less</i>	<i>90</i>	<i>120</i>	<i>140</i>
Person in Water	1.2	1.0	0.9	1.5	1.0	0.8	0.7
Raft - 1-4 Man	1.1	1.0	0.9	1.3	1.0	0.9	0.8
Raft - 6-25 Man	1.1	1.0	0.9	1.2	1.0	0.9	0.8
Power Boat - to 25 ft	1.1	1.0	0.9	1.2	1.0	0.9	0.8
Power Boat - 26-40 ft	1.1	1.0	0.9	1.1	1.0	0.9	0.9
Power Boat - 41-65 ft	1.1	1.0	1.0	1.1	1.0	0.9	0.9
Power Boat - 66-90 ft	1.1	1.0	1.0	1.1	1.0	1.0	0.9
Sail Boat - to 26 ft	1.1	1.0	0.9	1.2	1.0	0.9	0.9
Sail Boat - 30-52 ft	1.1	1.0	1.0	1.1	1.0	0.9	0.9
Sail Boat - 65-90 ft	1.1	1.0	1.0	1.1	1.0	1.0	0.9
Ship - over 90 ft	1.0	1.0	1.0	1.1	1.0	1.0	0.9

Table 4. Search aircraft speed correction (From National Search and Rescue Committee, 2000)

An issue that arises with the incorporation of both a maximum speed factor and a separate entity search speed factor is that it becomes possible for the ship search speed to exceed the ship’s maximum speed if the two factors are varied independently and their ranges of potential values overlap. For this reason, a control needs to be put in place, not only for the ship, but also for each helicopter and UAV as well.

One method that can be applied is to run the model as it is, and to run a simple check to verify that each entity’s maximum speed exceeds or meets each entity’s respective search speed. If it does not hold true, the run can be labeled “infeasible”. The benefit of this method would be that no coding would be required upfront, and the analysis process would have more clarity.

Another method that can be applied for control is to convert the search speed of the entity into a function of the maximum speed of the entity, and create a fractional factor to represent the entity’s Search Speed Ratio that can be varied as an input as shown in equation 11.

$$ShipSearchSpeed = ShipMaxSpeed \cdot SSSRatio \quad (\text{Equation 11})$$

Ranges(knots, continuous):

Ship Max Speed	Ship Search Speed	SSS Ratio
[0, 60]	[0, Ship Max Speed]	[0,1]

Similar methodology can be applied to Helicopter and UAV speeds, as shown in equations 12 and 13.

$$HeloSearchSpeed = HeloMaxSpeed \cdot HeloSSRatio \quad (\text{Equation 12})$$

Ranges(knots, continuous):

Helo Max Speed	Helo Search Speed	HeloSS Ratio
[60, 160]	[60, Helo Max Speed]	[0,1]

$$UAVSearchSpeed = UAVMaxSpeed \cdot UAVSSRatio \quad (\text{Equation 13})$$

Ranges(knots, continuous):

UAV Max Speed	UAV Search Speed	UAVSS Ratio
[150, 230]	[150, UAV Max Speed]	[0,1]

The benefit of this method is that only feasible computations are conducted, thereby reducing the amount of computation as well as the time required for computation. The latter method seems more efficient than the former, so it is incorporated in the NPSS model by requiring the user to enter search speed ratios, rather than actual search speeds, to obtain the results.

8. Search Box Generation

In order to analyze the same scenario introduced in the Italian model, the rectangular body of water in which the SAR mission is to be conducted, can be generated in the same fashion.

The SAR OPV begins the search an initial distance in nautical miles, labeled DatumCDR, measured from the ship's location to the center of the datum of uncertainty. This datum of uncertainty represents the ship's last known coordinates, and has a radius measured in nautical miles associated with it of length DatumU. With the same assumptions as in the Italian model, the target's constant speed is equal to:

$$DriftSpeed = \frac{1.5}{2.0} \cdot WindSpeed \quad (\text{Equation 14})$$

As in the Italian model, the direction of the target’s movement is assumed to be bounded by a fixed value equal to $\frac{\pi}{8}$ radians (labeled as WindBounds), centered in the direction of the wind labeled WindD (in radians).

Using the last known location of the datum, and the wind velocity (speed and direction), the rectangular search box is constructed through a similar methodology used by the Italian model shown in Figure 3. Figure 6 shows the inputs necessary to generate the search box. The inputs are shown in green, and WindBounds is in red since it is a fixed value throughout all excursions of the model. The search area *A* now constructed will be known in a given scenario with units of nm^2 .

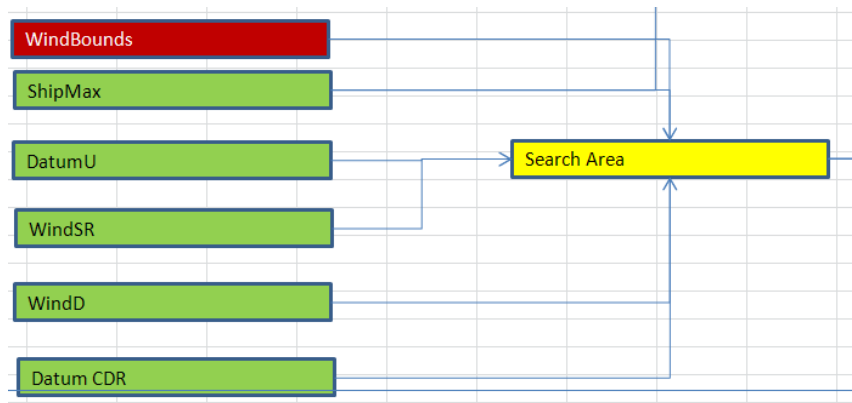


Figure 6. Inputs in search area generation

9. Wind Speed Correction

Incorporating Wind Speed into the NPSS model study requires some careful considerations. Although ideally it would make sense to allow the Wind Speed to conform to typical wind ranges, it would allow for certain unusual situations to arise. For example, consider a scenario when the ship is searching for the target without a helicopter or UAV assets, and the ShipMax is relatively slow. It would be possible for the Target’s Drift Speed to exceed ShipMax, which would create a situation in which the calculation of the MOE would become infeasible. Because the Target’s Drift Speed is a

direct function of the Wind Speed, it would be ideal to limit the Wind Speed such that the Target's Drift Speed never exceeds the maximum speed of the ship in a given scenario. In order to accomplish this, a new factor called the Wind Speed Ratio (WindSR) can be created, similar to the factor created in the issue with ShipMax and the Ship Search Speed. Note, that only the Ship speed would ever affect this issue; since the helicopter and the UAV have 60 knots and 150 knots respectively as their lower bound search speed limits, which would never dip below the maximum possible Wind Speed of 60 knots.

$$WindSpeed < [\frac{2.0}{1.5} \cdot SSS] \cdot WindSR \quad (\text{Equation 15})$$

Using substitution of equation 11 into equation 15:

$$WindSpeed < [\frac{2.0}{1.5} \cdot ShipMax \cdot SSSRatio] \cdot WindSR \quad (\text{Equation 16})$$

Ranges(knots, continuous):

ShipMax	Wind Speed	WindSR
[10, 60]	[0, 1.332*ShipMax*WindSR]	[0, 0.999]

10. Coverage Factor

Now that the Corrected Sweep Widths of each search asset, the size of the search area, and the search speeds for a given scenario can all be calculated, these values can be used to construct the coverage factor. The coverage factor represents the search effort expended in the numerator and total search area in the denominator, using the following formula:

$$CoverageFactor = \frac{W \cdot v \cdot t}{SearchArea} \quad (\text{Equation 17})$$

where v represents the search entity's search speed. The estimation and calculation of the sweep width, the velocities of each search entity, and the search area have already been discussed; the only question with this new term is how time will be incorporated in the model. One method would be to incorporate a while-loop, to have time count forward until the measures of effectiveness are met. A simpler approach would be to increment time forward a fixed amount of time, and to adjust as necessary, as the measure of

effectiveness requires additional time, and at each increment of time to calculate each search entity's Coverage Factor given their respective sweep width, search velocity, and the design point's search area. The NPSS model uses the latter approach and has an increment equal to 5% of an hour. Additionally, the search activity is cut off at a maximum of 65 hours. This places a limitation on the model; however as far as SAR operations are concerned, it seems to be a reasonable length of time for missions to be conducted.

11. Search Pattern and Detection Probability

Figure 7 shows the search pattern for the Italian model. The blue path lays out the sweeping pattern of the OPV, and the red path lays out the sweeping pattern of the helicopter with W^H representing the visual sweep width of the helicopter and W^{OPV+H} representing the visual sweep widths of the helicopter and OPV combined in the Italian model.

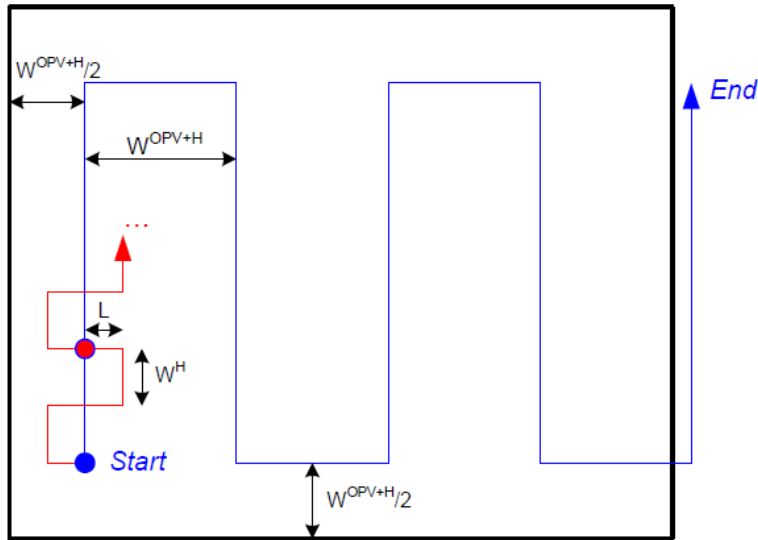


Figure 7. Italian model search pattern (From Anghinolfi et al., 2011)

An alternative to the specific pattern contained in the Italian Model is to generally consider that the search platforms search the area by a series of parallel sweeps, and apply a result from Search Theory known as the Inverse Cube Law (ICL) of Detection

(Wagner, Sanders, & Mylander, 1999) to obtain a good approximation of probability of detection for area search based on coverage factor.

From Wagner, the ICL result is that probability of detection for this area search can be estimated using the Standard Normal Distribution as follows:

$$Pd = 2 \cdot \int_0^z \phi(t) dt \quad (\text{Equation 18})$$

where ϕ is the standard normal probability density function with mean zero and variance one, and

$$z = \sqrt{\frac{\pi}{2}} \cdot \text{CoverageFactor} \quad (\text{Equation 19})$$

The ICL comes from the idea of conducting a parallel search with multiple sweeps of the area over parallel paths as shown in Figure 8.

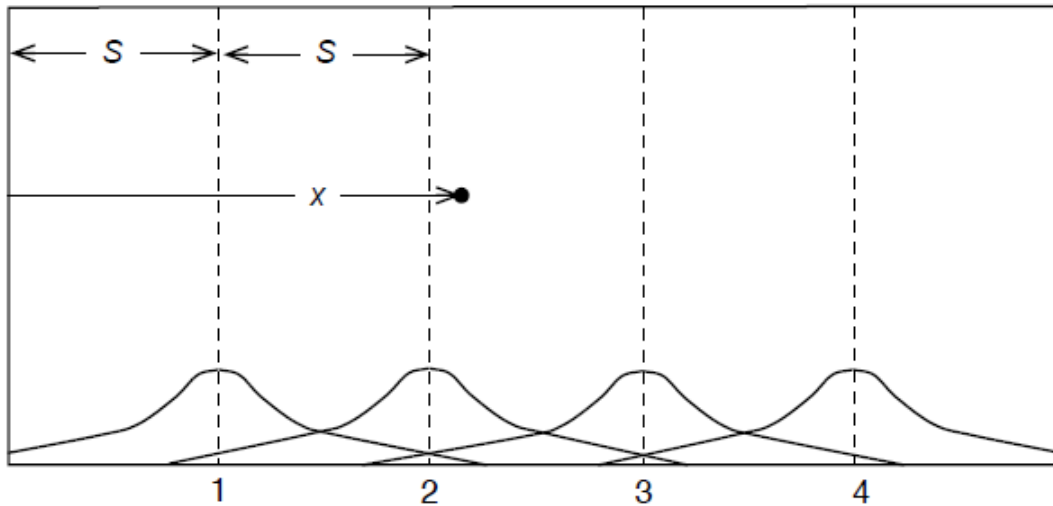


Figure 8. Four parallel searchers (From Washburn, 2002)

The parallel sweeps could be by multiple search entities, or by a single search entity that repositions at the end of each sweep to conduct the next parallel sweep. The area under each curve in Figure 8 represents the search entity's sweep width. The order the tracks are traversed does not matter. Using the ICL, "edge effects" are not considered.

The ICL assumes that the Target is uniformly randomly distributed in A (i.e., likely to be found in one part of the region as in any other), the search conducts a parallel sweep pattern, and each sweep of a given search entity is independent of each of the other of that particular search entity. The uniformly randomly distributed target assumption is also used in the Italian model.

