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THESIS

**UNMANNED AERIAL VEHICLE CONTRIBUTIONS
TO INTELLIGENCE, SURVEILLANCE, AND
RECONNAISSANCE MISSIONS FOR
EXPEDITIONARY OPERATIONS**

by

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September 2004

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**UNMANNED AERIAL VEHICLE CONTRIBUTIONS TO
INTELLIGENCE, SURVEILLANCE, AND RECONNAISSANCE MISSIONS FOR
EXPEDITIONARY OPERATIONS**

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

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ABSTRACT

This study analyzes the impact various capabilities have on intelligence gathering missions for a Marine Expeditionary Brigade (MEB) commander's 2015 unmanned aerial vehicle (UAV). The Marine Corps Warfighting Lab (MCWL) is developing requirements for an intelligence, surveillance, and reconnaissance (ISR) UAV that supports rapid planning and decision making for multiple concurrent operations and facilitates maneuver and precision engagement. Additionally, acquisition of a 2008 Pioneer replacement is underway at Marine Corps Systems Command (MARCORSYSCOM). The importance of various capabilities for this replacement UAV presently lacks quantitative analysis. Through modeling, agent-based simulation, and data mining, this study explores the validity of current requirements and provides insights into the importance of various UAV characteristics, such as airspeed, endurance, sweep width, and sensor capability. The results have design consequences for MCWL's Fleet Battle Experiment Sea Viking 20XX, its largest annual experiment, and provide key parameters for physics-based simulations such as COMBAT XXI. The advantage of tactical routing, a seven hour (or greater) on station time, a minimum 4,500 meter sweep width, and a probability of classification of at least 0.4 are verified for the Sea Viking scenario. This analysis indicates that a UAV in this scenario does not need to travel in excess of 200 knots.

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THESIS DISCLAIMER

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

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	OVERVIEW	1
B.	BACKGROUND AND MOTIVATION	2
C.	BENEFITS.....	4
D.	THESIS FLOW.....	4
II.	MODEL DEVELOPMENT	5
A.	AGENT-BASED MODELING	5
B.	THE AGENT-BASED MODEL MANA.....	8
C.	SEA VIKING SCENARIO.....	12
D.	INSTANTIATING A SEA VIKING SCENARIO IN MANA	13
1.	The Battlespace	15
2.	Agent Development.....	18
3.	Aggregation	21
4.	Measure of Effectiveness and Creative Modeling Alternatives.....	23
III.	DESIGN OF EXPERIMENTS	25
A.	CONTROLLABLE FACTORS—UAV CAPABILITIES	25
B.	ROBUST DESIGN AND NOISE FACTORS.....	32
C.	UNCONTROLLABLE FACTORS—ENEMY CAPABILITIES	33
D.	ORTHOGONAL LATIN HYPERCUBES	35
IV.	DATA ANALYSIS.....	39
A.	DATA COLLECTION AND POST PROCESSING.....	39
B.	MULTIPLE REGRESSION ANALYSIS.....	41
C.	CLASSIFICATION AND REGRESSION TREES.....	50
V.	CONCLUSIONS	55
A.	ANALYSIS SUMMARY	55
B.	KEY TACTICAL INSIGHTS	56
C.	ADDITIONAL INSIGHTS	57
D.	FOLLOW ON WORK	58
APPENDIX A.	SEA VIKING 04 SCENARIO DETAILS.....	61
APPENDIX B.	REGRESSION MODELS FOR MULTI-UAV SCENARIOS.....	65
LIST OF REFERENCES	69
BIBLIOGRAPHY	71
INITIAL DISTRIBUTION LIST	73

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LIST OF FIGURES

Figure 1.	Map Aware Non-uniform Automata opening screen provides contact information.....	8
Figure 2.	Example of MANA Edit Squad Properties page, tab one of nine: Personality. The display shows some of the many attributes which affect an agent’s behavior on the battlefield in the MANA environment.....	11
Figure 3.	Line of sight determination in version for this study versus subsequent versions. We see the desirable LOS characteristics of version 3.0.29 on the left, versus subsequent versions on the right. [Best viewed in color].....	12
Figure 4.	MANA Sea Viking base scenario. The display shows a sample initial friendly, enemy and civilian agent layout within the battle space. [Best viewed in color]	15
Figure 5.	Terrain effects parameter values as displayed in the MANA Scenario Map Editor.....	16
Figure 6.	Microsoft Excel spread sheet displaying battlefield conversions from reality to MANA.....	17
Figure 7.	Graph of sweep width obtained given a flight altitude and FOV. The display shows the range of possible sweep width values.	19
Figure 8.	A visual sample of the lateral range curves modeled. The display shows the resulting probability of classification as a function of lateral range from the UAV for a sensor with various probabilities of classification at various airspeeds.....	21
Figure 9.	Graph of classification proportions from twenty runs of the full and aggregated scenarios displaying the equivalence of the resulting distributions for high and low factor levels. [Best viewed in color].....	22
Figure 10.	An example of routing for a single UAV approved by MCWL.....	27
Figure 11.	Distributions of the proportion of enemy classified form Traditional Search Patterns versus Tactical Routing of the UAV in the SV scenario. Note the tactical routing proves to be 63% better on average.	28
Figure 12.	Sample UAV Range tab from Edit Squad Properties function in MANA. The display shows basic speed, sensor detection range, and sensor classification range and probability functional areas.....	32
Figure 13.	Red Mountain Infantry squad basic personality configuration. Values are manipulated to control dispersion, provide a mission, effect movement propensities, and manipulate cohesion with neutrals.....	35
Figure 14.	Pairwise scatter plot of design points utilizing a nearly orthogonal Latin hypercube crossed with a factorial design. Factor names appear along the diagonal. Each dot represents a design point for the corresponding factors...36	36
Figure 15.	Design of Experiments for the primary analysis. The display shows the factors, factor ranges, required number of runs, and a sample of the design points and levels for the controllable factors.	38

Figure 16.	Graphical comparison of the number of runs required to conduct this analysis with a traditional full factorial design versus a smarter design with orthogonal Latin hypercubes. [Best viewed in color].....	38
Figure 17.	Distribution of the MOE, mean proportion of enemy classified per hour, for the one UAV scenario. Notice the mean is 2.93% of the enemy classified per hour.....	40
Figure 18.	Normal Quantile Plot of resulting enemy classification proportion per hour from a randomly selected design point, number 2678. Most of the data fall on the diagonal and all fall within the 95% confidence interval indicating the normality of the measure of effectiveness for a typical design point.....	41
Figure 19.	Graph of fit of one UAV models by term. The figure shows the similarity between the models containing both controllable and uncontrollable factors and the models containing only controllable factors. Additionally, the preferred model with eight terms is indicated at the point of diminishing return in the fit on the graph. Note that all terms retained are controllable and there are no interactions between controllable and uncontrollable factors. [Best viewed in color].....	43
Figure 20.	Proportion of variation in one UAV mean enemy classification proportion per hour across all scenario factor levels as each term is added to the model. There is a clear point of diminishing return and similarity between the models with all factors and the models aggregated over the uncontrollable factors. [Best viewed in color].....	44
Figure 21.	Predicted versus actual mean enemy classification proportion per hour displaying the good fit of the preferred single UAV model with eight terms and associated residual plot verifying the absence of pattern in the residuals.....	46
Figure 22.	Preferred one UAV model. The R-squared value for this model is above 90%. The display shows the coefficients for each term and the significance of each of the terms as well as the overall model.....	47
Figure 23.	Interaction plots between UAV sweep width, UAV probability of classification, and max steps. The display shows the presence of an interaction between SW and PClass and the nonlinear effects of SW and time. [Best viewed in color].....	48
Figure 24.	Leverage plots of one UAV preferred model terms indicating degree to which each term affects the MOE, mean proportion of enemy classified per hour.....	50
Figure 25.	Decision tree split on the raw data by proportion of enemy classified per hour for each MANA run of the one UAV scenario, considering controllable and uncontrollable factors. The tree indicates the overall significance of sweep width and probability of classification, and the interaction with reactivity.....	52

Figure 26. CRT split on the raw data by proportion of enemy classified per mission for each MANA run of the one UAV scenario, considering controllable and uncontrollable factors. The tree indicates the significant time effect and the appearance of speed while retaining previous decision factors.53

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LIST OF KEY WORDS, SYMBOLS, ACRONYMS AND ABBREVIATIONS

AAA	Anti-Aircraft Artillery
ABM	Agent-Based Models
AGL	Above Ground Level
AoA	Analysis of Alternatives—Evaluation of operational effectiveness and costs of alternative material systems in the acquisition process.
AOR	Area of Responsibility
CASTFOREM	Combined Arms and Support Task Force Evaluation Model
C4ISR	Command, Control, Communication, Computers, Intelligence, Surveillance, and Reconnaissance
CRT	Classification and Regression Tree
CPU	Central Processing Unit
DoD	Department of Defense
DMSO	Defense Modeling and Simulation Office
EMW	Expeditionary Maneuver Warfare
FOV	Field of View
GUI	Graphical User Interface
HQMC	Headquarters Marine Corps
ICD	Initial Capabilities Document
ISR	Intelligence, Surveillance, and Reconnaissance
JCATS	Joint Conflict and Tactical Simulation
JSIMS	Joint Simulation System
LOS	Line of Sight

LRC	Lateral Range Curve
M&S	Modeling and Simulation
MAGTF	Marine Air Ground Task Force
MANA	Map Aware Non-uniform Automata
MARCORSYSCOM	Marine Corps Systems Command
MCWL	Marine Corps Warfighting Lab
MEB	Marine Expeditionary Brigade
MEF	Marine Expeditionary Force
MHPCC	Maui High Performance Computing Center
MOE	Measure of Effectiveness
NOLH	Nearly Orthogonal Latin Hypercube
OEF	Operation Enduring Freedom
OIF	Operation Iraqi Freedom
OLH	Orthogonal Latin Hypercube
OMFTS	Operational Maneuver From The Sea
PAIW 8	Project Albert International Workshop 8
SAM	Surface-to-Air Missile
STOM	Ship To Objective Maneuver
T&E	Test and Evaluation
TCT	Time Critical Target
TLAM	Tomahawk Land Attack Missile
UAV	Unmanned Aerial Vehicle
VUAV	Vertical Unmanned Aerial Vehicle

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EXECUTIVE SUMMARY

Unmanned Aerial Vehicles (UAVs) are a key component of today's Intelligence, Surveillance and Reconnaissance (ISR) missions. UAVs provide intelligence, a dynamic retasking capability, and real-time video imagery. The United States Marine Corps is currently reviewing its UAV employment. During Operation Iraqi Freedom (OIF), the Marine Expeditionary Brigade (MEB) commander utilized two squadrons of Pioneer UAVs. Each squadron provided the capability to fly one UAV for up to six hours with a maximum range of over 170 nautical miles. The Pioneer can be relieved on station twice with current assets and manpower, achieving a total coverage of 18-hours during surge operations with the current force structure in each squadron. The Marine Corps desires to improve this capability in an efficient and effective manner.