This P_d computed with the ICL represents the probability that the area search results in at least one detection, which is a cumulative probability of detection based on coverage factor by a particular search asset (with sweep width W , search speed v , and search time t). With the ICL, when coverage factor = 1, Equation 19 shows that $z = \sqrt{\frac{\pi}{2}} = 1.253$, and Equation 18 provides the result that P_d is 0.789. The time to achieve coverage factor of 1 can be calculated from Equation 17. Setting coverage factor to 1 gives:

$$t = \frac{\text{SearchArea}}{W \cdot v} \quad \text{(Equation 20)}$$

The time that is calculated in Equation 20 can now be known as a “pass”. Although it is not necessarily the time required to achieve complete coverage of the search area (this would be the case if the search entity utilized a cookie-cutter sweep width), it will be used to represent a uniform increment of time. Once the coverage factor has reached a value of 1, the maximum CDP of 0.789 is achieved for that search entity, while other search entities are allowed to continue searching and achieving greater respective CDPs. This is unrealistic, because it means the faster search assets (helicopter or UAV) might spend much less time on the search operation than the ship. A simple fix to this issue is to begin another independent search of the search box each time a search entity other than the ship completes searching the search box; every time a search entity completes a “pass”.

Although this fix solves one problem, it brings up another interesting issue; given numerous design configurations, in a worst case scenario what would be the maximum number of passes? Would the NPSS model be able to handle this? It turns out, that only a

small number of passes per entity really need to be accounted for, since the CDPs of a single search entity rapidly approaches 1 as the number of passes increase.

After a single pass once the coverage factor reaches 1, z is roughly equal to 1.253, and the CDP maxes out at roughly 0.789. After the second pass is completed, again assuming independence between the two passes of the same search entity, the CDP is:

$$Pd(\text{after second pass}) = 1 - (1 - Pd(1stPass)) \cdot (1 - Pd(2ndPass)) \quad (\text{Equation 21})$$

$$= 0.955$$

The same analogy can be applied to three, four and five passes, resulting in CDPs:

$$Pd \text{ after third pass} = 0.990$$

$$Pd \text{ after fourth pass} = 0.998$$

$$Pd \text{ after fifth pass} = 0.999$$

Since the NPSS model will always have at least one search entity searching for a target, it is safe to assume that anything beyond five passes, would add negligible CDP, and therefore the NPSS model will only be expected to calculate CDPs for each search entity with a total of up to five passes of the search box per entity. Because the assumptions required for the ICL are satisfied, the NPSS model can incorporate using the ICL to calculate CDP.

12. Number of Helicopters/UAVS

In order to incorporate the effects of multiple helicopters and UAVs into the model, the assumption can be made that all of the search entities are independent of one another. Again this assumption can be made since no new information will be passed to each of the search entities up until if the target is found, and the objective of the NPSS model will be to evaluate the performance of the configuration of the OPV in the SAR mission.

Once the Pd of a single search entity has been computed using the ICL, having independence across each search entity we may use De Morgan's laws to conduct a

calculation for total Pd using a specified number of helicopters labeled NumHelo, and a specified number of UAVs labeled NumUAV.

$$\begin{aligned} & \text{Pd(two helicopters)} \\ & = 1 - [(1 - Pd(Ship)) \cdot (1 - Pd(1stHelo)) \cdot (1 - Pd(2ndHelo))] \end{aligned} \quad \text{(Equation 22)}$$

Since $Pd(1stHelo) = Pd(2ndHelo)$

$$\text{Pd(N helicopters)} = 1 - [(1 - Pd(Ship)) \cdot (1 - Pd(1stHelo))^N] \quad \text{(Equation 23)}$$

(Similar method applies for UAVs)

$$\begin{aligned} & \text{Pd(N helicopters, M UAVs)} \\ & = 1 - [(1 - Pd(Ship)) \cdot (1 - Pd(Helo))^N \cdot (1 - Pd(UAV))^M] \end{aligned} \quad \text{(Equation 24)}$$

13. DOE–NOLH

Up to this point, the model has accumulated a total of fifteen different factors to take into account (shown in Table 5). ShipMax, Datum U, WindSR, WindD, and DatumCDR are used in developing the search box. Search speeds, the visibility, the target type, and ECF affect each searching entity's respective sweep width.

The idea behind the Design of Experiments (DOE) process is to systemically structure the values of multiple input factors in an attempt to gain insights about how the input factors and their interactions affect the response (Sanchez, Lucas, Sanchez, Wan, & Nannini, 2012). Using a DOE approach is a very efficient way to explore the SAR scenario, and much more efficient than a trial and error approach.

The DOE design which uses 465 design points has been custom generated by Alex Maccalman (MacCalman, Vieira, & Lucas, 2012) with correlations between the columns in the design matrix within the interval (-0.05, 0.05). It uses all 15 factors; 11 continuous, 3 discrete (two with 3 levels, and one with 25 levels), and 1 categorical factor (with 4 levels), with the low and high level of the range of the factors indicated in Table 5. Note that the target is treated as discrete, rather than categorical, since the Target factor (1-25) corresponds to a general increase in target size, and a 25-level categorical factor would require a substantially larger design. Note that for continuous factors, the number of levels using a space filling nearly orthogonal Latin hypercube (NOLH) design

corresponds to 465. “Nearly orthogonal” refers to a good space-filling design in which the design points are scattered throughout the experimental region with minimal unsampled regions, and are nearly orthogonal; for example, all correlations between the columns in the design matrix are in the interval (-0.03, 0.03) (Cioppa & Lucas, 2007). If the factors for the model were calculated using a full factorial design with the number of levels shown in Table 5, the number of design points (calculated below using equation 25) would be astronomical.

$$\begin{aligned} \# \text{ of Design Points (full factorial)} &= (\# \text{ of Levels})^{(\# \text{ of factors})} && \text{(Equation 25)} \\ &= (465)^{(11)} * (4)^{(1)} * (3)^{(2)} * (25)^{(1)} = 197,799,409,721,224,801,632,875,976,562,500 \end{aligned}$$

Even if the continuous factors were explored at a much smaller number of levels (say, 11), a full factorial would still result in over 2.5×10^{14} design points.

Factor Type	Input Factor	Description	# of Levels	Lower Bound	Upper Bound	Units
Decision	ShipMax	Maximum Ship Speed	465	10	60	knots
Decision	NumHelo	Number of Helos in the scenario	3	0	2	helicopters
Decision	NumUAV	Number of UAVs in the scenario	3	0	2	UAVs
Noise	DatumCDR	Initial Distance of ship to center of datum	465	50	200	nm
Noise	UAVMax	Maximum UAV Speed	465	150	230	knots
Noise	HeloMax	Maximum Helo Speed	465	60	160	knots
Noise	ECF	Environmental Control Factor(Wind, Sea state thresholds)	4	1	4	
Noise	Vis	Visibility	465	1	30	nm
Noise	UAVSS(Fract of Max)	UAV Search Speed(Represented as a fraction of the Max UAV Speed)	465	0	1	
Noise	ShipSS(Fract of Max)	Ship Search Speed(Represented as a fraction of the Max Ship Speed)	465	0	1	
Noise	HeloSS(Fract of Max)	Helo Search Speed(Represented as a fraction of the Max Helo Speed)	465	0	1	
Noise	WindSR	Wind Speed(Represented as a fraction of the Max Ship Speed)	465	0	1	
Noise	WindD	Wind Direction(In radians)	465	0	6.283185307	radians
Noise	DatumU	Datum Uncertainty	465	0	10	nm
Noise	Target	Type of Search Target	25	1	25	

Table 5. Input factor ranges and levels

14. Measure of Effectiveness

In any kind of disaster, SAR operations are vital, and time is of the essence. Although the cumulative probability of detection is important, it is also important to minimize search time in an attempt to rescue the survivor(s) if he/she (they) are still alive.

With two competing objectives, it becomes difficult to localize what the proper objective should be to use as a measure of effectiveness. One method in dealing with this issue is to make the measure of effectiveness a function of the competing objectives, and then using a multi-pronged approach, analyze various different ratios of the objectives.

In this case, instead of solely using a given ship design point's CDP as the measure of effectiveness, or the average time required to locate the target, the CDP can be tabularized as a function of time. Allowing this would enable the analysis to be conducted for any given threshold of time as a cutoff. For simplicity, the measure of effectiveness "Average Time Required given a Pd threshold" can be sliced into four different bins:

MOE 1: Time Required for Configuration to Achieve 0.95 Pd

MOE 2: Time Required for Configuration to Achieve 0.75 Pd

MOE 3: Time Required for Configuration to Achieve 0.50 Pd

MOE 4: Time Required for Configuration to Achieve 0.25 Pd

III. ANALYSIS

For the analysis of the search model's output, three analysis objectives need to be completed. Firstly, the NPSS model's data can be represented in a statistical metamodel built using the "full" set of factors varied during the experiment (The term "metamodel" is used to avoid confusion between the NPSS model itself, and the analysis regression models). Using this analysis, it may be useful to break down and understand under which circumstances the decision factors have the most impact on the performance of the ship in its mission. In this section, the name of each metamodel is composed of the MOE followed by an "a" to represent that all factors (noise and control) are incorporated in the model.

Secondly, the NPSS model's data can be used to build a statistical metamodel using only a handful of the total number of factors in the NPSS model, specifically, using the operational "decision" factors. The purpose of this objective is to link the importance of each factor amongst the group of controllable factors, to operational performance of the NPSS mission. This is useful because it provides an idea of how physically different ship configurations directly impact the measure of effectiveness in the presence of numerous noise variables. In this section, the name of each metamodel is composed of the MOE followed by a "b" to represent that the noise factors are not incorporated in the model.

Lastly, the NPSS model's data can be used in an analysis of how the results of this model compare to the Italian group's results. The first and second analysis objectives are conducted on all four measures of effectiveness.

The tool that will be used primarily in this analysis is the JMP software package. JMP is a computer program first developed by John Sall, which allows complex statistical analyses. The benefits of the JMP software package include ease of use, and the dynamic behavior of its graphics, data tables, which facilitate the understanding of even the most complex problems (Jones & Sall, 2011).

A. ANALYSIS 1: THE FULL FACTOR METAMODEL

The first thing that would be interesting to look at is to get an idea of what the distribution of the MOE outputs look like. Figure 9 shows the distribution summary of all four MOEs. Immediately what is apparent is the large density of counts in each of the 60-70 count bins in the figure (circled in red).

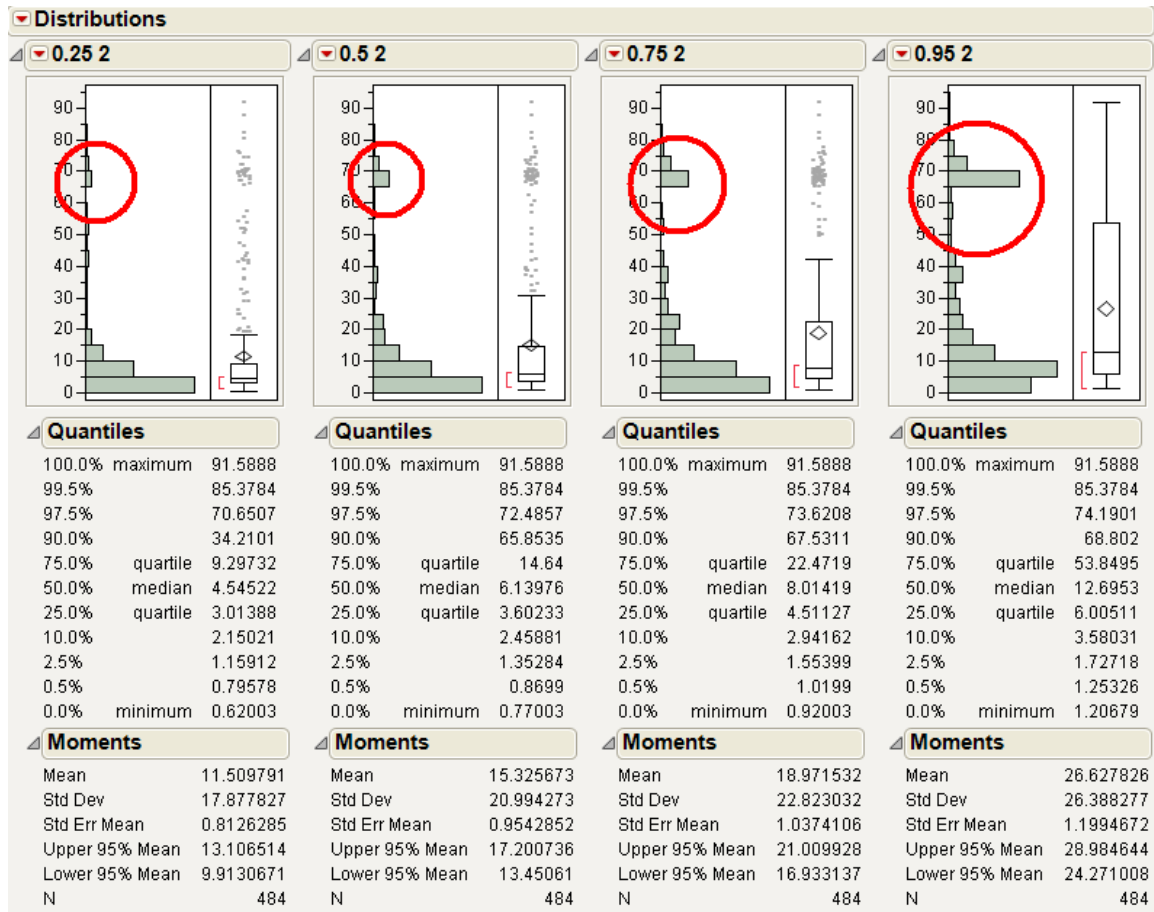


Figure 9. Distributions of MOEs - Analysis 1

These spike points are obviously due to the 65 hour limit placed on the NPSS model's coverage factor time limit. The outputs show no signs of having negative values, which is expected since the time output cannot be negative in this model. The cumulative probability threshold increases from 0.25 to 0.95, the mean and median values of the

MOEs increase in time, which is intuitive, and function as expected. Additionally the outputs have large ranges, so it makes sense to do further analyses to see which factors affect the outputs

1. Analysis 1 Rough Regression

To get a rough idea of which factors in the full factor model are important to each of the MOEs, each set of data can be fit to a 2nd order regression using a forward Stepwise approach with a minimum Bayesian information criterion (BIC) stopping condition. In these regressions, the metamodels are able to achieve coefficient of determination (Rsquare) adjusted value of 0.767, 0.705, 0.674, and 0.613 for the MOEs with Pd thresholds of 0.95, 0.75, 0.5, and 0.25 respectively. The regression summaries and the first few significant factors for each of the MOE metamodels are shown in Figures 10–17.