The planned Pioneer replacement, the Vertical Unmanned Aerial Vehicle, is in the beginning stages of conceptualization and currently has an Initial Capabilities Document. It is expected to proceed through the design and acquisition process for fleet use in 2008. Marine Corps Systems Command (MARCORSYSCOM) provides guidance regarding the relative importance of the capabilities this VUAV could possess, such as speed, endurance, and sensor performance.

The Marine Corps Warfighting Lab (MCWL) has been tasked with answering a vague question. Headquarters Marine Corps (HQMC) wants to know "the required MEB ISR capability sets needed in order to meet the following 2015 Expeditionary Maneuver Warfare requirements?"

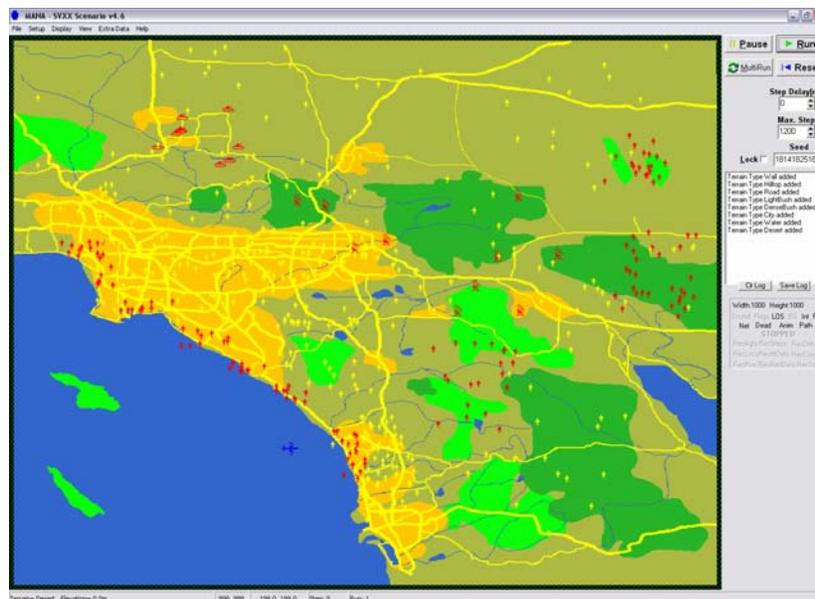
1. Support the commander's rapid planning and decision-making process.
2. Maintain a comprehensive ISR network to support multiple concurrent expeditionary operations.
3. Facilitate operational maneuver and precision engagement."

(Commandant's Sub Team Guidance, 2003)

Based on recent performance and a dynamic retasking capability, the UAV has been determined to be the key component of the sensor network required to meet these requirements. Detailed analysis is required to determine the capability set for this MEB commander's UAV of the future.

There are over 57 UAVs in development or production by corporations in the United States and over 216 worldwide. Each has its own unique capabilities and design factors. These design factors combine with various uncontrollable factors like geography, terrain and enemy capabilities to form a very difficult problem when attempting to determine the most important factors and the appropriate needs of the Marine Corps. A problem that, even with the fastest computers, most efficient simulations, and a team of analysts, would take more than a life time to answer using traditional experimental designs. A smarter design is required to comprehensively explore how these factors affect a UAV's ability to perform in expeditionary operations.

This study looks at UAV operations in the Sea Viking scenario provided by MCWL in the MANA agent-based modeling environment utilizing robust design, Orthogonal and Nearly-orthogonal Latin hypercubes, data farming techniques, the Maui High Performance Computing Center, and the JMP Statistical Discovery Software package. The Sea Viking Fleet Battle Experiment, the Marine Corps' largest annual experiment, provides a credible scenario for model development. The model uses stochastic techniques to consider the effects of terrain, the enemy portrayed in the Sea Viking scenario, and UAV operations from the MEB on the Amphibious Readiness Group off the coast of Camp Pendleton. A sample screen shot of a typical starting condition is shown below.

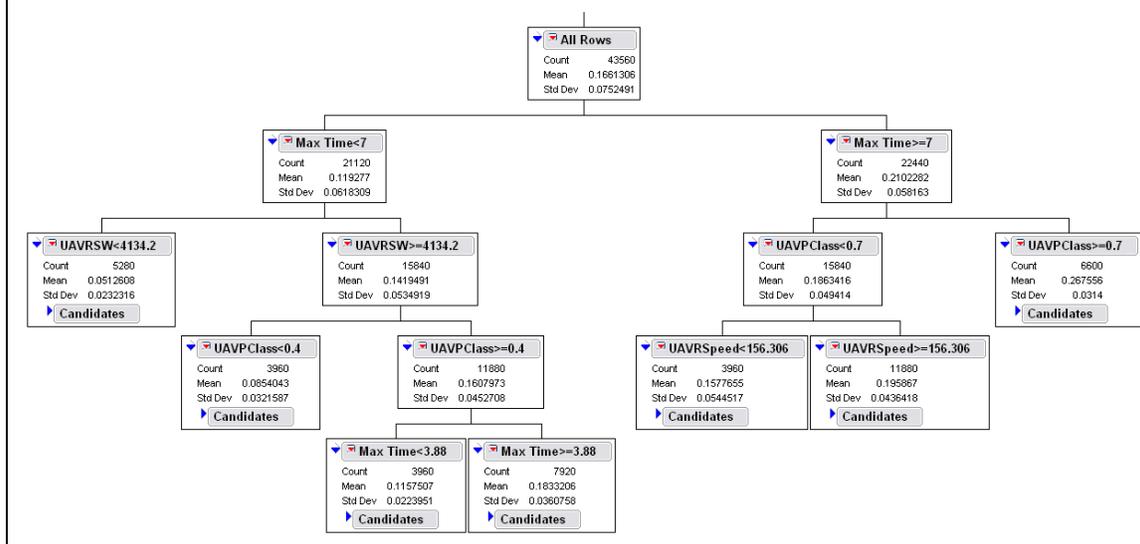


Six UAV elements are explored: routing, time, number of UAVs, speed, sweep width, probability of classification, and employment considerations. Five enemy capabilities are also considered: detection range, stealth, time critical target frequency and duration, and relationship with neutrals or non-combatants. In all, over 130,000 mission simulations produce the measures of effectiveness: proportion of enemy classified per hour and proportion of enemy classified per mission.

Classification and Regression Trees (CRTs) provide a way to analyze the relationship between factors and the MOE. A regression tree is a recursive partition of the raw data into sets of inputs containing similar responses. Partitioning of the data occurs successively according to the optimal splitting value determined from all possible values of each available variable. The optimal splitting value is the value of the predictor variable that minimizes sum of square error among all predictors. After each split, the next optimal split is determined within each partition. This may be the same variable as the initial split or a different variable obtained from all available factors and can be different for each partition. Considering each partition conditionally independently of the previous partitions automatically accounts for interactions.

The CRT on the following page is a recursive partition of the raw data from all 43,560 MANA runs on all controllable and uncontrollable factors for the one UAV scenario. As partitioning of the data proceeds, the most significant factors produce the first splits. The partitioning point for a factor range suggests an upper or lower limit for a factor capability producing significant improvement in the second MOE: proportion of enemy classified per mission. Each box (or node) indicates the optimal factor to partition upon and the optimal level of the split itself. Details within the box include the number of data points within the node, the mean enemy classification proportion per mission, and the standard deviation within the node.

MOE 2 Classification and Regression Tree (Proportion of Enemy Classified per Mission)



As expected, endurance, referred to as “max time,” is the primary factor when considering the total amount of enemy classified during a mission. A UAV on station at least seven hours will classify nearly twice the proportion of the enemy than a UAV with fewer than seven hours on station time when averaged over all the other variables. Additionally, given seven hours to search, a UAV with any sweep width or low probability of classification will perform reasonably well. This suggests that endurance can make up for moderate short comings in sensor capability.

A similar analysis on the proportion of enemy classified per hour reveals that the most important factor when considering time sensitive Intelligence Preparation of the Battlespace in the Sea Viking Scenario is the sweep width of the UAV. In general, wider sweep widths yield higher expected proportions of enemy classified each hour—as much as twice as much. This is qualified by the assumption that the sensor package can maintain a fairly high probability of classification as the sweep width increases. In less than seven hours, a UAV/sensor package capable of producing a probability of classification of at least 0.4 over a 4,500 meter sweep width may be expected to produce

a rate of enemy classification nearly three times greater, on average, than a UAV that does not meet these standards for the scenario detailed in this study. This may be crucial in a time-constrained situation.

Whether considering a rate of classification or the proportion classified for an entire mission, use of tactical routing is more effective than traditional search patterns. This makes tactical sense and lends credibility to the model. For employment considerations, when more intelligence is available, it is more important to follow preplanned routing as opposed to chasing unclassified contacts. The balance between reactivity and strictly following a route is difficult to quantify. With that caveat, reserving about one-third of the on station time for chasing unknowns and using the remainder to follow a tactical route appears to be the best combination for the Sea Viking scenario. A large sweep width and low probability of classification may result in too much wasted time if reactivity is high. Conversely, high reactivity can be effective if the sweep width is low.

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I. INTRODUCTION

A. OVERVIEW

The United States Military engages in conflicts, peacekeeping operations, and power projection around the world. As the world's greatest superpower, the nation expects ever-greater achievements worldwide with less military force committed, fewer American casualties, and lower costs—all faster than ever before. While no force may be able to stand up to the U.S. in combat, the fog of war often creates uncertainties and difficulties resulting in casualties. The military attempts to lift this fog of war and reduce uncertainty through Intelligence, Surveillance, and Reconnaissance (ISR) missions. The more knowledge of the battlespace our commanders have, the greater their ability to plan and execute a successful mission with minimal losses.

Unmanned Aerial Vehicles (UAVs) are a key component of today's ISR missions. UAVs provide intelligence, a dynamic retasking capability, and real-time video imagery. The Intelligence Officer for the First Marine Expeditionary Force (I-MEF) indicated this combination proved to be invaluable to our forces on the ground during both Operation Enduring Freedom (OEF) and Operation Iraqi Freedom (OIF). While the operators believe current UAV assets are effectively employed, they are limited. UAVs are in great demand and only the highest priority missions receive their support. (Howcroft, 2003) As a result of Operation Iraqi Freedom Major Combat Operations, lessons learned indicate that a “better asset to collect battlespace intelligence is crucial to the way forward.” (US Joint Forces Command, 2004) UAVs provide an alternative to complement manned aircraft and satellites in filling this gap.