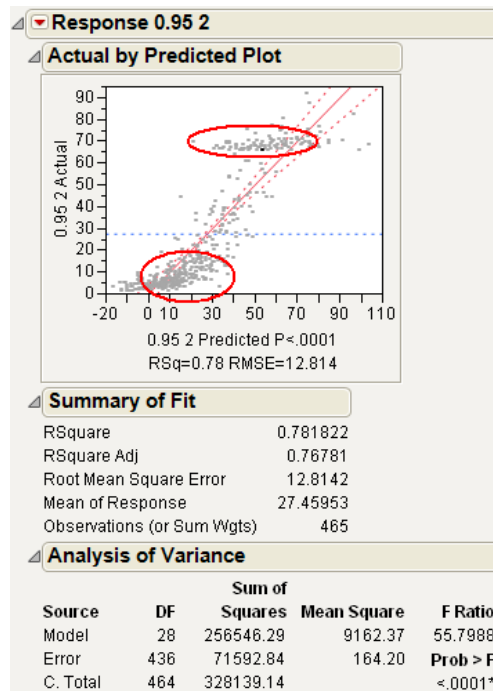


Figure 10. Regression summary (MOE 1a)

Sorted Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob>
NumUAV	-11.15325	0.737844	-15.12	<.000
WindSR	30.377097	2.091526	14.52	<.000
Target	-1.009388	0.084447	-11.95	<.000
(NumUAV-0.9914)*(NumHelo-0.99355)	10.599412	0.898154	11.80	<.000
NumHelo	-8.275559	0.739989	-11.18	<.000
ShipMax	-0.348873	0.041624	-8.38	<.000
WindD	-2.727366	0.330551	-8.25	<.000
DatumCDR	0.1100771	0.01397	7.88	<.000
ShipSS(Fract of Max)	14.853399	2.064667	7.19	<.000

Figure 11. First few significant factors (MOE 1a)

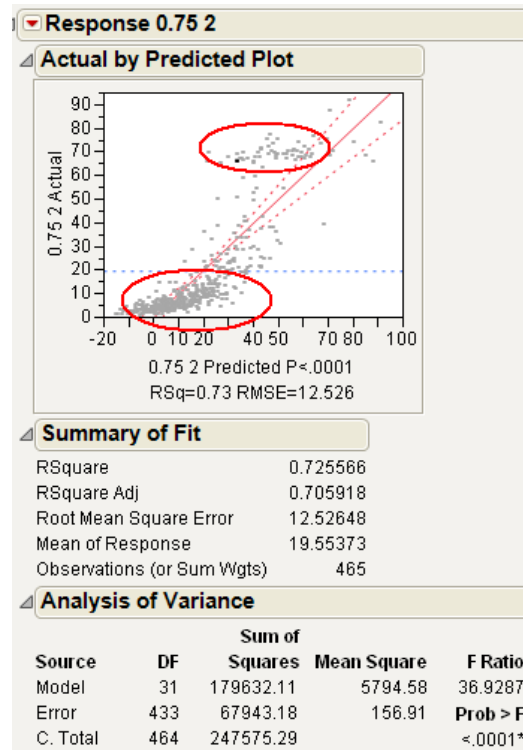


Figure 12. Regression summary (MOE 2a)

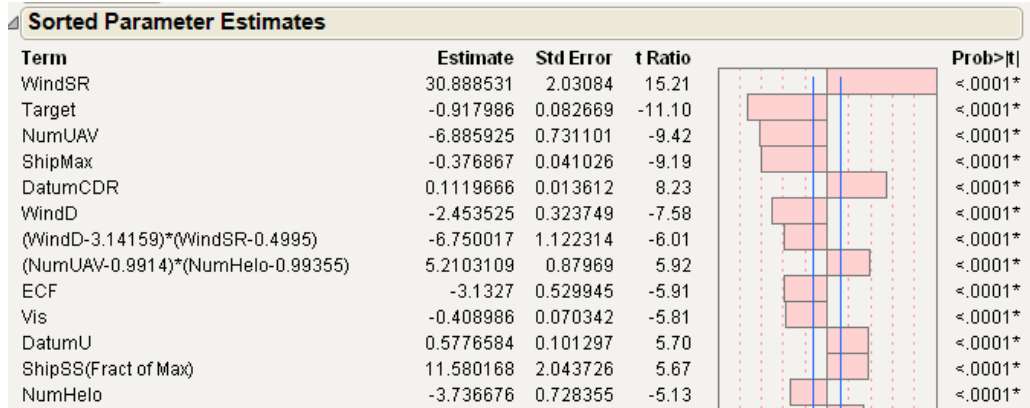


Figure 13. First few significant factors (MOE 2a)

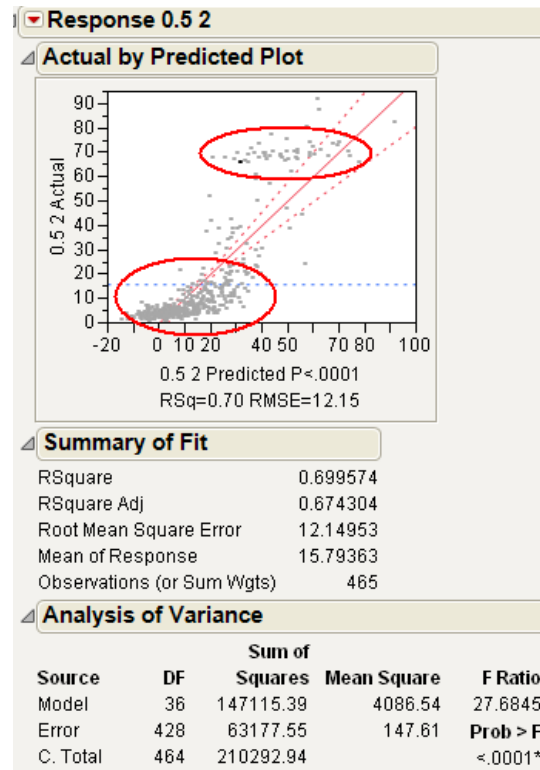


Figure 14. Regression summary (MOE 3a)

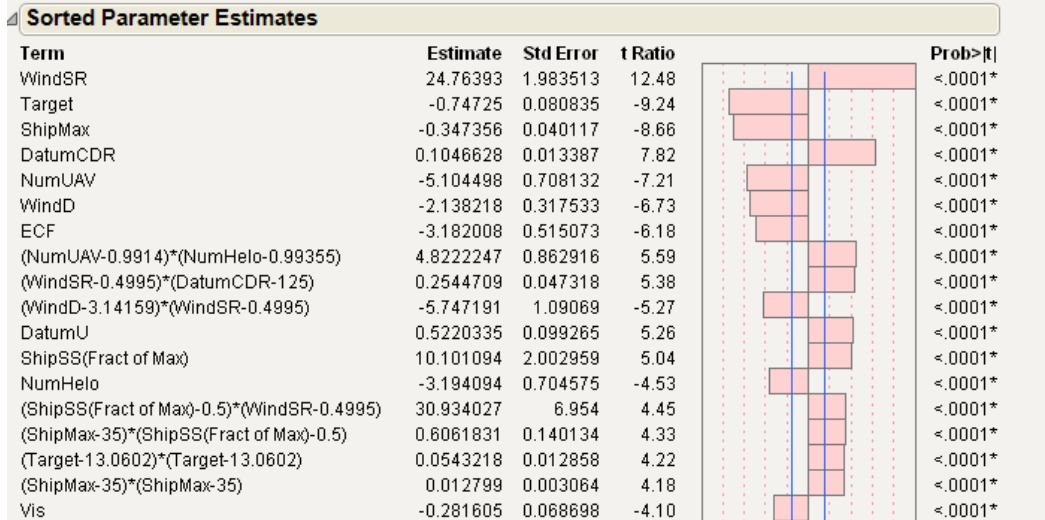


Figure 15. First few significant factors (MOE 3a)

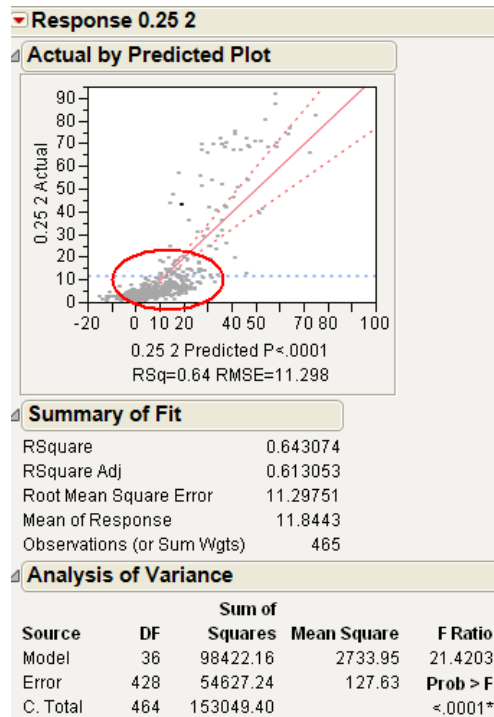


Figure 16. Regression summary (MOE 4a)

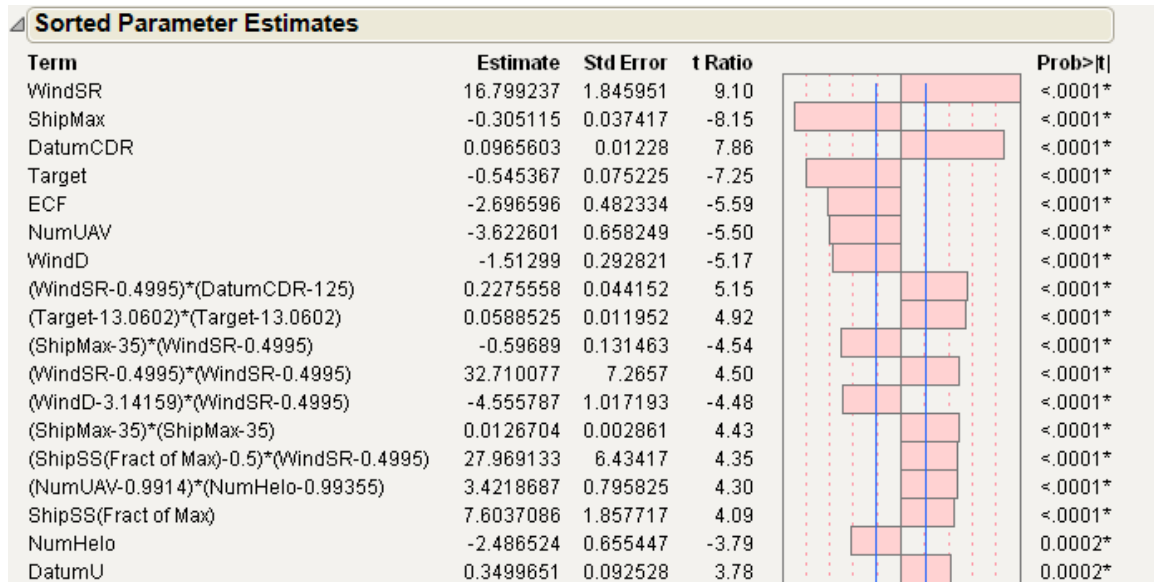


Figure 17. First few significant factors (MOE 4a)

The Rsquare adjusted values in each of the models indicate that these particular metamodels are able to explain 61.3–76.7% of the variation in each respective model using 2nd order polynomials. Looking at the actual versus predicted plots indicate that the regression metamodels have a difficult time dealing with low values of the MOE, where they predict search times below zero, as well as behavior around time equal to 65 hours, where the model has a limitation; these problem areas are circled in red on Figures 10, 12, 14, and 16. Due to these issues, along with the overly large number of terms in the metamodels themselves (between 28 and 36), it may be a better idea to try to fit a partition tree to the data; the partition tree metamodel may be able to better account for instantaneous jumps in the data.

2. Partition Tree Analysis

After the first few splits in the each of the four MOEs fitted by partition trees using all factors in the model, the Rsquares of the partition trees begin to experience diminishing returns as more splits occur. Rsquares of 0.519 0.375, 0.537, 0.356 are achieved after 6, 5, 11, 11 splits for MOEs 1a, 2a, 3a, and 4a respectively (Figures 18, 21,

24, 28). Taking a look at factor contributions of each of these metamodels yield that some factors up to its respective split contribute nothing to the sum of squares (shown in Figures 20, 23, 27, 31).

a. MOE 1a: Average Time to Achieve Cumulative Pd of 0.95

Comparing Figures 11 and 19, it is interesting to note the biggest contributors to the full factor regression and partition metamodels seem to match up relatively well. From all potential factors (including noise), the partition tree emphasizes the importance of the presence (at least one) of a UAV for MOE 1a as the most important factor. It is interesting that in the case that a ship lacks the presence of a UAV, the metamodel suggests that a search helicopter would be the next best factor. Additionally, in the case that a ship configuration lacks both helicopters and UAVs, according to the metamodel, the ship would benefit the most for ensuring the ship's speed has the capability to move quicker than 27 knots.