The United States Marine Corps is currently reviewing its UAV employment. During OIF, the Marine Expeditionary Brigade (MEB) commander utilized two squadrons of Pioneer UAVs. Each squadron provided the capability to fly one UAV for up to six hours with a maximum range of over 170 nautical miles. The Pioneer can be relieved on station twice with current assets and manpower, achieving a total coverage of

18-hours during surge operations with the current force structure in each squadron. The Marine Corps desires to improve this capability in an efficient and effective manner. (Hirsch, 2003)

B. BACKGROUND AND MOTIVATION

The planned Pioneer replacement, the Vertical Unmanned Aerial Vehicle (VUAV), is in the beginning stages of conceptualization and currently has an Initial Capabilities Document (ICD). It is expected to proceed through the design and acquisition process for fleet use in 2008. (Headquarters Marine Corps, 2003) Marine Corps Systems Command (MARCORSYSCOM) provides guidance regarding the relative importance of the capabilities this VUAV could possess, such as speed, endurance, and sensor performance. If the requirement is for the VUAV to fly at 320 knots, and one design achieves only 310 knots, should it be ignored? What if the slower alternative has a significantly greater endurance or sweep width? What is significant? Is it worth the added cost to develop a VUAV capable of 400 knots or is 220 knots sufficient, at substantial savings? These alternatives require analysis because intuition and experience alone may not provide the best answer.

The Marine Corps Warfighting Lab (MCWL) has been tasked with answering a vague question. Headquarters Marine Corps wants to know “the required MEB ISR capability sets needed in order to meet the following 2015 Expeditionary Maneuver Warfare (EMW) requirements?

1. Support the commander’s rapid planning and decision-making process.
2. Maintain a comprehensive ISR network to support multiple concurrent expeditionary operations.
3. Facilitate operational maneuver and precision engagement.”

(Commandant’s Sub Team Guidance, 2003)

Based on recent performance and a dynamic retasking capability, the UAV has been determined to be the key component of the sensor network required to meet these requirements. Similar to the questions MARCORSYSCOM has regarding the VUAV, detailed analysis is required to determine the capability set for this MEB commander’s UAV of the future.

The procedure for determining the future capability requirements for this UAV involves demanding maximum performance based on expected technology advancements. This is not only speculative, but may be overkill for some capabilities. For example, the Marine Corps may not need a UAV capable of 72 hours endurance or 500 knots air speed for the 250 nautical mile max radius expected for MEB expeditionary operations. (Hirsch, 2003) There is no formal analysis of the trade space provided by the various capability characteristics. Currently, once the requirements have been set, meeting them is a pass or fail situation. That is, if a competing contractor proposes a UAV, the product either meets all parameters or does not. If a UAV under consideration were to fly 2 knots slower than required, it would fail. What if that product had endurance 10 times greater than the others? MCWL does not have an analysis tool to assist them in determining the value of one capability characteristic over another.

There are over 57 UAVs in development or production by corporations in the United States and over 216 worldwide. The UAVs employed by the US military today fly at speeds between 40 and 340 knots, with a combat radius from one nautical mile to an over the horizon capability. Some can be launched by hand, some from a ship, and some require a full runway. The sensors on board these UAVs have various sweep widths, resolutions, sampling rates, and weather effects. (American Institute of Aeronautics and Astronautics, 2004)

These design factors combine with various uncontrollable factors like geography, terrain and enemy capabilities to form a very difficult problem. A problem that, even with the fastest computers, most efficient simulations, and a team of analysts, would take more than a life time to answer using traditional experimental designs. A smarter design is required.

Each year, the Navy/Marine Corps team conducts Fleet Battle Experiment Sea Viking in Southern California. The primary objective is Command and Control and ISR development. This is an opportunity to validate future combat systems and purposed implementation concepts. It also provides a scenario for basing and possibly validating a model. (Marine Corps Warfighting Lab website, 2004) The model scenario for this

study adopts that from Sea Viking 2004, making the results applicable for developing employment techniques and capabilities to be evaluated in future Sea Viking experiments.

C. BENEFITS

This thesis provides benefit in five main areas. First, it yields insight into the relative importance of various UAV capabilities in ISR missions for expeditionary operations. This directly assists in the development of the 2008 Pioneer replacement VUAV currently under acquisition. It aids in determining the required capabilities of a system of UAVs to meet the future missions of the MEB commander in 2015. The research provides possible mission profiles and employment techniques for validation during future Sea Viking Fleet Battle Experiments. The tactics and procedures evolving from modeling supports initial Navy doctrine for integrating unmanned vehicles into maritime missions specifically addressing current issues from the Fleet. Finally, this thesis provides focus for future analysis involving physics-based simulations such as Combat XXI and determines key parameters for consideration.

D. THESIS FLOW

The following chapter contains a discussion of Agent-Based Models (ABMs) in Modeling and Simulation (M&S) and the ABM used for this thesis, Map Aware Non-uniform Automata (MANA). The scenario upon which the model is based and the representation of entities in the model is also presented. Chapter III examines the model's controllable and uncontrollable factors effecting UAV operations, robust experimental design uses for this work, and the implementation of Orthogonal and Nearly Orthogonal Latin Hypercubes. Chapter IV discusses the data farming process, post processing of the data from batch runs, and data analysis. The final chapter presents tactical insights and suggests some possible follow on work for future Operations Research theses.

II. MODEL DEVELOPMENT

All models are wrong, but some are useful.

-George Box

This chapter provides a brief overview of Agent-Based Models (ABMs), discusses how their use contrasts with other combat models available today, and introduces the ABM Map Aware Non-uniform Automata or MANA. The scenario implementation, including terrain and agent portrayal in the MANA environment based on Fleet Battle Experiment Sea Viking 2004 is discussed.

A. AGENT-BASED MODELING

In today's world of high-priced, high-tech systems with competing alternatives and joint considerations, decision makers require detailed program analysis. Often expert opinion and historical references do not provide adequate information for this analysis. The systems may even be too new to have "experts." Live Test and Evaluation (T&E), while part of any system development, is often too costly to explore the full range of possibilities that warrant consideration. Furthermore, T&E tends to be one of the first areas cut when time or money is tight. (Hoivik, 2003) This is where modeling and simulation can provide performance expectations and insights. The Defense Modeling and Simulation Office (DMSO) goal is to:

Provide readily available, operationally valid environments for use by DoD components:

- To train jointly, develop doctrine and tactics, formulate operational plans, and assess warfighting situations.
- To support technology assessment, system upgrade, prototype and full scale development, and force structuring.

Furthermore, common use of these environments will promote a closer interaction between the operations and acquisition communities in carrying out their respective responsibilities. To allow maximum utility

and flexibility, these modeling and simulation environments will be constructed from affordable, reusable components interoperating through an open systems architecture.

(Defense Modeling and Simulation Office website, 2004)

Significant problems with most currently used combat models include time and manpower requirements. Building a data base, implementing a scenario, completing a statistically sufficient number of runs, processing the output, and conducting an analysis often requires months. Teams of specialists develop these combat models. Often the team members have a thorough understanding of only a small portion of the model that is finally produced. Tying all the pieces together can prove to be the most difficult developmental piece. The Joint Simulation System (JSIMS) was conceived as the Department of Defense's (DoD's) "Flagship" simulation to model joint combat operations. Despite over a billion dollars spent on the development of this system, difficulties in integrating the many programs used in the system may be the end of the initiative. Many in the field believe this program is already dead. (Manago, 2004)

It is not uncommon for the databases developed for a combat model to have questionable accuracy. Sometimes databases may hold unclassified parameter values for developmental or training purposes. Discovery and correction of errors in the data entry process, whether unintentional mistakes or undocumented temporary guesses, does not always occur during verification. The 1999 DMSO award winning simulation Joint Conflict And Tactical Simulation (JCATS) is one of the key training models employed today. During a training exercise it was discovered that the sensor for a Tomahawk Land Attack Missile (TLAM), a long range, subsonic cruise missile, was in fact represented by an 8x magnification binocular. This is a rather serious error. (Manago, 2004)

However, this is not an attempt to question current M&S efforts. These examples merely bring to light the point of the quote at the beginning of this chapter by George Box: "All models are wrong, but some are useful." In the end, all the physics equations and detailed parameters of high resolution, physics-based models feed into a combined probability or weight. This probability or weight feeds into another complex equation designed to determine a hit, detection, movement, or other outcome.

Another approach to modeling and simulation is from the ground up. Rather than attempting to simulate activity as close to reality as possible by modeling every detail, why not model only those entity attributes which have a significant impact on the situation? ABMs, also called “distillations,” follow this philosophy. (Marine Corps Warfighting Lab website, 2004) They are distillations of the real world. Individual entities, called “agents,” are given capabilities and behaviors. Capabilities may include parameters such as movement speed, available weapon systems and sensor attributes. Behaviors include factors like an agent’s propensity to follow orders, congregate with friendly agents or attack enemies. Each agent is autonomous and reacts according to its behavior characteristics and what it perceives within its own situational awareness picture. The interactions of the agents on the digital “battlefield” result in scenarios which resemble key characteristics of the real world in which we live.

Most ABMs are stochastic with each iteration of a scenario resulting in a different outcome. (Lucas, 2003) Execution of many iterations produces expected outcomes and identifies variations. Uncommon results, or outliers, can be the most interesting cases. Combining this with the ABM’s easy set up and modification characteristics, quick run time, and high performance computers allows for exploration of a wide range of parameter values. This results in a powerful tool for an operations analyst’s toolbox.

Data farming is a technique commonly used in conjunction with ABMs. The purpose of data farming is to explore the effects of a parameter in a model across its range of possible values. Changing a parameter and viewing its effects through multiple iterations of a simulation enables effective estimation of the impact that parameter has. Completing this process for all parameters of interest ascertains the significant parameters. (Brandstein and Horne, 1998)

Project Albert is a division of the MCWL which utilizes data farming and ABMs as a

method to address decision-maker's questions that applies high performance computing to modeling in order to examine and understand the landscape of

potential simulated outcomes, enhance intuition, find surprises and outliers, and identify potential options. (Marine Corps Warfighting Lab website, 2004)

One of the many ABMs in the Project Albert suite is Map Aware Non-Uniform Automata.

B. THE AGENT-BASED MODEL MANA

Map Aware Non-uniform Automata, or MANA, is the agent-based modeling environment selected for this research. David Galligan and Michael Lauren began development of MANA for the New Zealand Army and Defense Force in 1999. Contact information is provided on the opening MANA screen (Figure 1) providing tribute to the work. Since then, MANA has been added to the data farming tools in the Project Albert suite of ABMs maintained by MCWL.



Figure 1. Map Aware Non-uniform Automata opening screen provides contact information.

In the MANA environment, the agents are:

- Map Aware—Agent's situational awareness includes the depicted terrain as well as battlespace activities in the simulation.
- Non-uniform—Each agent may have different behavior parameters and capabilities. That is, they do not all have to move or act the same way.
- Automata—Agents react independently on the battlefield according to their own individual situational awareness and personalities.

This distillation allows for graphical depiction of the terrain and agents to the desired level of detail. MANA is a straight forward application that is intuitive and easy to use with a well developed Graphical User Interface (GUI). The data farming techniques built in provide the ability to explore an extensive range of capabilities in minimal time. More details are readily available in the MANA User's Manual. (Galligan, 2003)

Developing the terrain for a scenario is a fairly easy process making use of the graphical editor built into MANA which produces basic scenario maps. If a scenario map is available, it can be converted digitally with any graphical editing software, such as MS Paint, Paint Shop Pro, or even Power Point, into a format MANA recognizes. In this ABM, terrain characteristics affect an agent's movement speed, cover, concealment, and line of sight. These settings are relative to each other and/or conversions from tactical parameters.