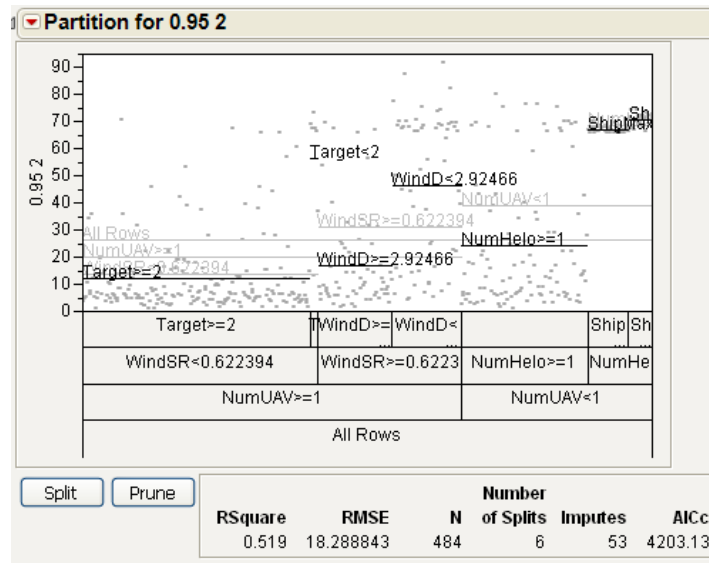


Figure 18. Partition summary (MOE 1a)

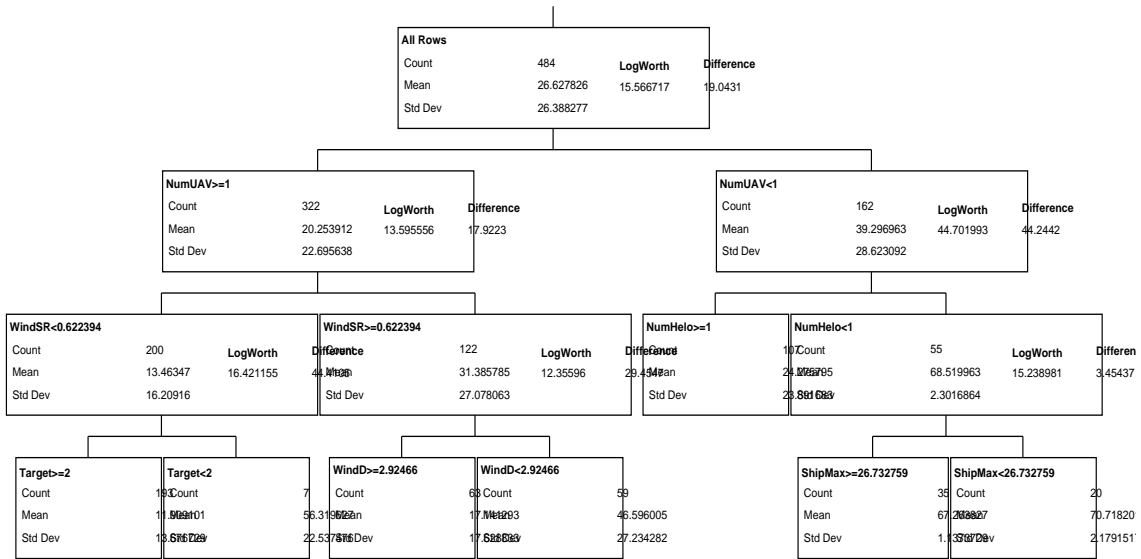


Figure 19. Partition tree (MOE 1a)

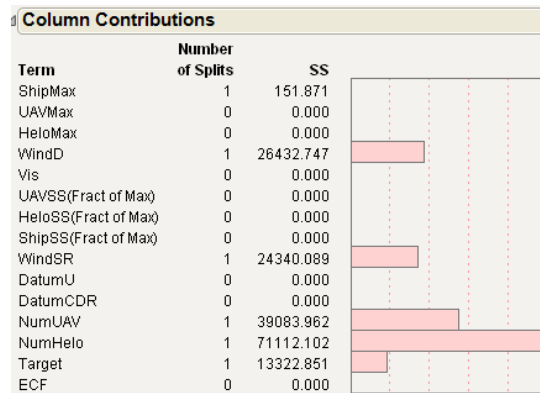


Figure 20. Contributing factors (MOE 1.a)

b. MOE 2a: Average Time to Achieve Cumulative Pd of 0.75

Similar to the comparison of MOE 1a’s contributing factors, MOE 2a’s regression and partition tree contributing factors can be compared (Figures 13 and 22). WindSR, Target, and NumUAV are still contributing factors in the partition model, however ShipMax has become less important, and NumHelo and WindD have become more important in the partition metamodel. Also, in the left branch of the partition metamodel (Figure 22), the factor Target has been split at 2. This does make some sense, since the target data comes from the National SAR manual, specifically the uncorrected

sweep width tables (Table 2). Looking at these tables, it is apparent that each target's uncorrected sweep width increases as a function of visibility, except for Target 1, namely "Person in Water". This may explain the natural split noted in the partition tree.

In the right branch of the partition tree, the WindSR is relatively high, meaning the actual wind speed in the design point is high as well. Since the drift speed of the target is a function of wind speed, and the search area is a function of drift speed, it may imply that everything in the right branch tends to occur in a larger search area A . The next split in the right branch occurs in the WindD, the wind direction. Interestingly enough, it splits at the radian value 3.126, which is roughly the value of π . Along with the wind's direction, the WindD also represents the general drifting direction of the target (bounded by Windbounds). In essence, the split on WindD emphasizes which side above or below the center of the initial datum location the search area resides. If $\text{WindD} \in (\pi, 2\pi)$, the search area will most likely reside below the center of the initial target datum, meaning the ship generally has less distance to travel to reach the search area. If the $\text{WindD} \in (0, \pi)$, the search area will most likely reside above the center of the initial target datum, meaning the ship generally has more distance to travel to reach the search area. In the specific case that the search area is closer to the ship, in the presence of relatively high winds, the presence of a UAV is the most important factor over every other factor in the metamodel, followed by the presence of a helicopter when lacking the presence of a UAV.

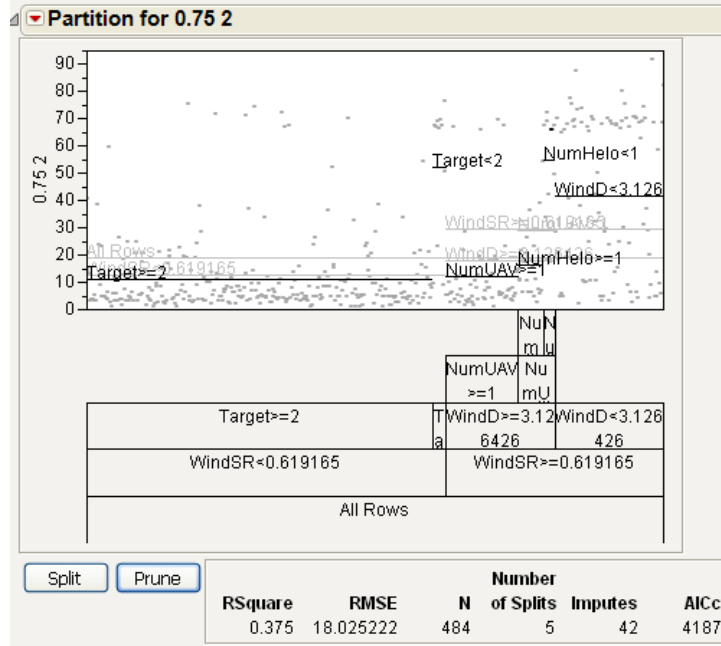


Figure 21. Partition summary (MOE 2a)

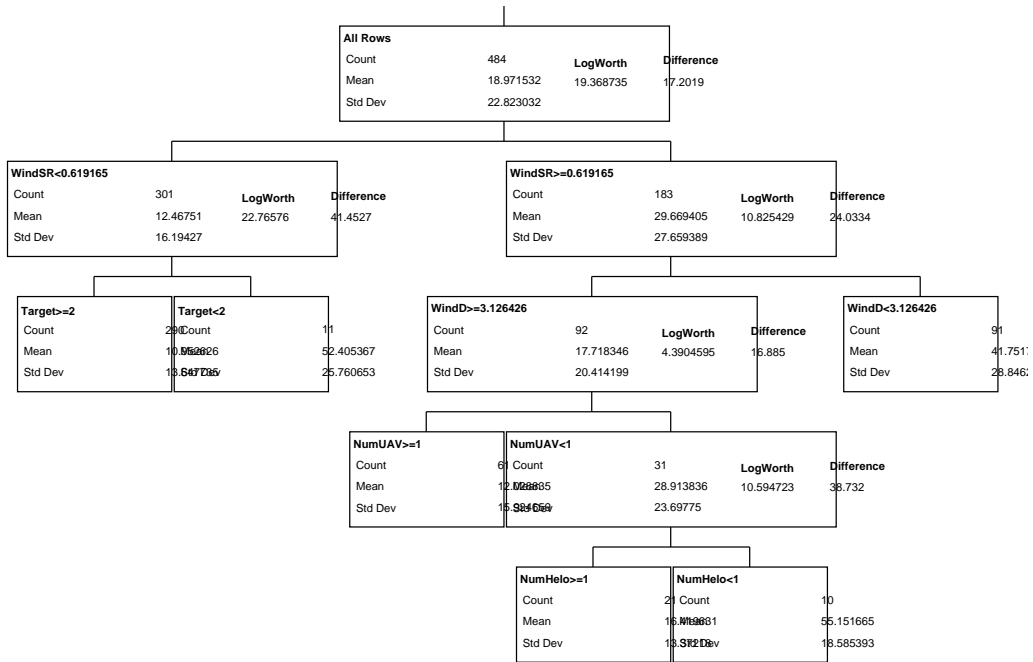


Figure 22. Partition tree (MOE 2a)

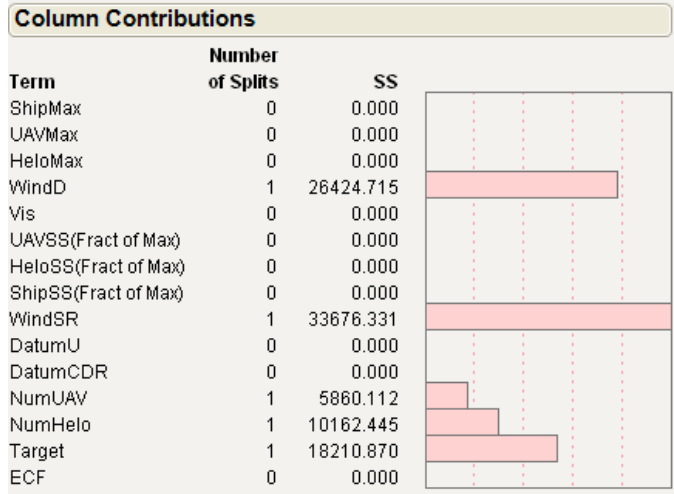


Figure 23. Contributing factors (MOE 2a)

c. MOE 3a: Average Time to Achieve Cumulative Pd of 0.5

Comparing the regression and partition metamodels of MOE 3a (Figure 15 with Figures 25 and 26), the factors Target, NumUAV, and NumHelo can be noted to have become more important in the partition tree, otherwise every other factor seems to be as important in both metamodels relative to the other factors.

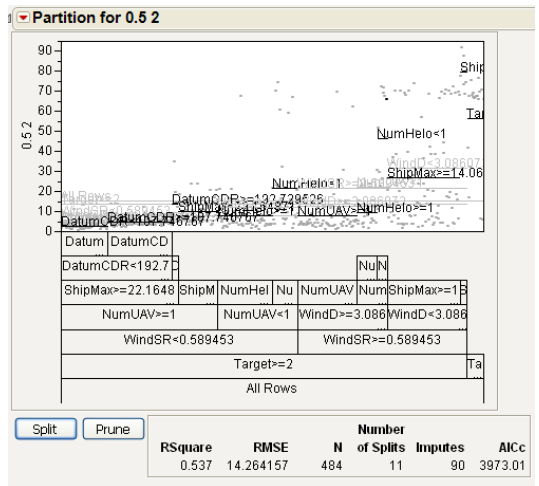


Figure 24. Partition summary (MOE 3a)

Looking at the left branch of the partition metamodel (Figure 26), the initial important break occurs in the factor Target, again at the value of 2, and may be caused by the same issue discussed previously in MOE 2a. In the partition metamodel,

assuming the Target factor is any target between the 2 and 25, and that the WindSR is relatively small, NumUAV is the most important contributing factor. Lacking the presence of a UAV, the presence of a helicopter then becomes the most important factor.