Agent parameters in MANA are in four basic types: personality weightings, move constraints, basic capabilities, and movement characteristics. The personality weightings determine an agent's propensity to move toward or away from battlefield entities such as waypoints, cover, concealment, and other agents.

Move constraints are conditional modifiers to the personality weights. For example, a UAV agent may be more likely to seek out and follow enemy agents when it is within a certain distance of the objective. MANA enables use of real world performance parameters for basic capabilities for conversion to the scale of the simulation scenario. Basic capabilities include parameters, set in the real world, that are converted to the scale of the scenario. These include maximum speed, sensor range and ability, and weapon range and effect, among others. Finally, movement characteristic parameters determine the type of algorithm used and the degree of randomness employed

by an agent. This affects behaviors like obstacle avoidance and the effects of terrain. Over 200 parameters may be employed in 49 possible states for each agent, providing the ability to capture a broad range of behaviors and capabilities of battlefield entities. (Galligan, 2003)

The personality page from the Edit Squad Properties menu, displayed in Figure 2, shows how an agent's propensities for movement may be modified from -100 to 100 and given an effective range. In this case, the agent's propensity to move toward the next waypoint is 20, indicating a desire to move toward it. A negative propensity value indicates a propensity to move away, such as this example shows for the top category, enemies. Additionally, MANA allows for determining the effective range of a personality weighting. In this case, if a way point is between 0 and 1000 cells away, the indicated weighting applies. This agent also has its greatest propensity to move toward cover. The behavior for this agent may be summarized as desiring to stay covered or protected while moving towards its next waypoint and staying away from enemy contacts. The ratios created from these weightings feed the movement equation along with other parameters to determine the agent's most desirable move. A detailed description of how the movement propensities affect the agent's movement can be found in MANA's users guide. (Galligan, 2003)

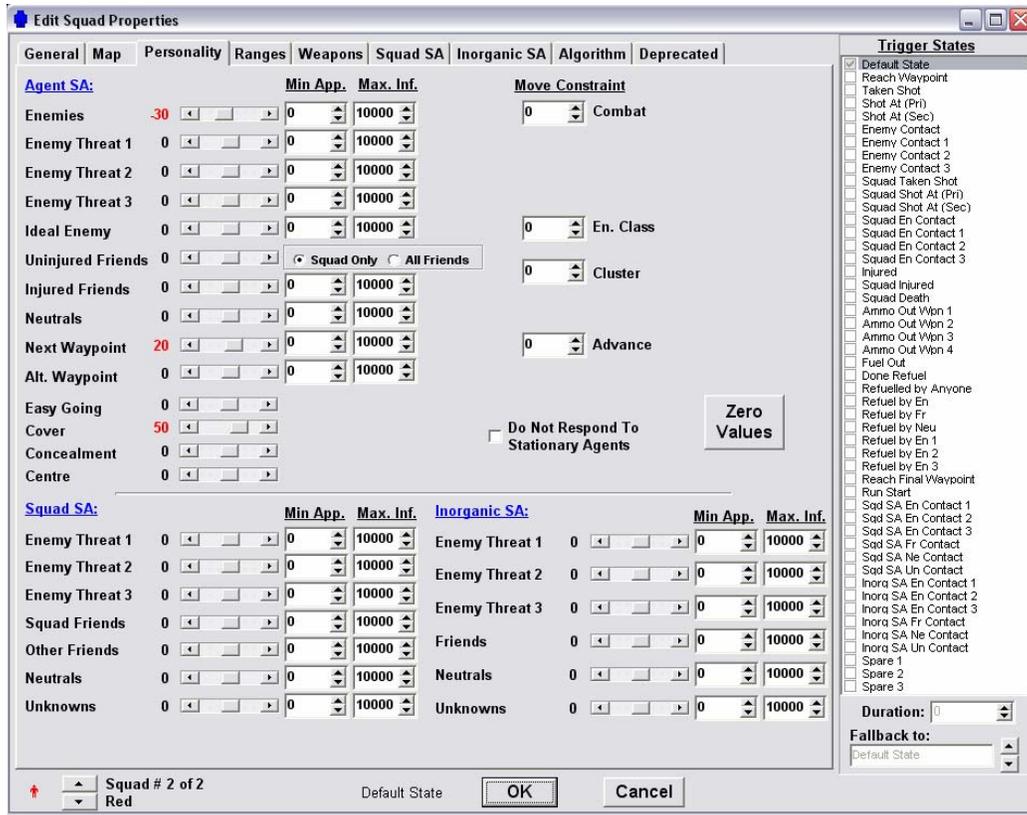


Figure 2. Example of MANA Edit Squad Properties page, tab one of nine: Personality. The display shows some of the many attributes which affect an agent's behavior on the battlefield in the MANA environment.

The support for ABMs in the Project Albert suite is excellent. It ranges from analysis to modeling, and provides the capability to make large batch runs remotely via Internet. Users can farm hundreds of thousands of data points from their own worksite. Scenario development support for MANA users is available from the software developers themselves. It is not uncommon for the programmers to provide version updates within a month of emerging requirements to capture a key element or vary a parameter not available in the current version at a user's request.

During the time frame of this study alone, many updates and versions to the MANA program have been released. This study uses only version 3.0.29 because of its methodology for computing line of sight (LOS). Subsequent versions calculate (LOS) in an undesirable manner for this study. If a line between observer and target crosses an obstruction square (i.e., with 0.92 concealment in MANA) then line of sight is not

possible. To determine LOS, version 3.0.29 calculates the probability of seeing through each square between the observer and a target in range. Newer versions compute this based on relative elevations.

Figure 3 is a visual representation of the difference between the two methods. On the left is the LOS depiction for an agent in “Dense Brush,” “Light Brush, and “Billiard Table,” or an open area, for the version used in this study. On the right is the LOS depiction for the same agent in the same environments for subsequent versions. The table in the middle displays the values for Going, Cover and Concealment for various terrain types. Notice the various levels of Concealment offered by the Billiard Table, 0.00 in black, Light Brush, 0.30 in light green, and Dense Brush, 0.90 in dark green. Intuitively, an agent should see less in Dense Brush than in Light Brush or the Billiard Table terrain. This characteristic is only demonstrated in version 3.0.29.

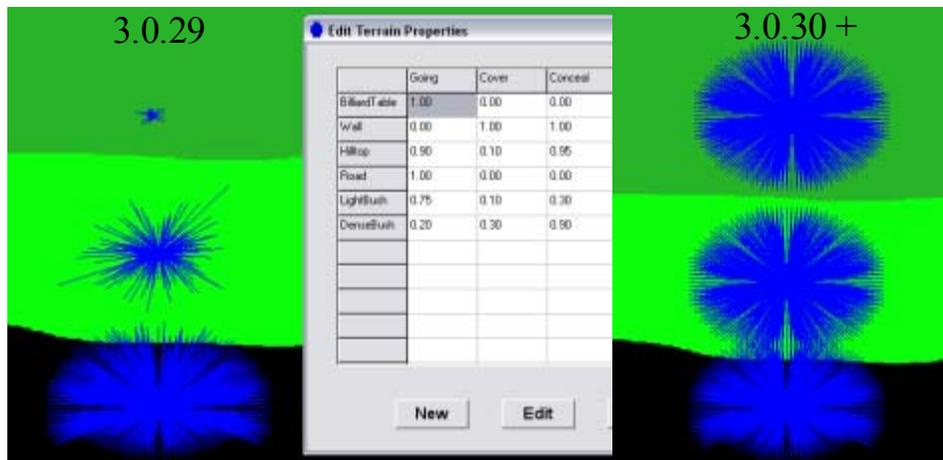


Figure 3. Line of sight determination in version for this study versus subsequent versions. We see the desirable LOS characteristics of version 3.0.29 on the left, versus subsequent versions on the right. [Best viewed in color]

C. SEA VIKING SCENARIO

The Sea Viking Fleet Battle Experiment, developed by MCWL, provides the scenario for the model to explore important UAV capability questions. Sea Viking is an experimentation program designed to allow exploration of ways in which the MAGTF can be transformed to increase combat power, operational versatility, utility, and deployability. It is a Navy/Marine Corps exercise for developing C4ISR techniques and

tactics that improve our ability to focus forward presence and Operational Maneuver From The Sea (OMFTS). The desired end-state is to make the Ship-To-Objective Maneuver (STOM) concept an operational reality for the Navy/Marine Corps Team. (Marine Corps Warfighting Lab Website, 2004)

The annual experiments involve imposing a reality-based threat scenario from a current area of interest on operations in the Southern California area. Utilizing Naval Base San Diego, Marine Corps Air Station (MCAS) Miramar, Marine Corps Base (MCB) Camp Pendleton, March Air Reserve Base, MCAS Yuma, and MCB 29 Palms, the full range of tactical operations may be conducted with Marines and sailors from the ship to the objective via air, land, and sea.

The scenario from Sea Viking 2004 provides a validated threat and mission context for the model which is acceptable to the principal stakeholders in UAV development for the Marine Corps. Mountain Infantry units, Coastal Infantry units, an Armor unit, and Time Critical Targets (TCT) are included in the force structure. The host nation is expected to provide no support. The geographic region is approximately 150 nautical miles by 150 nautical miles. Details from the Sea Viking Scenario are in Appendix A. The focus for this study is on the Intelligence Preparation of the Battlespace (IPB) during the initial phases of operations for the MEB. This directly addresses the first portion of the EMW requirements posed to MCWL above, as well as many of the questions from the VUAV Project Manager. (Marine Corps Warfighting Lab, 2003)

D. INSTANTIATING A SEA VIKING SCENARIO IN MANA

This section presents the modeling concepts and includes some examples where appropriate to provide an understanding of the level of detail in this study. This includes a description of the battlespace, agent development, aggregation, and creative alternatives. More information on MANA functionality and algorithms may be found in the MANA User's Manual. The details of the model development and the final model are available by contacting the author or advisors.

The model includes representations of the Southern California terrain, Sea Viking enemy organization and capabilities, as well as civilian (neutral) presence. Friendly force representation is limited to UAV operations in support of the ISR mission. Figure 4 displays a screen shot from the start of a typical run. The numbered circles identify the different friendly and enemy units modeled.

For orientation purposes, the display shows Los Angeles and San Diego city areas in dark yellow and 29 Palms (the objective) in the upper right corner. Bright yellow depicts all major and most secondary roads. Over 515 agents make up the scenario, including 345 civilians, 9 enemy tanks, 150 enemy infantry, 10 enemy TCTs, and 1 to 3 friendly UAVs.

Area 1 includes the UAVs, two in this case, at sea on Naval ships. Each iteration of the scenario starts with a different random number seed which varies the initial position of all agents on the battlefield. The UAVs have a planned tactical route to follow over land to cover key tactical objectives. Area 2 encompasses the Red (enemy) Coastal Infantry agents from the Sea Viking scenario intended to patrol the beach line. Area 3 identifies the Red Low Infantry which operate in low level terrain outside the city. The mission for this group is to move towards the city in search of neutrals to convert to enemy. The Red Mountain Infantry are in area 4. The mountain infantry move toward the choke point at the juncture of Banning Pass and Yucca Valley. Area 5 to the Northeast includes the Red Objective Area Forces. Infantry on the objective are protecting the senior leadership. Some of their forces move down Yucca Valley to meet up with the forces coming down from the mountains. In the Northwest is the Red Armor Unit within area 6. The armor moves southeast to take a defensive position in the vicinity of Banning Pass. Center stage in area 7 are the TCTs located in the channelized terrain representing a Surface-to- Air Missile (SAM) systems or Anti-Aircraft Artillery (AAA). Throughout the region are yellow “Neutral” or civilian agents.

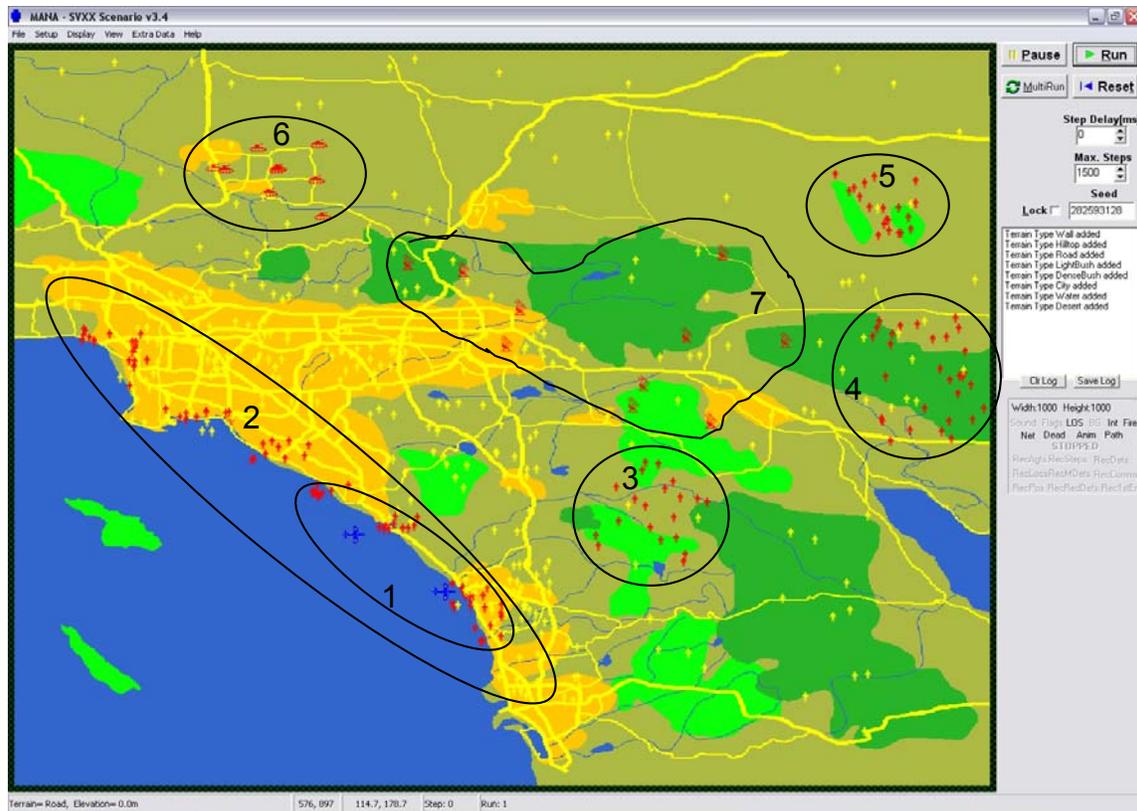


Figure 4. MANA Sea Viking base scenario. The display shows a sample initial friendly, enemy and civilian agent layout within the battle space. [Best viewed in color]

Key enemy characteristics include movement speed, dispersion, tendency to seek cover & concealment, sensor range, enemy–neutral cohesion, stealth or detectability characteristics, and a mission. UAV parameters include speed, endurance, sweep width, sensor capability, reactivity and number of units employed.

1. The Battlespace

As mentioned, terrain depiction in MANA is straight forward. Multiple JOG AIR maps of the Southern California Area make up the official Sea Viking 2004 Scenario map. (Marine Corps Warfighting Lab, 2003) The area of operations is identified, captured digitally, and enhanced, tracing over roads, urban terrain, water, desert, and light and dense vegetation areas in visually appropriate colors, with specified RGB values. After being converted to bitmap format, the image is imported to MANA. Using the MANA Scenario Map Editor, the values for the parameters that determine how these

different terrain features affect an agent’s speed, concealment, and cover are entered. Many of the values used are default settings in MANA. Others result from previous MANA work, interpolation, and the tactical experience of several Marine officers. Figure 5 depicts the values from the MANA Scenario Map Editor.

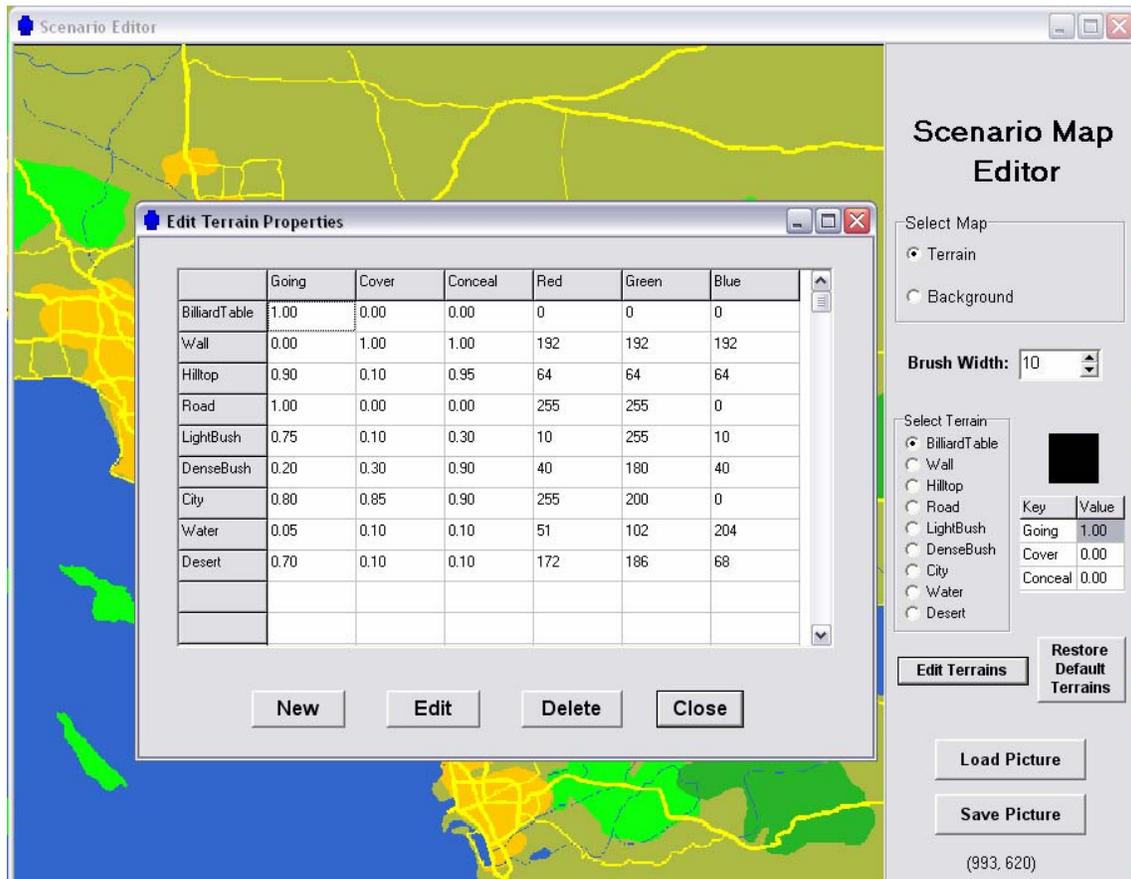


Figure 5. Terrain effects parameter values as displayed in the MANA Scenario Map Editor.

Terrain parameter values for Road, Light Brush, and Dense Brush utilize the default settings, make intuitive sense, and have been utilized previously in other studies. (Brown, 2000) For example, the terrain type “Road” has a parameter value of 1.00 for “Going,” meaning an agent’s speed parameter value is multiplied by a factor of 1.00, or unaffected, since roads are not intended to limit movement. Conversely, the “Cover” and “Conceal” parameters for the “Road” terrain type are both zero since roads provide no cover or concealment. Terrain types that provide cover have a value greater than zero but less than one, indicating the probabilistic effect the terrain has on the likelihood that an

Due to the size of the geographic area in the scenario, consideration is given to the variation in distance between lines of longitude. At the latitude for the center of the Sea Viking Fleet Battle Experiment, one degree of longitude is equivalent to about 49.83 nautical miles vice 60 nautical miles at the equator. Figure 6 shows the effect of this detail in the MANA battlefield.

2. Agent Development

The values for the four types of agent parameters, mentioned previously, are developed by a variety of means. Some parameters, such as agent movement speed, can be easily determined based on known real world values converted to the scale of the model. For example, a tank which travels at a maximum speed of 60 miles per hour in the real world will move 1.09 cells per time step in this MANA scenario. Others are more difficult to determine, such as a UAV's propensity to move towards the next way point. Difficulties arise when attempting to determine the value to use for that same UAV's propensity to move toward, or follow, detected enemy. What should be the ratio between these two competing goals?

This is where data farming comes in. Farming is the act of running the simulation for multiple iterations at a variety of levels to determine the effect of that parameter on the scenario outcome. These results provide appropriate values to set for questionable parameters to produce a behavior that makes logical and tactical sense. Variations of significant factors in the final analysis help to focus on the effects of these factors and their interactions with other variables in the model.

The primary focus of this study is the ability of a UAV to detect and classify forces on the ground. To this end, priority is on modeling UAV sensor capabilities as well as its endurance, speed, routing, and tactical employment. Any particular sensor has a specified Field of View (FOV). The sweep width of the UAV/sensor combination changes with altitude. For example, a 15° FOV sensor employed at 2000 feet Above Ground Level (AGL) has a sweep width of about 527 feet. This same sensor employed at 14,000 feet AGL will have a sweep width of about 3686 feet. The predominate factor in this situation is sweep width. With this in mind, sweep width is modeled for this study

with the knowledge that a FOV/flight altitude combination may be derived for a given sweep width.

Figure 7 permits determination of the sweep width for a given combination of FOV and flight altitude. The plots show how quickly a 10,000 meter FOV is achieved at a moderate altitude considering that potential design altitudes for UAVs are as high as 40,000 feet AGL. The vertical axis provides the sweep width in meters. The horizontal axis lists altitudes up to 25,000 feet AGL. Each line represents a different FOV. Thus, for a particular FOV, the left axis indicates the sweep width obtained at a given altitude. Sweep width is varied from 2,000 meters to 10,000 meters in this study to capture significant possibilities.