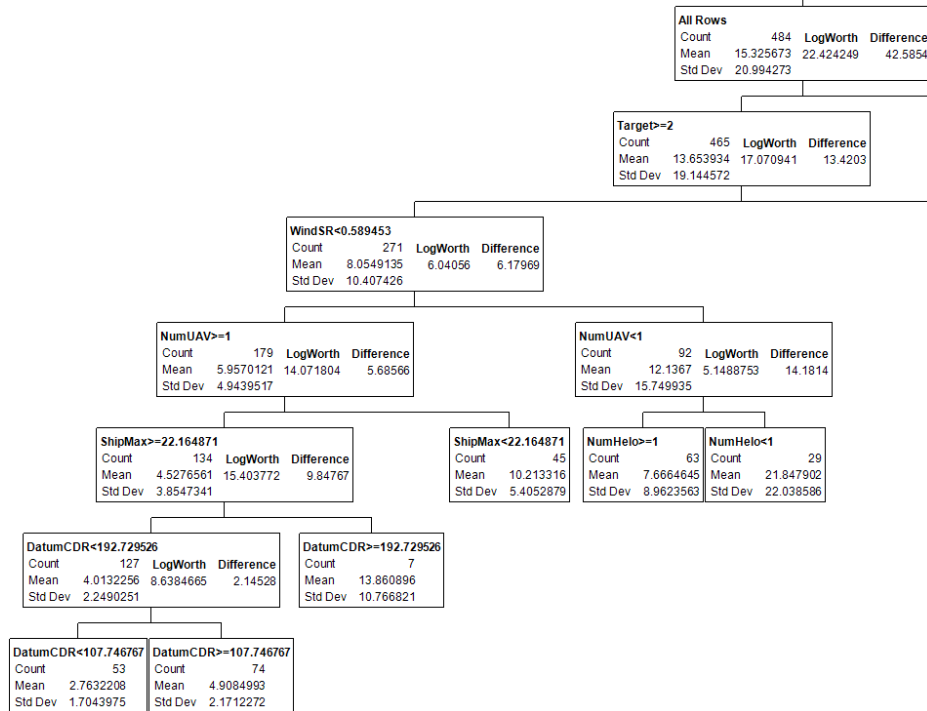


Figure 25. Partition tree (MOE 3a – left branch)

Looking at the right branch of the partition tree metamodel(Figure 26), after assuming the Target is not a single individual in the water, WindSR is relatively high, and the wind is blowing towards the ship ($WindD \in (\pi, 2\pi)$), the presence of UAVs is the most important factor, followed by the presence of helicopters when lacking UAVs. If the wind is blowing away from the ship ($WindD \in (0, \pi)$), the most important factor becomes whether or not the ship’s maximum speed exceeds 14 knots.

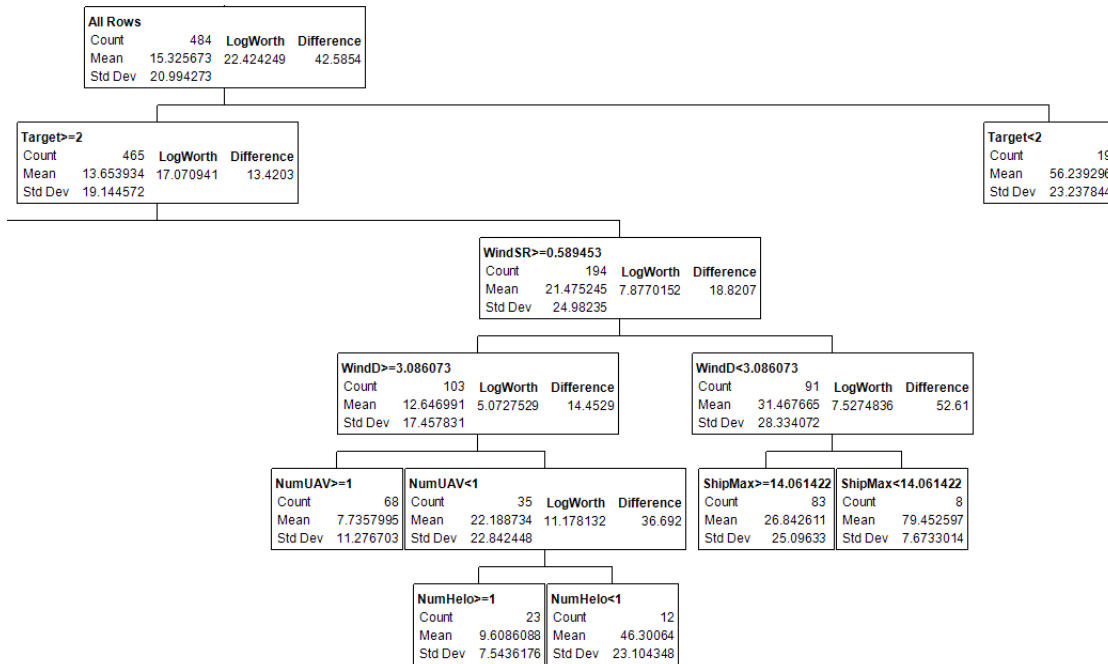


Figure 26. Partition tree (MOE 3a – right branch)

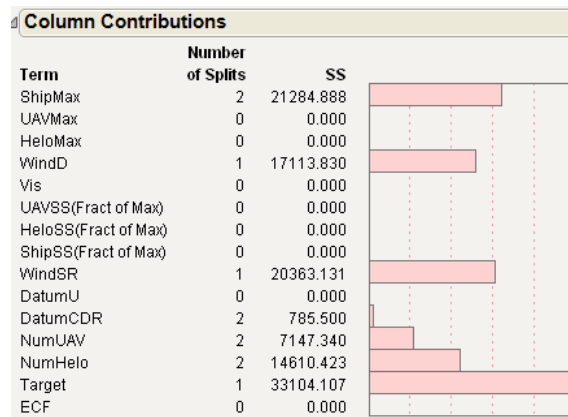


Figure 27. Contributing factors (MOE 3a)

d. MOE 4a: Average Time to Achieve Cumulative Pd of 0.25

Comparing MOE 4a’s regression metamodel with its partition tree (Figure 17 with 29 and 30), the importance of the factors ShipMax, Target, and UAVMax increase in the partition tree. The most interesting factor in this partition tree, would have been the presence of UAVMax, however since the split only has a count of 5 design point occurrences, it does not impact the overall model significantly.

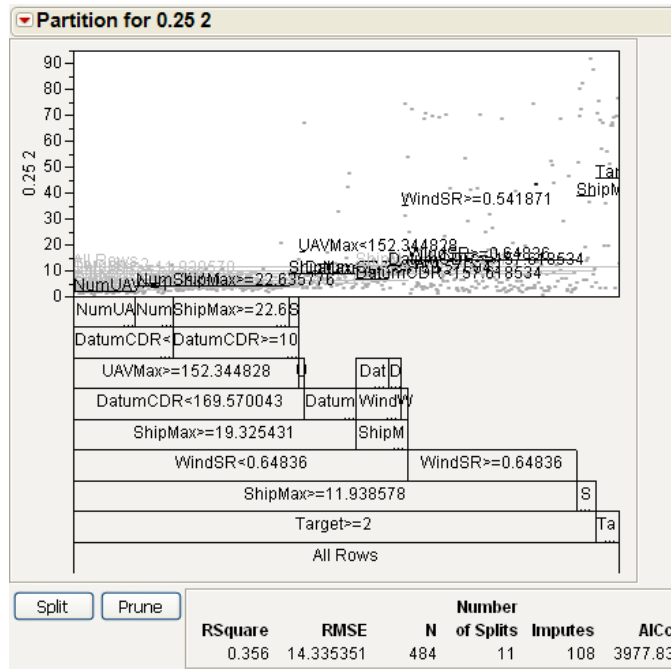


Figure 28. Partition summary (MOE 4a threshold)

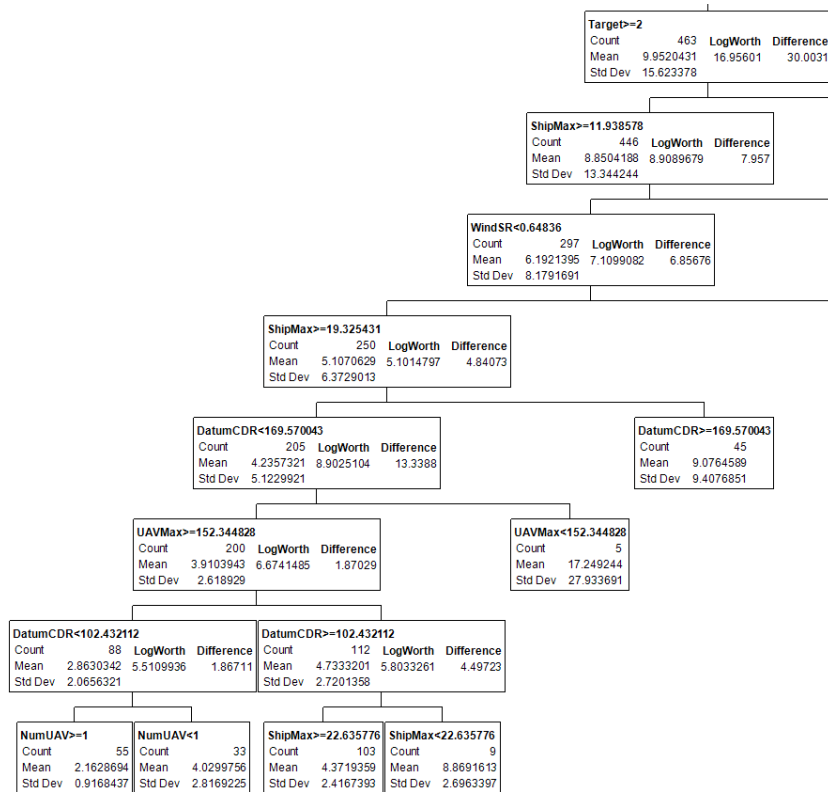


Figure 29. Partition tree (MOE 4a – left branch)

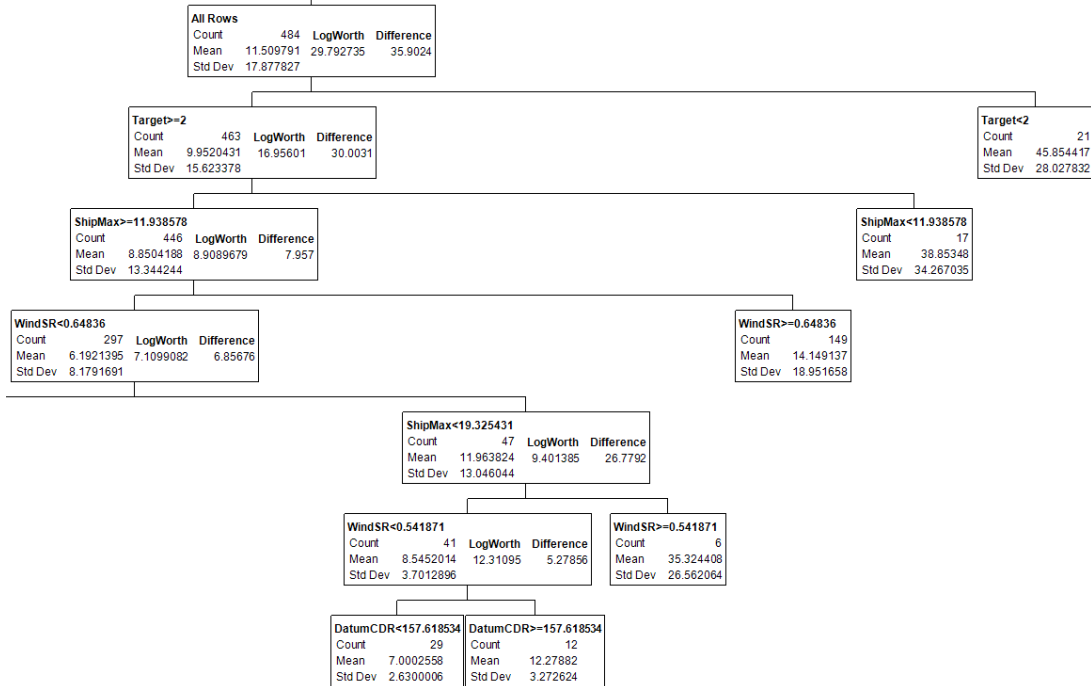


Figure 30. Partition tree (MOE 4a – right branch)

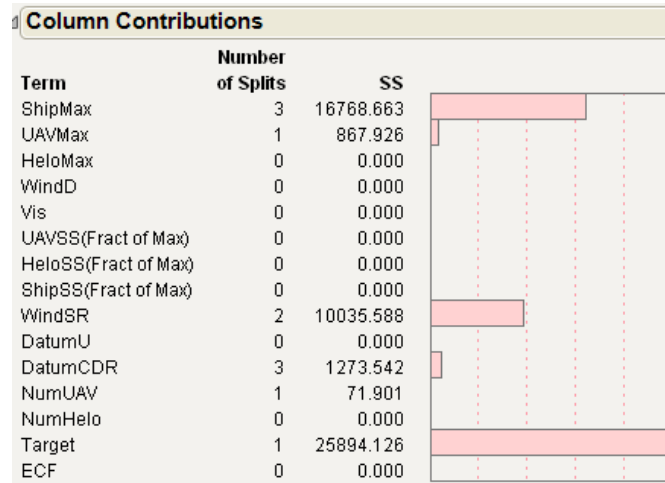


Figure 31. Contributing factors (MOE 4a)

e. Comparing all Four MOEs

Collecting the broad spectrum of insights provided by each individual MOE metamodel, a pattern begins to develop. Looking at contributions of factors to their respective MOE model (Figure 32), the factors of NumUAV and NumHelo can be seen heavily contributing to MOE 1a, and becoming less and less important as the CDP

threshold for the MOE decreases, reaching no contribution in MOE 4a. Alternatively, the factor Target and ShipMax seemingly contribute very little to MOE 1a, gradually increase their contributions to the MOEs as the CDP threshold for the MOEs decrease, and eventually become the most important factors in MOE 4a. Additionally, it is important to note that WindSR is a significant factor in all four MOEs, and that HeloMax (the helicopter’s maximum speed), Vis, DatumU, ECF, and all three of the search speed ratios UAVSS, HeloSS, and ShipSS have negligible contributions in all four MOEs.

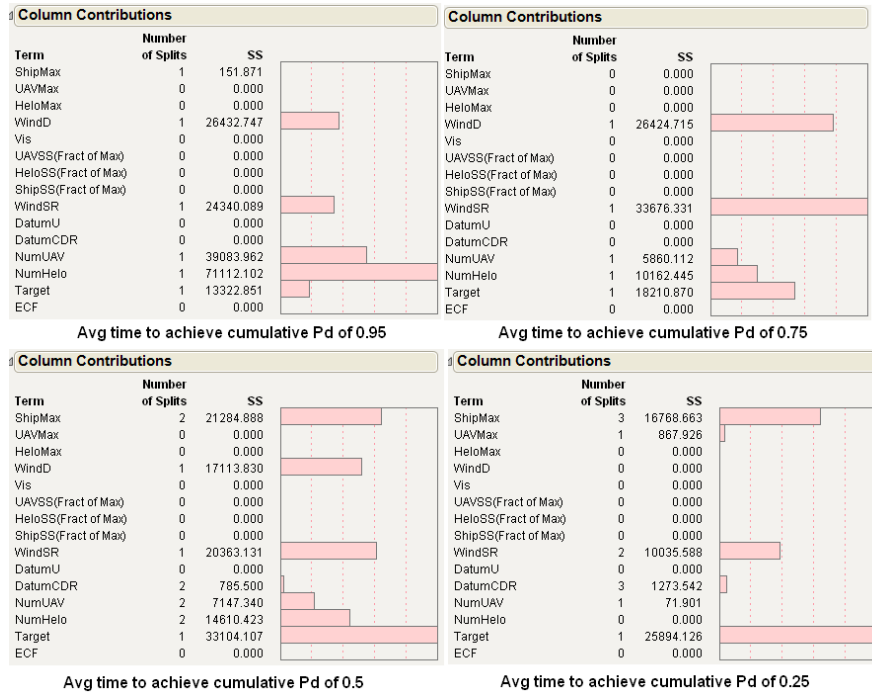


Figure 32. Contributing factors (MOEs 1a, 2a, 3a, 4a)

3. Number of Splits versus Rsquare

To get an idea of the variability in the partition fit, the Rsquare of each of the “a” series MOEs is tabularized as a function of CDP threshold and the number of splits (see Table 6). Note that for each MOE (see Table 6), the Rsquare remains relatively low, even after twelve splits, meaning that it is relatively difficult to predict the performance of the ship with the NPSS model in the presence of the various noise factors.

		Pd threshold			
		0.95	0.75	0.5	0.25
# of Splits	1	0.114	0.129	0.156	0.193
	2	0.327	0.194	0.26	0.274
	3	0.328	0.293	0.347	0.314
	4	0.398	0.32	0.437	0.326
	5	0.437	0.375	0.448	0.35
	6	0.438	0.406	0.453	0.352
	7	0.522	0.414	0.456	0.357
	8	0.582	0.422	0.456	0.362
	9	0.594	0.429	0.473	0.363
	10	0.607	0.432	0.48	0.365
	11	0.612	0.436	0.482	0.365
	12	0.624	0.468	0.482	0.366

Table 6. Rsquare for MOE “a” series

Table 6 can also be used to decide when to stop splitting. For example, for the Pd threshold of 0.25, there is very little improvement in Rsquare between the fifth and twelfth splits.

B. ANALYSIS 2: THE METAMODEL FOR THE CONTROLLABLE FACTORS

Instead of using all of the SAR model’s factors in the partition metamodels, a partition tree can be built using only the decision factors. In doing so, it may allow better comparisons amongst the modeling factors than the previous analysis, at the cost of a decreased ability to obtain a good fit in the absence of noise factor terms. However, if ship configurations can be found that yield low means and low standard deviations of the MOEs, these can be considered robust ship configurations. Once again, partition trees of each one of the four MOEs will be obtained, and then compared amongst each other. Additionally, an analysis of number of splits versus partition metamodel Rsquare will be conducted.

1. Partition Tree Analysis: Comparing MOE 1b, 2b, 3b, 4b

In MOE 1b’s partition metamodel (Figure 34), the factor with the most impact on the outcome is NumUAV; whether or not UAVs are present in the ship configuration. This factor is trailed by ShipMax, followed by NumHelo. In the partition models for MOE 2b, 3b, and 4b (Figures 35–40) however, ShipMax becomes the most dominant

factor. Additionally, for the first time, the partition trees for MOE 2b and 3b distinguish the effect of having 2 UAVs versus a single UAV or no UAVs, displaying an average mean search time drop from 20 to 9 hours(SD drop from 22 to 13 hours), and 15 to 7 hours(SD drop from 20 to 11 hours).

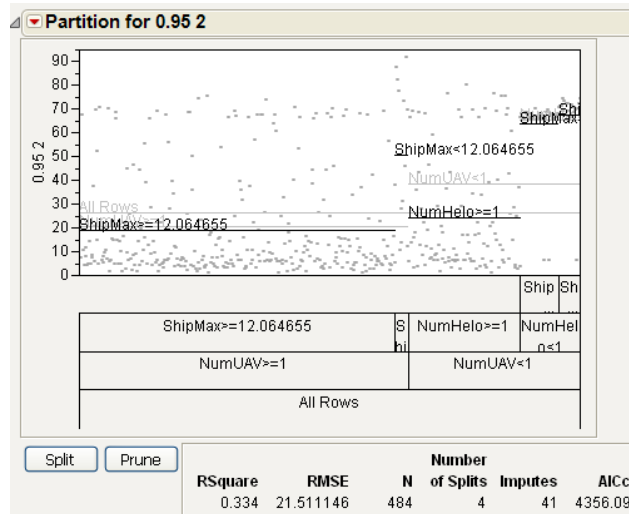


Figure 33. Partition summary (MOE 1b)

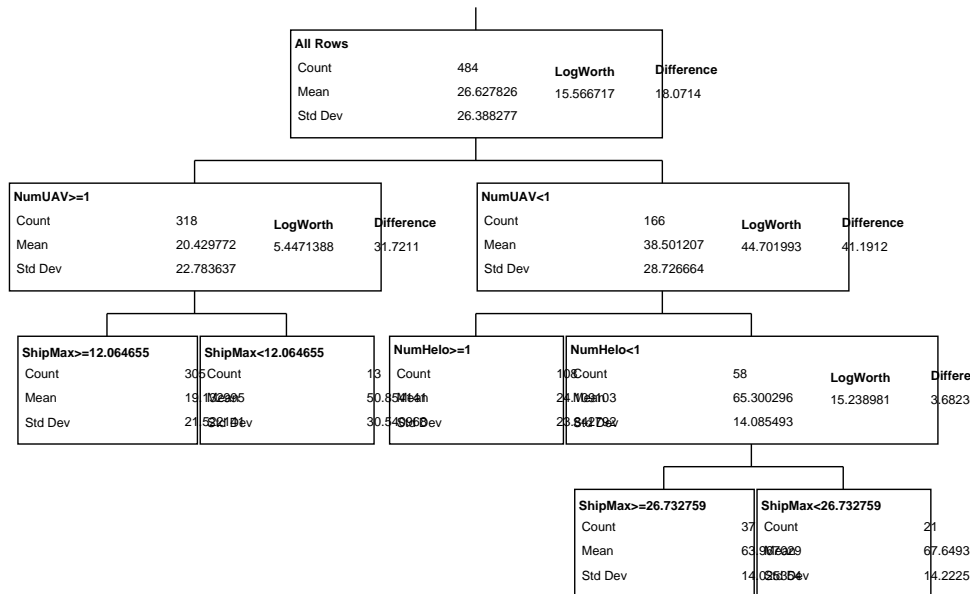


Figure 34. Partition tree (MOE 1b)

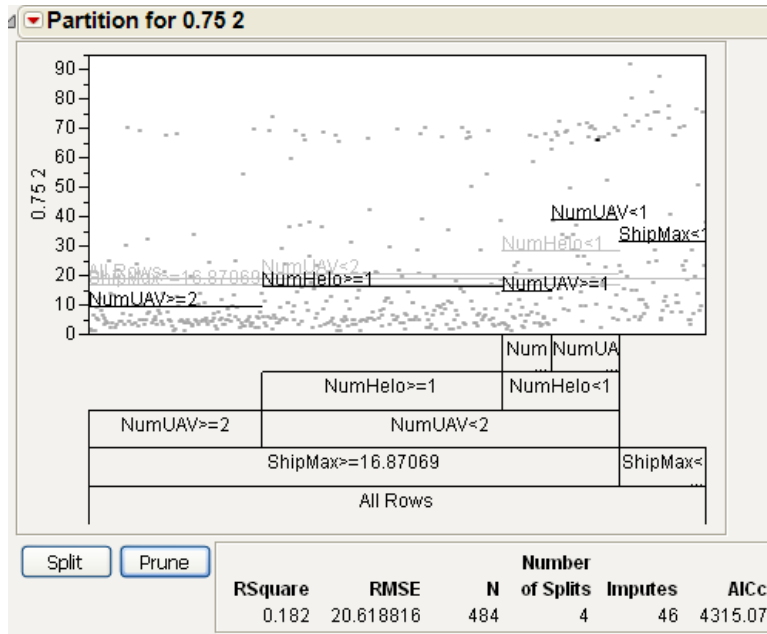


Figure 35. Partition summary (MOE 2b)

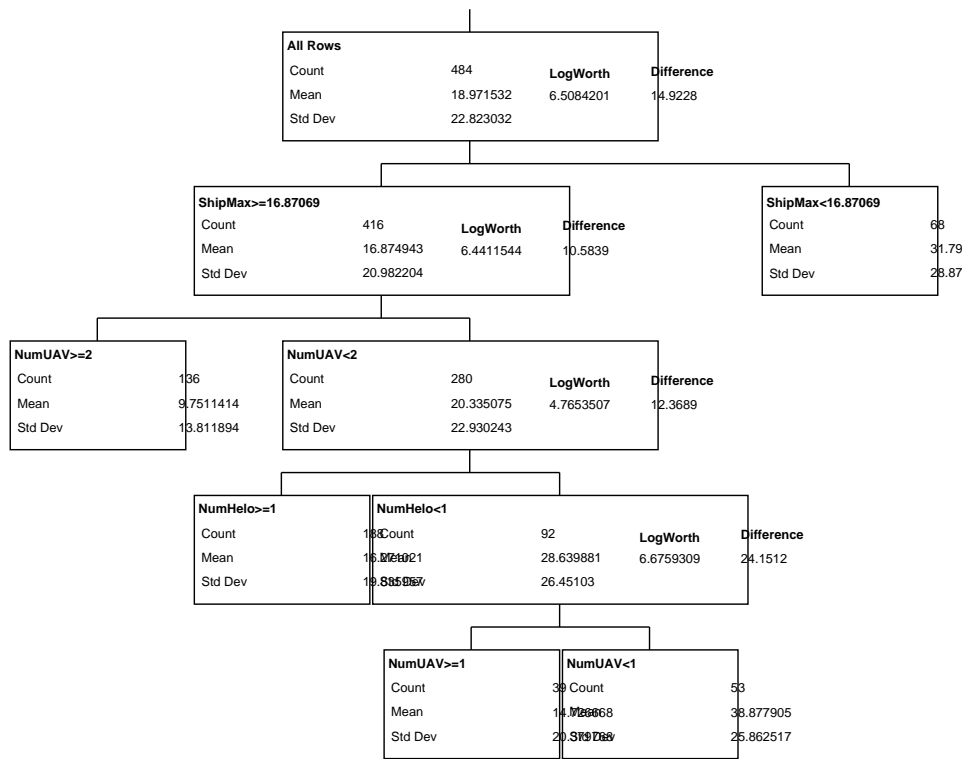


Figure 36. Partition tree (MOE 2b)

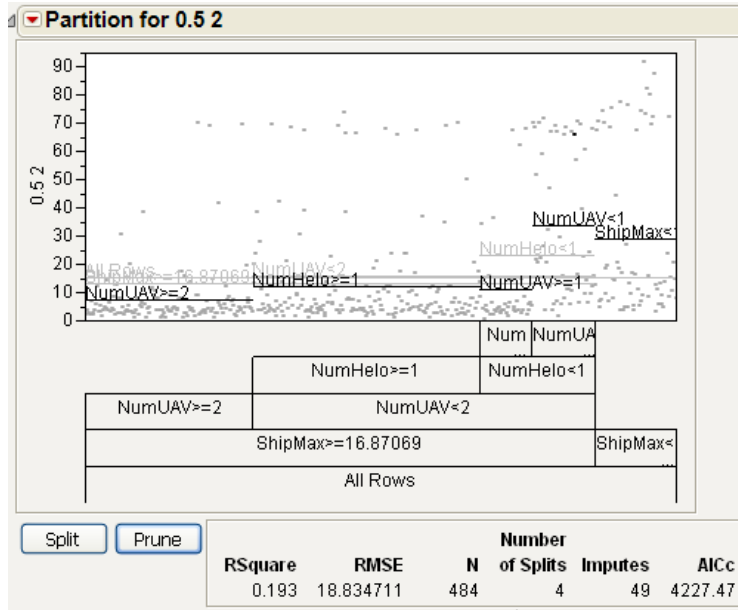


Figure 37. Partition summary (MOE 3b)