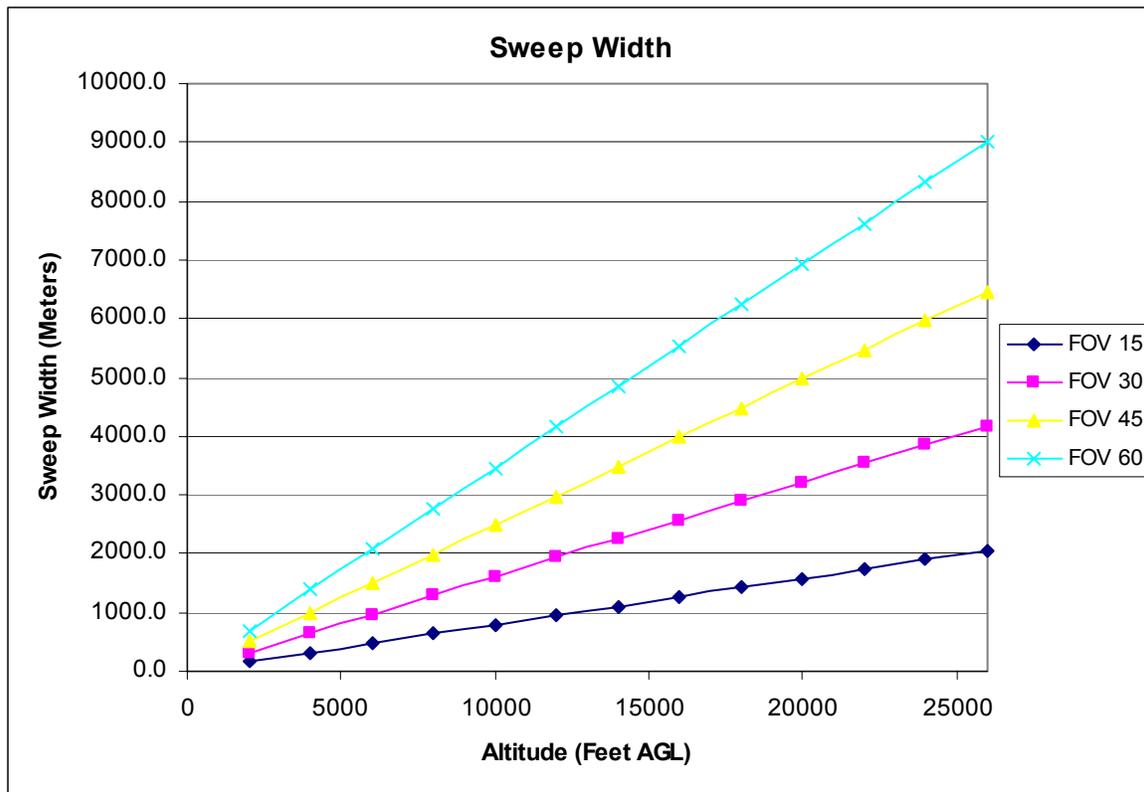


Figure 7. Graph of sweep width obtained given a flight altitude and FOV. The display shows the range of possible sweep width values.

The other sensor factor which deserves attention is probability of detection/classification. For a given sensor, the single glimpse probability of detecting/classifying a given target at a given range is generally known—under ideal

conditions. Ideal conditions may include weather, solar/lunar position, atmospheric conditions, clutter, contrast, and signal strength. For example, an optical sensor may have a probability of detection of 0.7 for a tank from 10,000 feet AGL with clear skies, a relative humidity of less than 20%, and the sun overhead. As cloud cover increases, humidity increases, the sun changes position, a dust storm pops up, or condensation builds up on the lens, this probability will drop. Also, higher altitudes are associated with reduced resolution, signal strength, increased interference as well as other confounding effects on probability of detection/classification.

In this MANA model, single glimpse probability is the probability of classifying a target in one time step. As the sensor sweeps an area, a target in the area may pass down the center of the sensor path or may be near the edge. If the target is near the edge, it may only be possible to acquire it on a single time step. In this case, target classification likelihood is the single glimpse probability. On the other hand, if a target passes down the center of the sensor's path, it may be in range for several time steps. In this case, the probability of classifying this target is additive, using the laws of probability and assuming independent glimpses, for each time step it is within the sweep width.

Figure 8 displays a sampling of the various resulting lateral range curves modeled in this study. The maximum and minimum capability UAVs, in regard to resulting probability of classification, are presented along with three intermediate examples. Each line provides the probability of classifying a target for the given distance from the UAV's flight path indicated along the x-axis. The most capable sensor nearly equates to a cookie cutter with a probability of detection of 1 within about 9,500 meters. This UAV is traveling at the slowest setting, 100 knots, with the widest sweep width, 10,000 meters, and the highest probability of classification, 0.9, for a single glimpse.

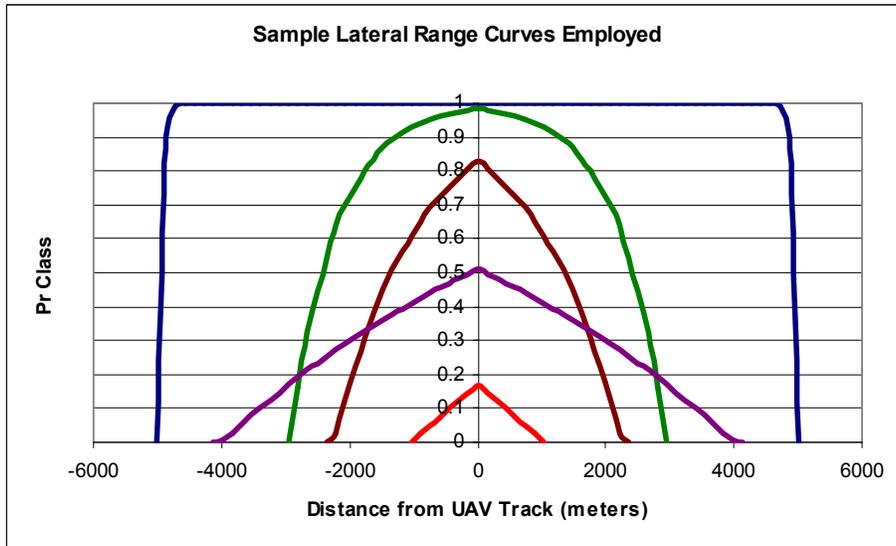


Figure 8. A visual sample of the lateral range curves modeled. The display shows the resulting probability of classification as a function of lateral range from the UAV for a sensor with various probabilities of classification at various airspeeds.

In this study, the actual single glimpse probability assigned to the sensor varies, accounting for possibilities beyond that which exists or is expected in the near future. This demonstrates another advantage of the data farming process: the ability to determine if a significant advantage may result from a capability outside of what is currently under consideration. Probability of detection ranges are varied from 0.1 to 0.9, allowing for consideration of more highly capable sensors than are currently available as well as degradation to current sensor capabilities, due to weather, altitude, or other factors.

3. Aggregation

Force aggregation is a common technique in modeling and simulation. The primary model used for this study does not have an agent for each soldier described in the Sea Viking scenario. Approximately one-third the number of infantry, tanks, and TCTs are portrayed in the primary (aggregated) model to reduce the run time of the MANA software package. The aggregated model runs in less than thirty seconds where as the full model can take over four and a half minutes on a 2.81 GHz Pentium 4 with 512 MB of RAM. This makes a big difference in the time required to complete hundreds of thousands of runs. The robust design implementation (Section 3.3) to explore the desired

variety of factors would take over a year of CPU time to complete with the full implementation of the enemy forces in the Sea Viking scenario. A consideration is whether this representation of only one-third the forces is valid.

A validation test with the full level of enemy forces run many times at high, medium, and low levels for all variables can determine if this aggregation scales properly. These levels are similarly run in the aggregated model. The resulting data provides the proportion of enemy classified in both the full model and the aggregated model under equivalent conditions at three different levels. Analysis of this data using the nonparametric Kruskal-Wallis Test (Conover, 1999) indicates that the distribution of detection ratios produced from each of these models are statistically indistinguishable.

Figure 9 displays plots of two of the levels. The vertical axis provides the proportion of enemy classified for a particular run, which is listed on the horizontal axis. The graph shows the similarity between the non-aggregated and aggregated models at high levels, roughly between 0.2 and 0.3, and the low levels, below 0.05. The conclusion from the aggregated and full comparison is that analysis based on the aggregated scenario is valid for the full scenario in regard to classification proportion.

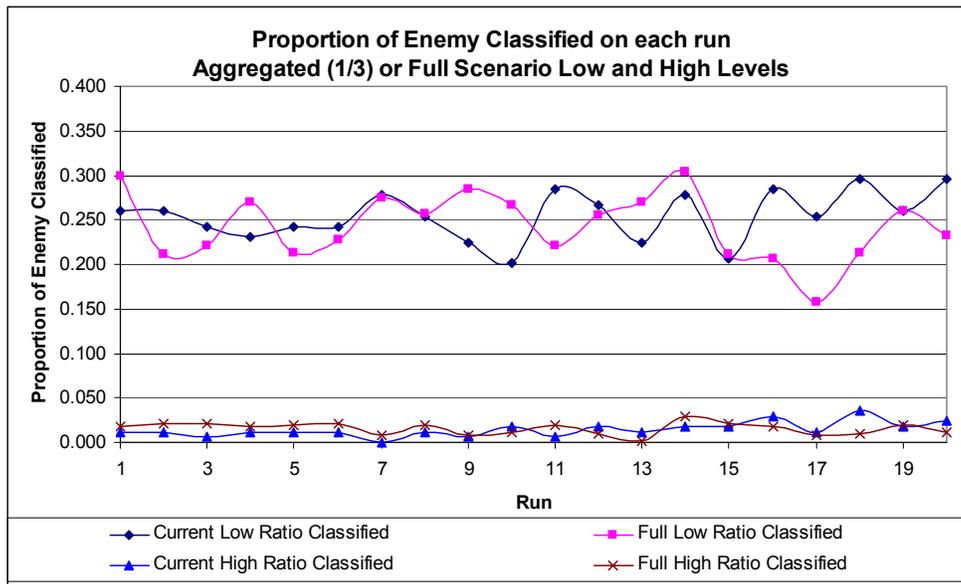


Figure 9. Graph of classification proportions from twenty runs of the full and aggregated scenarios displaying the equivalence of the resulting distributions for high and low factor levels. [Best viewed in color]

4. Measure of Effectiveness and Creative Modeling Alternatives

MANA enables access to a variety of parameters, including over 200 available for data farming, and Measures of Effectiveness (MOEs) which can be evaluated for each simulation run. The primary MOE for this study is proportion of enemy detected over time. MANA can record detection data for each agent at each time step. While this provides high resolution on the MOE, for such a large scenario, the output files eventually crash the operating system due to a limit on the number of subdirectories within a directory. Utilizing the default output from MANA provides a more efficient sampling of the MOE that proves sufficient. The default output provides a summary statistic, number of agents killed, for each type of agent following each scenario run. Over multiple iterations at each set of parameter values, or design points, a mean and standard deviation for the number killed for each agent type is obtained.