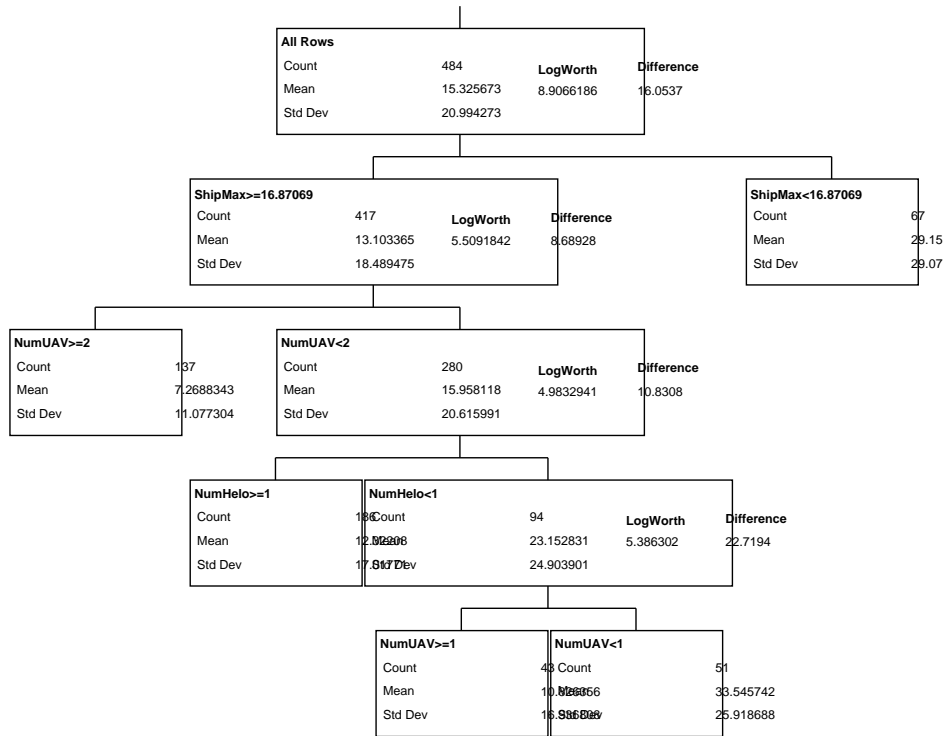


Figure 38. Partition tree (MOE 3b)

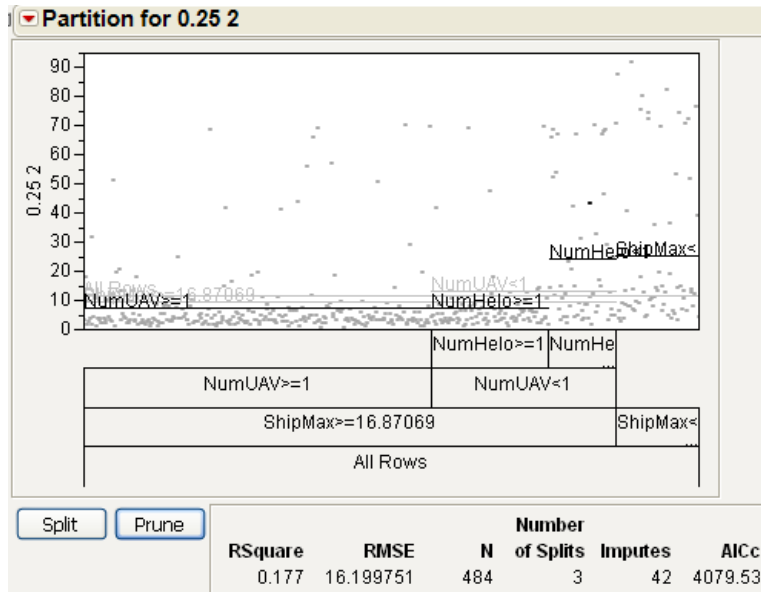


Figure 39. Partition summary (MOE 4b)

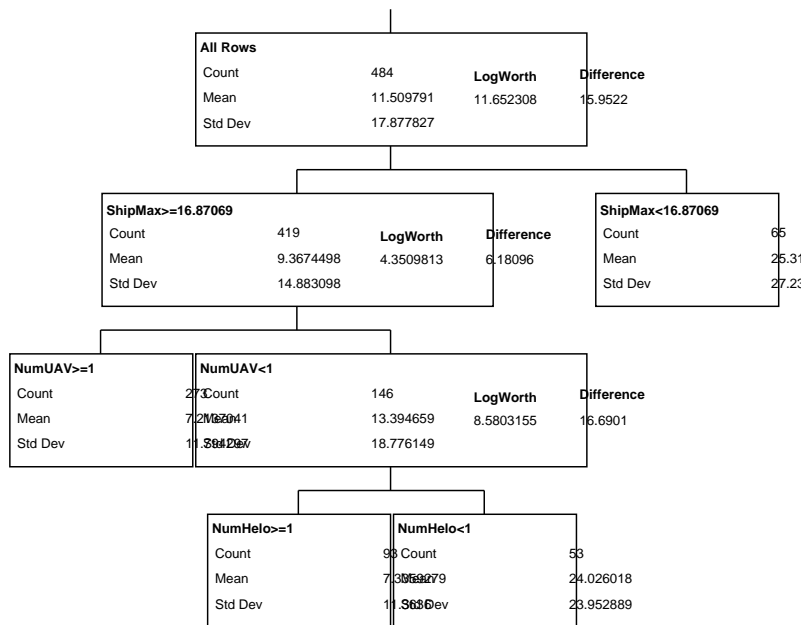


Figure 40. Partition tree (MOE 4b)

The controllable factor metamodels are relatively worse than the full factor metamodels as far as explaining the variability in the NPSS model’s output data. The Rsquare values achieved in these partition metamodels are 0.334, 0.182, 0.193, and 0.177 for MOE 1b, MOE 2b, MOE 3b, and MOE 4b respectively.

2. Number of Splits versus Rsquare

To get an idea of the partition fit, the Rsquare of each of the “b” series MOEs is tabularized as a function of CDP threshold and the number of splits (Table 7).

		Pd threshold			
		0.95	0.75	0.5	0.25
# of Splits	1	0.106	0.052	0.073	0.093
	2	0.296	0.092	0.105	0.116
	3	0.296	0.128	0.141	0.18
	4	0.329	0.182	0.192	0.186
	5	0.346	0.199	0.221	0.209
	6	0.361	0.215	0.246	0.242
	7	0.37	0.231	0.268	0.248
	8	0.37	0.249	0.271	0.255
	9	0.375	0.252	0.292	0.277
	10	0.382	0.253	0.294	0.295
	11	0.389	0.258	0.3	0.296
	12	0.398	0.259	0.31	0.299

Table 7. Rsquare for MOE “b” series

Note that for each MOE (see Table 7), again as expected, the Rsquare remains relatively low, even after twelve splits, meaning that it is relatively difficult to predict the performance of the ship with the NPSS model using the decision factors in the presence of the various noise factors. Additionally when comparing Table 7 with Table 6, Rsquare entries in Table 7 are lower than those in Table 6, since Table 7 uses fewer factors to describe the same MOEs.

C. COMPARISON: NPSS MODEL WITH ITALIAN MODEL

The Italian model’s measure of effectiveness is based on using simulation data collected at the end of each iteration to estimate the probability of detection. Although like the Italian model, the NPSS model runs from the beginning to the end of each design point/iteration, the average time is calculated for specific CDP thresholds. Because of this, the MOEs of the two models are different, and cannot be directly compared analytically; the comparison analysis will be limited to comparing factors that heavily impact each respective model’s measure of effectiveness.

In order for the Italian model and the NPSS model to be compared effectively, the results of the new SAR model need to represent the scenarios in the Italian model. Certain parameters in the NPSS model must be fixed or have a limited range to match the Italian model’s inputs (shown in Table 6). Note the factor NumUAV must be set to zero, since the Italian model does not utilize UAVs. The Sweep widths of the ship and helicopter also need to be set to fixed values, rather than functions of multiple factors. The ranges of ShipMax, NumHelo, and Target need to be reduced as shown in the table. NumHelo must be reduced to a binary variable, since the Italian model does not analyze a multiple helicopter scenario. As for the factor Target, it is unclear what the size of the “Fishing Boat” is in the Italian model. Typically a fishing boat can be characterized as a “power boat” up to 90 ft. in length, and so for comparison purposes, in the NPSS model, the Target factor can be limited to target numbers 10–15.

Original Factors of New Model			Changes in Factors of New Model		
ShipSearchSpeed =	[0,ShipMax]	knots	ShipSearchSpeed =	15	knots
HeloSearchSpeed =	[60,HeloMax]	knots	HeloSearchSpeed =	70	knots
DatumU =	[0,20]	nm	DatumU =	2	nm
WindSpeed =	[0,80]	knots	WindSpeed =	20	knots
NumUAV =	[0,1,2]		NumUAV =	0	
Corrected W ship =	f(Vis,Target)	nm	Corrected W ship =	2	nm
Corrected W helo =	f(Vis,Target,HeloSearchSpeed,ECF)	nm	Corrected W helo =	5.8	nm
ShipMax =	[10,60]	knots	ShipMax =	[22,40]	knots
NumHelo =	[0,1,2]		NumHelo =	[0,1]	
Target =	[1,2,....,25]		Target =	[10,....,14]	

Table 8. NPSS model changes

Fitting the Italian model’s data to a forward moving 2nd order stepwise regression using minimum BIC as the stopping criteria, (shown in Figure 41) results in an analytical model with an Rsquare adjusted of 0.998. Additionally, the regression fit suggests that the biggest impact to the scenario is primarily due to the presence of a helicopter, followed by the distance (which corresponds to DatumCDR in the NPSS model), and lastly due to the ship’s maximum speed (which corresponds to ShipMax).

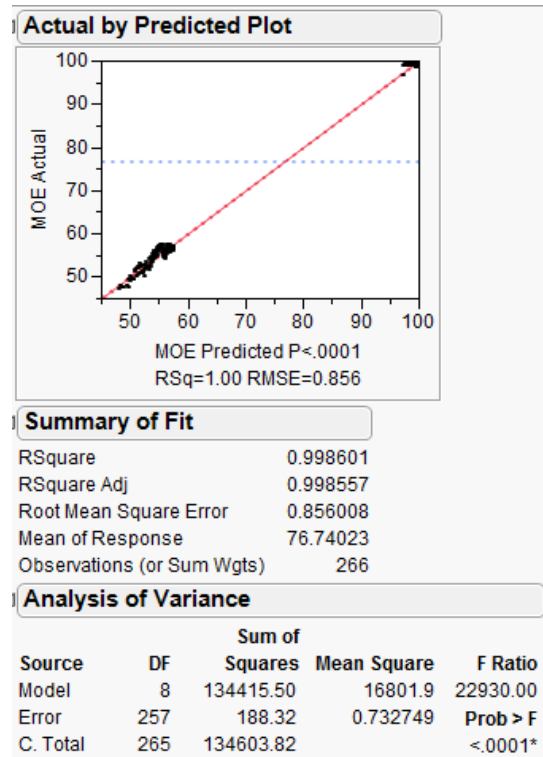


Figure 41. Regression summary (Italian results)

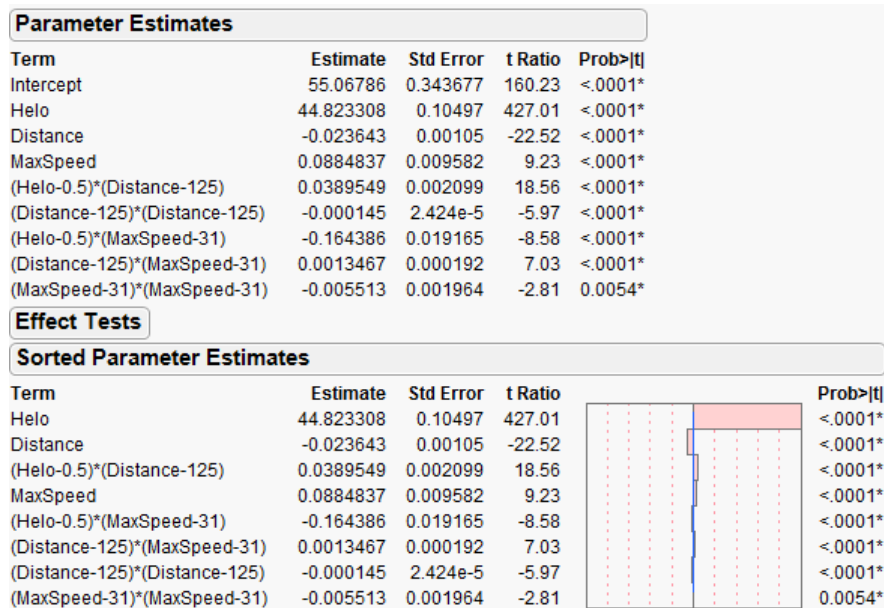


Figure 42. Regression fit (Italian results)

After making the changes in Table 6, using an arbitrary MOE (in this case MOE 1) and fitting the output data to a forward 2nd order stepwise regression using minimum BIC as the stopping criteria regression, the statistical metamodel achieves an Rsquare adjusted of 0.922. Note that this regression (details in Figure 44) also suggests that the presence of the helicopter has the most impact on the MOE, followed by the DatumCDR, and then by ShipMax, although the directions of each of the impacts are reversed.