This study focuses on ISR, looking at UAV classifications, not at its ability to destroy the enemy. This is where the creative modeling comes in. By providing the UAV with a weapon having a probability of hit of 1.0 and unlimited rounds, the UAV “kills” each agent it detects and classifies. Since the UAV flight path in this scenario does not cover the same terrain more than once, multiple detections, or lack thereof, is a minimal concern.

False alarms occur when a UAV attempts to classify an unknown contact and it turns out to be a neutral vice an enemy. The MANA output contains this information in the form of number of neutrals classified. The expected outcome is a ratio between neutral classified to enemy classified. Since we have a two to one ratio of neutral to enemy agents that appear on the battlefield this ratio would be about two to one on average.

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III. DESIGN OF EXPERIMENTS

A challenge in conducting analysis on various UAV capabilities is the large number of factors, their wide range of levels, and their interactions. This chapter presents the factors in two sets, controllable and uncontrollable. Discussion follows regarding the utilization of methods to effectively explore the parameter space, robust design and orthogonal Latin hypercubes (OLH). The intent is to relay the value and capabilities of each technique as well as provide an understanding of their employment. References provide a more thorough understanding of how to utilize robust designs or OLHs.

A. CONTROLLABLE FACTORS—UAV CAPABILITIES

The controllable factors potentially affecting a UAV's ability to detect enemy units and vehicles on the ground not only have a large amount of variability, but also have significant interactions. It may seem obvious that the desired case is a wide field of view (FOV) and high resolution yielding a high probability of detection. In the real world, as FOV increases, resolution decreases for a particular sensor. Similarly, it may appear desirable to have the fastest UAV possible to cover the most area. However, there are two confounding factors in this case. First, the faster the UAV travels, the less endurance it generally has. This may result in a requirement for more UAVs to maintain coverage of an area. Second, the faster a UAV searches an area the less time is spent on any one location, driving detection probabilities down.

Each of these factors should be considered in system design to develop a UAV to accomplish a desired mission. This study focuses on the UAV's ability to detect enemy forces during the intelligence preparation of the battlefield in a MEB-sized operation. The controllable UAV factors determined to be of greatest importance through preliminary analysis and discussions with the sponsor include:

- Routing
- Number of UAVs employed
- Time available
- Speed
- Sweep width (function of Altitude and FOV)
- Classification probability
- Reactivity

The effect of the first of these factors, UAV routing, was explored in some preliminary work conducted during the Project Albert International Workshop 8 (PAIW 8) in Singapore. The remaining factors are the focal point of this modeling and analysis effort.

The route a UAV follows on any given search mission affects the number of enemy forces detected and classified. If the UAV does not fly over any enemy locations, there are no detections or classifications. In military operations today, forces often have some idea of where the enemy is likely to be, through satellite imagery, ground intelligence, or terrain analysis of avenues of approach. We do not rely on random or generic search pattern techniques for this type of employment. Tactical routing, designed around where our forces are going and where enemy forces are likely to be, is preferred.

Preliminary analysis examined various routing considerations. At PAIW 8, a team of defense analysts from a variety of countries developed several independent routes for the Sea Viking scenario. Some developed routes having no knowledge of the enemy locations, while others possessed knowledge of general enemy locations, such as, “An enemy armor unit is expected to be located north of the large urban area.” Each route required starting and ending at the ship off the coast. Of the sixteen different routes produced, three categories emerged. One category was a lawn mower type search pattern, another uses knowledge of likely enemy locations to set the UAV waypoints, and the last uses tactical routing.

The study produced four final routes, three from the categories described above and one previously approved as likely routing by MCWL. As an example, the routing approved by MCWL appears in Figure 10. It was originally developed based on terrain analysis and location of the objective area. While there would be different waypoints for any UAV commander who planned this mission, this one is as likely as any that might be planned. It includes the urban areas and routes most likely to be traversed on ingress, channeling terrain, key defense points, and the objective area itself.

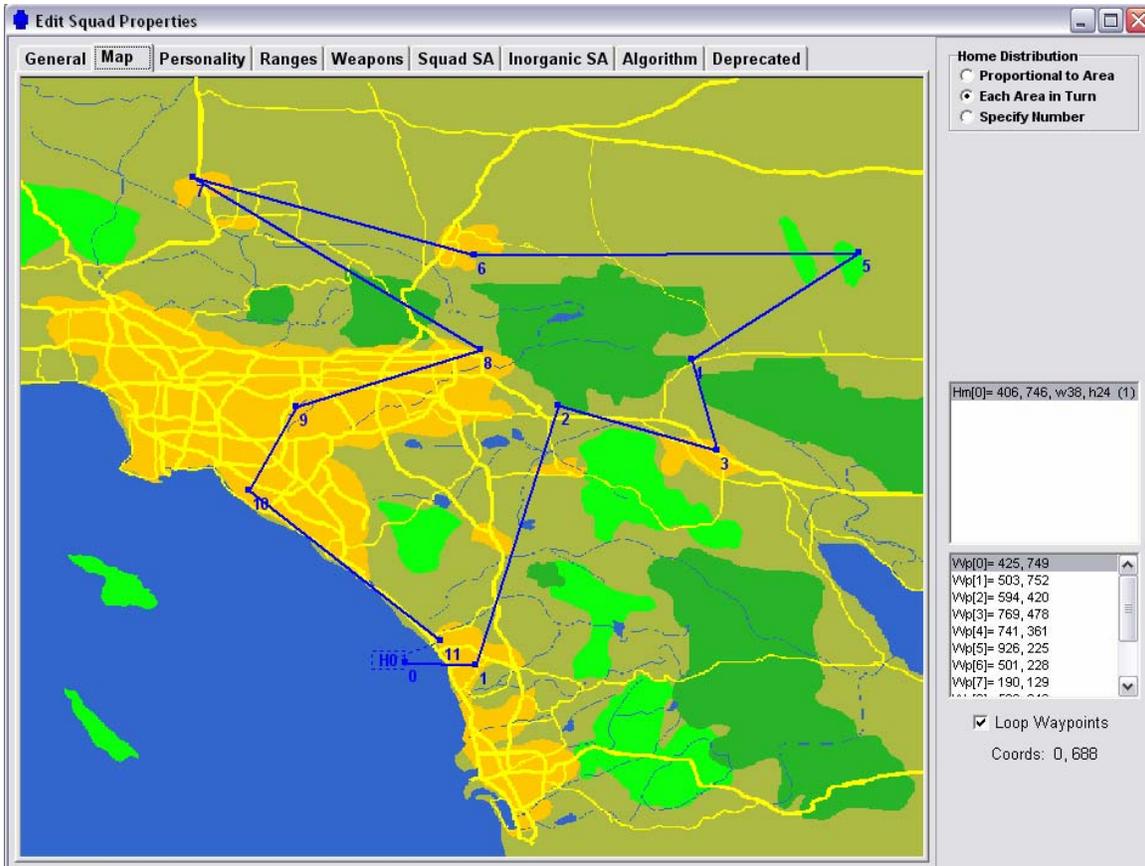


Figure 10. An example of routing for a single UAV approved by MCWL.

The focus on routing as one of the primary variables yielded 10,560 MANA runs across 264 design points (combinations of input factors). Figure 11 shows the distribution of the outcomes from the traditional search pattern type routing and the tactical routing. The results clearly indicated that tactical routing was superior to random or lawnmower type search patterns. The 95% confidence intervals for the two subsets do not overlap, and the tactical routing is over 60% better, on average, for this scenario. This makes intuitive sense and provides support of the model. Based on these outcomes, the current study uses the tactical routing approved by MCWL for all runs.

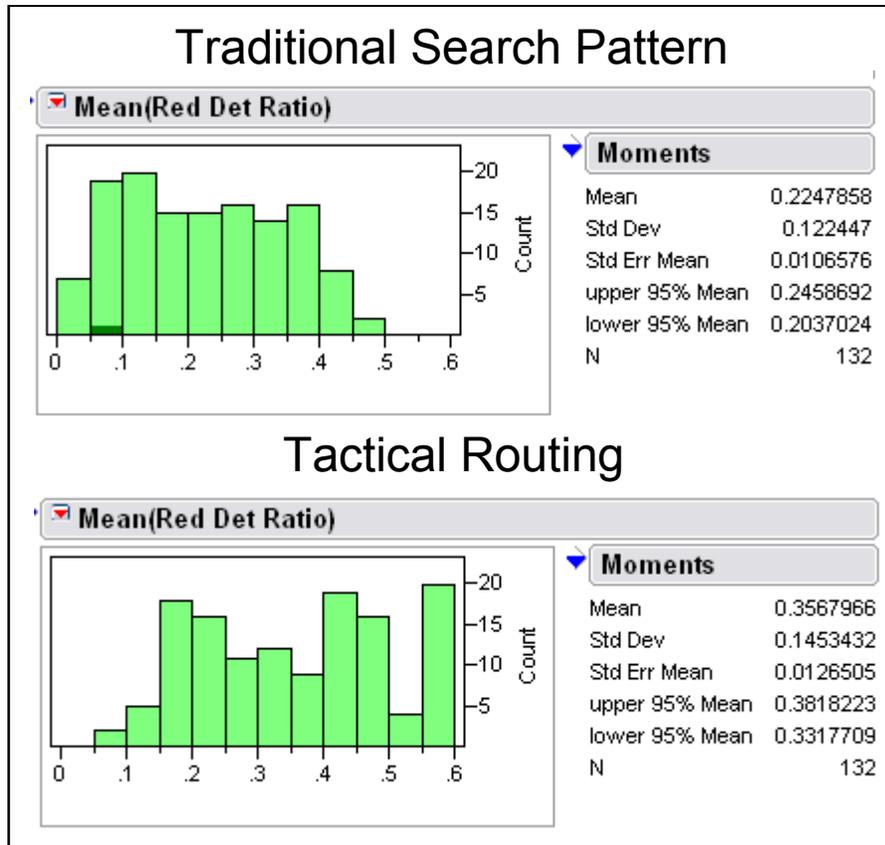


Figure 11. Distributions of the proportion of enemy classified form Traditional Search Patterns versus Tactical Routing of the UAV in the SV scenario. Note the tactical routing proves to be 63% better on average.

The number of UAVs employed affects how much area can be covered and how long it takes to complete the search. Interactions with speed and sweep width are intuitive, but must be quantified. Are two UAVs flying at 150 knots better than one flying at 300 knots? How do different sweep widths affect the performance? An upper limit of three UAVs has been selected for this study based on discussions with the sponsors and the Sea Viking scenario. It has been determined to be unlikely that the Marine Corps will have the funding or personnel to employ more than three UAVs simultaneously as standard operating procedure for a Marine Expeditionary Brigade (MEB) size Area of Responsibility (AOR). (Hirsch, 2003)

Time and space separate multiple UAVs active in the scenario. This follows general tactical airspace control rules which indicate that aircraft commanders should

plan for deconfliction by a minimum of two of the following three means: time, space, or altitude. (Department of Transportation, 2004) This has the added benefit of ensuring there are no multiple detections possible in the scenario. All of these points support the modeling and data collection method described in the previous chapter, using kills to record classifications.