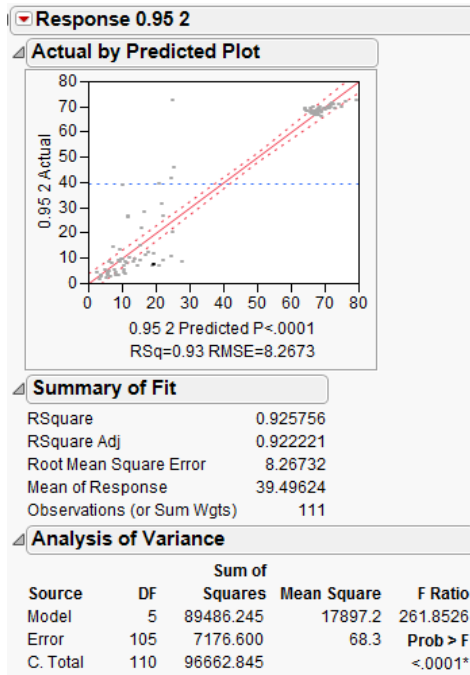


Figure 43. Regression summary (NPSS model)

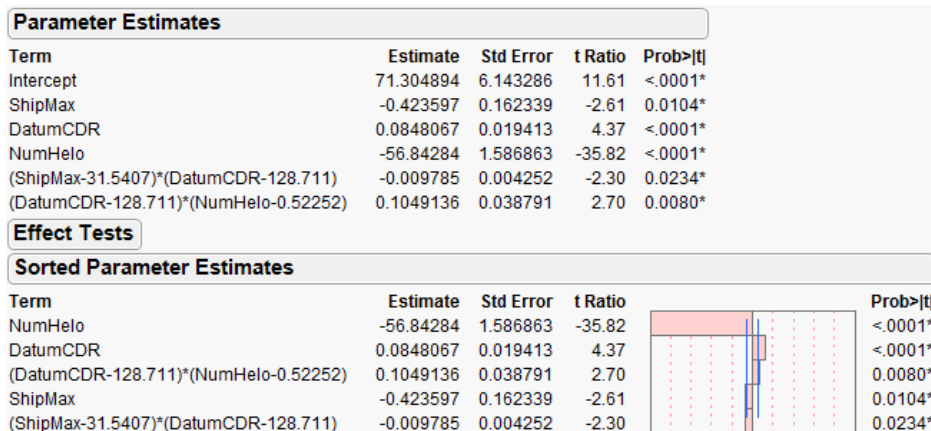


Figure 44. Regression fit (NPSS model)

After comparing the first MOE to the Italian model, it may be interesting to compare the Italian model with all four of the MOEs of the NPSS model. Table 7 is populated with regression data which includes main effect coefficients and interaction term coefficients for all four of the NPSS model MOEs as well as the same data for the Italian model, for comparison purposes.

		Italian Model	NPSS Model				
			MOE 1(0.95)	MOE 2(0.75)	MOE 3(0.5)	MOE 4(0.25)	
Main Effects		R ² Adj.	0.998	0.922	0.527	0.526	0.520
		# of Terms	8	5	5	5	5
	NumHelo	44.823	-56.842	-27.873	-20.591	-10.83	
	(standard error)	0.104	1.586	2.96	2.371	1.455	
	DatumCDR	-0.0236	0.084	0.186	0.16	0.106	
	(standard error)	0.001	0.019	0.036	0.029	0.017	
	ShipMax	0.088	-0.423	-0.73	-0.699	-0.425	
	(standard error)	0.0095	0.162	0.302	0.242	0.149	
Interaction Terms	NumHelo*DatumCDR	0.038	0.105	-0.218	-0.222	-0.138	
	(standard error)	0.002	0.038	0.072	0.058	0.036	
	ShipMax*DatumCDR	0.0013	-0.0097	-0.018	-0.015	-0.009	
	(standard error)	0.00019	0.0042	0.0079	0.0063	0.004	
	DatumCDR ²	-0.000145					
	(standard error)	0.000024					
	NumHelo*ShipMax	-0.164					
	(standard error)	0.019					
	ShipMax ²	-0.0055					
	(standard error)	0.0019					

Table 9. Metamodel comparison

It is interesting to note that the Rsquare adjusted value greatly drops going from MOE 1 to MOE 2, and continues to remain around 0.52 for each subsequent MOE. This seems to suggest that even though the scenario is fixed to mimic the Italian model, if the desired cumulative probability detection threshold is relatively low, the variability in the model can be relatively high, meaning it would be less useful for predictive purposes. Additionally, from the four MOE fits of the NPSS model, MOE 1 seems to replicate the trends and fit of the Italian model the best. The signs on the coefficients are reversed, but this is appropriate because good alternatives for the Italian model correspond to large values of their MOE (CDP), while good alternatives for the NPSS model correspond to low values of the MOEs (times to achieve a particular CDP threshold).

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IV. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

From Chapter I, recall that the primary and secondary questions are:

Can a model of SAR Operations be developed using Microsoft Excel to show potential mission effectiveness of a ship design concept with results comparable to the Italian research team's simulation results?

Can this new model be improved through more realistic operational representation and explored using enhanced experimental design techniques in order to provide broader insights than the results from the original Italian model?

To address the primary question, the NPSS model that is developed throughout Chapter II is built in a Microsoft Excel file. Although the new search model may have benefitted from a decrease in computation time if it were to be written in computer code such as Java, or C++, Microsoft Excel has proven to be capable of conducting the calculations. In Chapter III, the NPSS model's data is used to build a full factor metamodel, and then again to build a controlled analytic model which aims to minimize variability by fitting the model in the absence of noise factors. In both cases, the metamodels achieve relatively low Rsquare values, which leads to the conclusion, that the search mission has a large amount of variability associated with it. When the NPSS model is examined only in scenarios that mimic the scenarios analyzed by the Italian model, its output becomes much more predictable. As a result, a metamodel for MOE 1 achieves an Rsquare of 0.922, and for comparative purposes, establishes the same main effect ordering of importance. This shows that for the restricted set of search operations examined in the Italian study, the output of both the Italian model and the NPSS model are very predictable.

As for the secondary question, the experiment using the NPSS model incorporates many more factors than the original experiment using the Italian model; mostly noise factors, which do exist in the operational environment. Additionally, the option of having fixed-wing UAVs is incorporated in the NPSS model. Also, the NPSS model allows for

the analysis of multiple UAVs and helicopters as opposed to the Italian model's sole helicopter option. Lastly, the NPSS model allows air search assets to explore and search independently from the ship, and to search at a range of search speeds, rather than being limited to a fixed speed directly dependent on the search speed of the ship. These additions allow the experiment involving the NPSS model to explore various dimensions that cannot be analyzed by the current Italian model. When more factors are varied in the NPSS experiment, it is difficult to achieve metamodels with a relatively high Rsquare. This means that the way all these factors combine in different circumstances is quite complex, and not something that can be described with a single simple equation. In reality, there are too many variables that can affect the performance of a ship configuration.

B. RECOMMENDATIONS AND FUTURE WORK

1. Italian Model Recommendations

Although the output from the experiment conducted in the Italian study can be fit quite well with a simple regression metamodel (that is, the metamodel is able to explain much of the variability in the model's output data), the results from the NPSS experiment suggest that this will not occur when realistic noise factors are allowed to vary. Performing a similar, large-scale experiment using the Italian model would provide the users with a more realistic representation of the uncertainty associated with search missions.

Additionally the Italian experiment may want to incorporate time either as a separate MOE, or to join it with the current MOE, in order to be more operationally relevant. The analysis shows that the importance of certain factors increase, while others decrease as a function of cumulative probability detection threshold. Since by definition, the cumulative probability of detection is a monotonically increasing function of time, using time as a threshold rather than the cumulative probability of detection will yield similar results.

2. NPSS Model Future Work

a. *Non-Rectangular Search Box*

Instead of using the rectangular search box incorporated by the Italian model, the shape of the box may be modified to search more efficiently (shown in yellow in Figure 45); only in those areas most likely for the target to be located. Since the coverage factor used in the ICL uses the value of the search area A directly, the modification is a seamless substitution of the new value of the area.

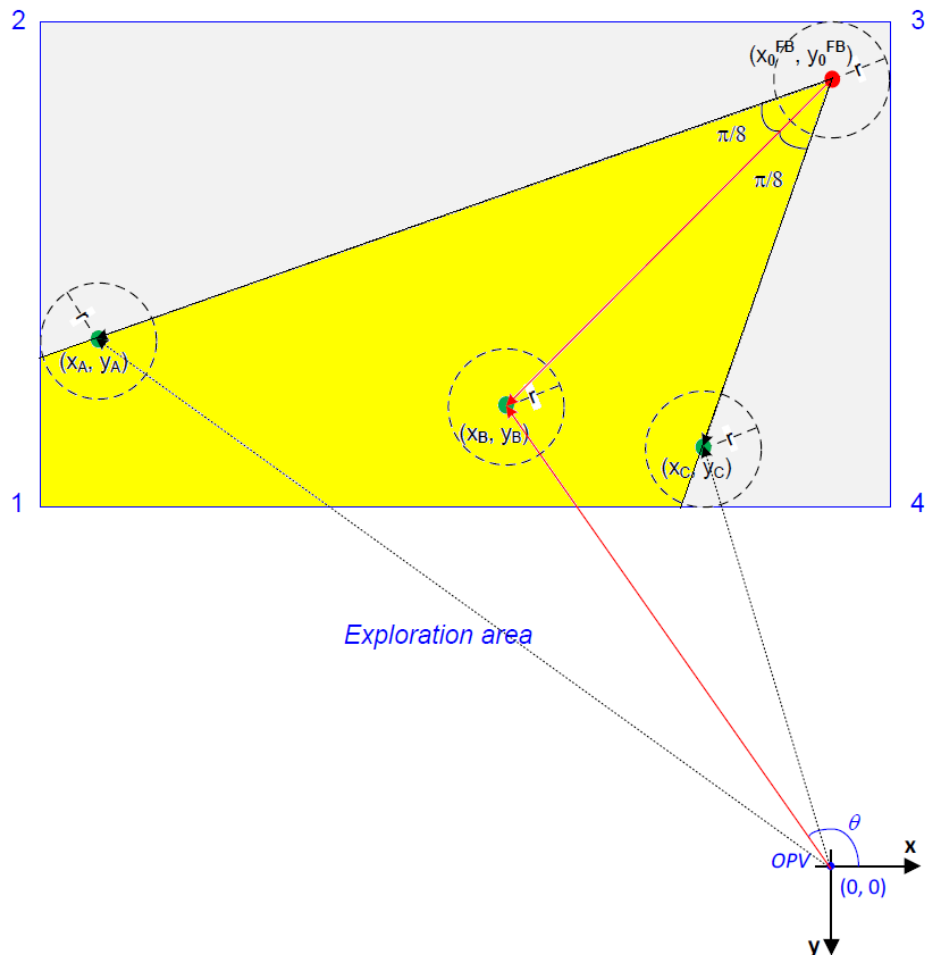


Figure 45. More efficient search box (After Anghinolfi et al., 2011)

b. “Rescue” Aspect of Mission

The NPSS model currently does not account for the rescue process of the mission. It primarily focuses on the search and location of the target. Unless a UAV is capable of rescuing the survivor(s), once a UAV locates a target, a rescue time delay must be incorporated to account for either the closest helicopter or the ship to move from its current position to the target.

c. SAR Hazards

Depending on whether the target is submersed in water, and an additional noise variable to represent water temperature, the plot on Figure 46 can be used to determine a successful rescue.

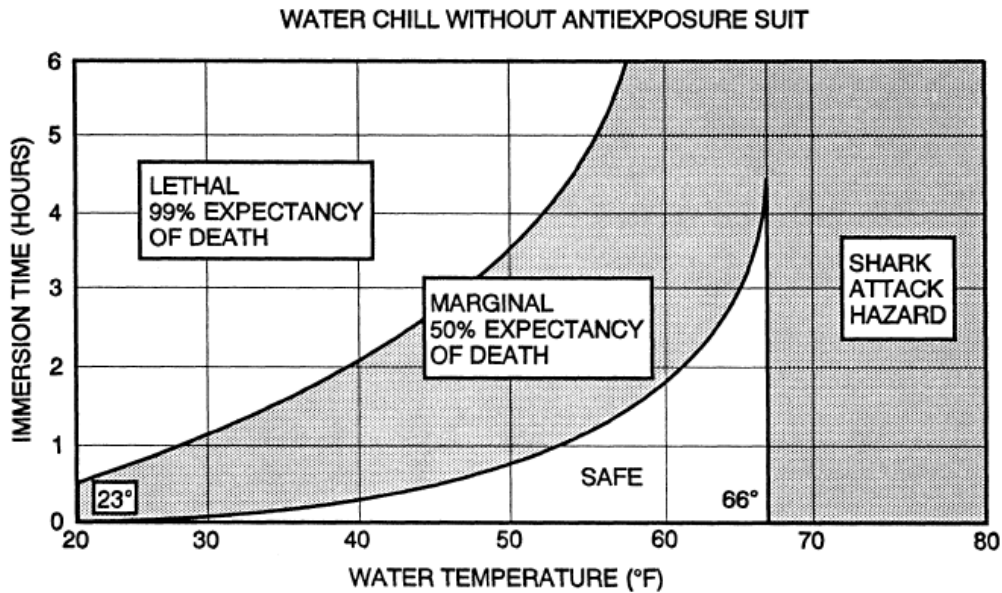


Figure 46. Water chill without anti-exposure suit (From Office of the Chief of Naval Operations, 1997)

d. Helicopter/UAV Refueling/Maintenance

In addition to rescue time delays, refueling delays can be incorporated for helicopters and UAVs conducting the search. Additionally, helicopters and UAVs undergo wear and tear, and have scheduled and unscheduled maintenance periods that

can be incorporated in the NPSS model. A new count variable may need to be incorporated to keep track of how many search entities are undergoing maintenance.

e. Additional Noise Variables

There are a few other noise factors that can be incorporated in the NPSS model for future work. Some are readily available in the National SAR manual, specifically flight altitudes of aerial search entities, and sweep width correction factors associated with the target. Both of these noise factors can affect the overall sweep width of the search entity, and in turn the performance of the ship configuration.

C. SUMMARY

This thesis provides a link between physical ship design factors and operational effectiveness of the SAR mission. The results contribute to a larger project that aims at developing a methodology for evaluating the operational effectiveness of OPVs for a variety of missions before proceeding to the detailed design of these units.

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