Time in the AOR, run time, in conjunction with the proportion of the enemy classified provides a measurement of the expected rate of proportion of enemy classified over time for a UAV with a particular set of capabilities. In the real world, a commander may send out a UAV to search an area, but the information coming back to the command center is constantly monitored and, at a minimum, hourly updates are reported. In the simulation, each iteration stops at a predetermined time or when the UAV arrives back at the ship. Collecting the statistics on number and type of enemy detected up to the stop point provides a single data point for that set of capabilities. Many iterations of the scenario are run for each set of capabilities, yielding sample means to enable examination of the relative effectiveness of a set of capabilities over time.

Endurance is a difficult factor to model. Developing different routing for each endurance level is not practical for this study. Instead, estimating the effects of time using the methods described above provide insight into endurance. Routes are varied from one enabling a single slow UAV to complete a route to a set of three routes for three fast UAVs.

It should be noted that many other factors affect the required endurance level for a MEB sized operation. The first is the many possible variations in scenario parameters regarding distance from launch site to target area. Second, for Intelligence Preparation of the Battlespace (IPB), knowing how much information can be expected hour by hour may be just as important as mission by mission. Finally, these UAVs are currently intended to relieve each other on station, moving the significance of endurance considerations from the focus of this study to deck cycles and launch and recovery issues. These tactical considerations certainly warrant attention. Manned aircraft generally have priority on the

ship and the physics of how well a UAV fits into the deck cycle for shipboard operations may be a larger driving factor. For this study, the endurance needed to cover the SV area is assumed.

In concert with the Sea Viking 2004 scenario, the UAV starts each mission from a ship just off the coast. Limiting run time to halt each iteration at a specific experimental point or back at the ship yields the desired performance measure, number of enemy classified, up to that point.

UAV speed is a representation of the airspeed the UAV flies at for the mission. There is no variability in airspeed during a single iteration of the scenario. Airspeed in the MANA environment is obtained by multiplying the desired real world airspeed by the nautical mile conversion factor, 6.2713, which converts a nautical mile to a MANA cell width for the geographic area represented. This number is then divided by three to keep all possible airspeed values within the parameter limits of MANA. This scaling by a factor of 1/3 is conducted for all movement speeds in the scenario, thereby keeping all speed relations equivalent.

The range of speeds considered is from current UAV capabilities to a speed comparable with some manned aircraft. The low end is 100 knots and the upper end is 400 knots. There are many proponents for a UAV which will have dash speed over an Osprey, which has a maximum airspeed of 305 knots (Global Securities, 2004). While dash speed is not specifically considered in this scenario, the impact of this airspeed capability is considered for completeness.

UAV sweep width describes how wide the search area is for a single glimpse by the sensor. Sweep width is modeled using the sensor range parameter in MANA. Specifically, the UAV agent's detection and classification ranges are varied in lock step. A UAV agent detects a target as a function of the UAV's detection range, line of sight, the target's stealth, and available concealment on the terrain. Once detected, a target is then classified based on the UAV's probability of classification parameter, discussed below.

Sweep width ranges from 2,000 meters to 10,000 meters to encompass the current UAV capabilities and future possibilities. Employing a UAV at over 25,000 feet AGL is

a possibility for the MEB commander and Figure 7 in the previous chapter displays the possible sweep widths obtained for various FOV. Although there are several UAVs on the market today which operate at altitudes over 40,000 feet AGL, the sweep width range in this study encompasses current expectations for the type and size UAV under consideration by the Marine Corps.

UAV classification probability is the probability that a detected target is classified as friendly, enemy, or neutral on a single glimpse. In this model, the single glimpse probability of classification is held constant throughout the range of the sensor for any single iteration. The resulting effect as the UAV/sensor combination travels over the ground is that agents on the edge of the sensor range have a lower probability of classification than targets which the UAV passes directly over and are within range for a longer period of time. This provides a different lateral range curve for each sweep width/probability combination. The probability of classification range in this study is from 0.1 to 0.9, effectively capturing the full range of possibilities.

UAV reactivity is a term to describe the UAV's propensity to follow unclassified agents or to stay on its route. It is how "reactive" the UAV is to contacts. The intent is to explore the possible employment considerations a UAV commander may have. Given any area to search, the UAV commander will ideally plan a route to cover the entire area. The question is, once flying the route, should the UAV commander send the UAV after unclassified contacts in an attempt to determine if they are enemy, or should he follow the planned routing to ensure complete coverage?

In MANA, UAV reactivity is modeled by changing the UAV's propensity to follow detected "unknown" or unclassified agents relative to its propensity to move toward the next way point. This ratio is varied from one-third as desirous to move towards unknowns to three times as desirous to move towards unknowns in MANA personality weights. In any one time step, the UAV agent will consider this ratio along with the proximity of other UAVs and contacts already classified as enemy in determining its next move.

Figure 12 presents the basic set up for a UAV in MANA. The key factors, movement speed, classification range, and classification probability are set at a middle

level for the base case and varied in the experimental design. These middle factors permit a realistic run time viewing that is easy to understand and follow visually for debugging purposes.

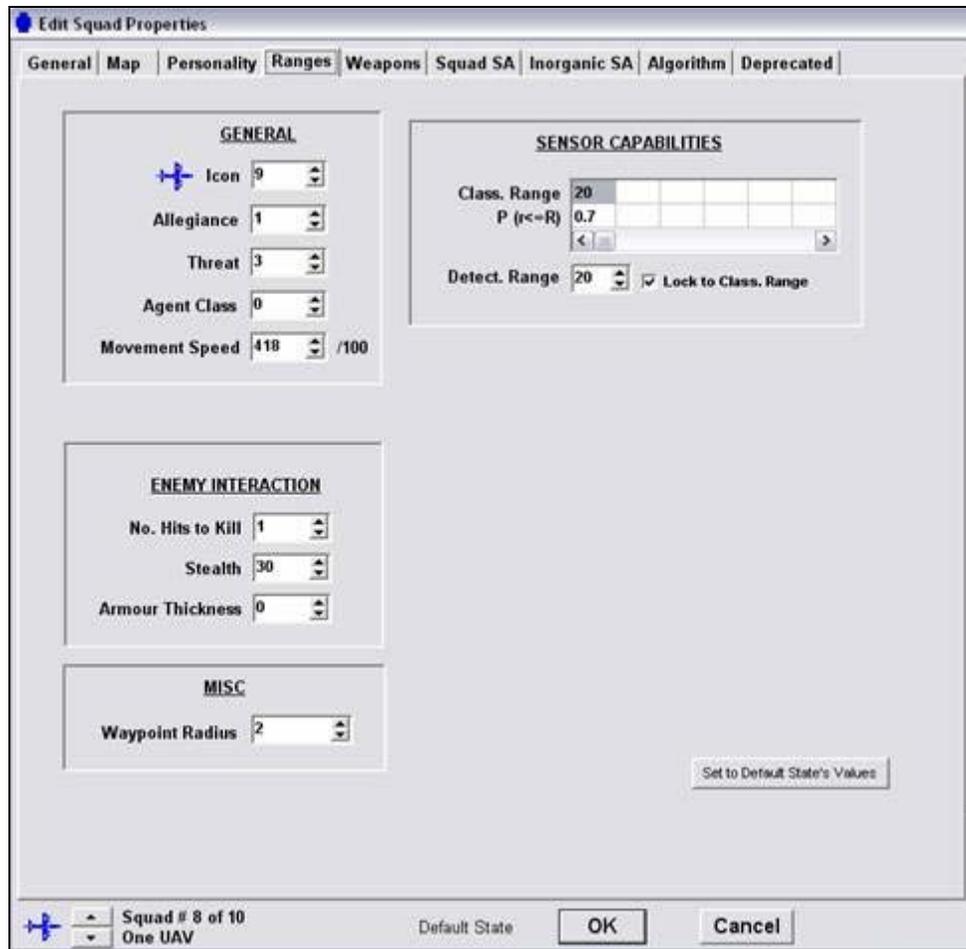


Figure 12. Sample UAV Range tab from Edit Squad Properties function in MANA. The display shows basic speed, sensor detection range, and sensor classification range and probability functional areas.

B. ROBUST DESIGN AND NOISE FACTORS

Robust design was pioneered by Genichi Taguchi in the 1980s for quality planning and engineering product design activities. (Taguchi and Wu, 1980) The fact that often a process may contain many variables which may be uncontrollable, or costly to control, can weigh heavily on the best course of action to take in attempts to optimize that process. For example, if the enemy has the ability to detect an approaching UAV

before becoming within range of the UAV's sensors, the enemy may hide and perhaps avoid detection. If the enemy's detection range were known, a UAV could be constructed which has a sensor range greater than that of the enemy. However, the enemy's detection range is variable. In the case of counter detection, it can depend on wind speed, wind direction, flight altitude, and background noise. Additionally, the cost of increasing the sensor range of a UAV sensor is generally a loss in resolution of that sensor, monetary costs aside. (Federation of American Scientists, 2004) This loss in resolution may be too great a cost for effective classification of targets.

Traditional experimental designs attempt to hold uncontrollable variables, or 'noise' variables, constant. This is intended to ensure that the impact due to these uncontrollable variables is constant throughout the experimental runs. This results in an "apples to apples" comparison and some mean performance indicator or Measure of Effectiveness (MOE) may be obtained. However, this also results in decisions made on a narrow set of circumstances. A robust design ensures the controllable factor levels are optimized with regard to the uncontrollable variables that affect performance. (Sanchez, 1994) By exploring the influence of noise variables, a set of design parameters, which may not perform the best in a particular instance, may perform best across a wide variety of circumstances in which the US military finds itself employed these days.

The intent of distillations is not to model every aspect of reality, but to focus on the significant factors and relationships. (Brandstein and Horne, 1998) The significant factors can be effectively determined through iterative evaluation of the noise variables. The end result is a subset of the significant factors which are uncontrollable in the real world but whose effects can be explored through M&S.

C. UNCONTROLLABLE FACTORS—ENEMY CAPABILITIES

In developing this model, several factors, not typically under the control of the UAV developer or MEB commander, require investigation. The following factors were determined to be significant enough to warrant inclusion in the subset of uncontrollable factors in the final analysis:

- Enemy detection range
- Enemy stealth

- Neutral-Enemy cohesion
- TCT vulnerability frequency
- TCT vulnerability duration

Enemy detection range is fairly self-explanatory and covered in a previous example. Enemy stealth is equally intuitive. It represents how well a target proceeds unnoticed. In the MANA environment, this is the weighted probability that an agent is not seen by a particular agent in any one time step regardless of other concealment, cover, or line of sight factors. These two factors are used in conjunction with a MANA state change. When the enemy detects the approaching UAV, it conducts a state change to an enemy contact state where the agent possesses a higher stealth to simulate a duck and cover reaction.

Enemy-Neutral cohesion represents the ability of combatants to congregate with neutrals in an attempt to avoid detection. The MANA parameter controlling this aspect of the agent's behavior is the propensity to move towards neutrals. Along with the agent's desire to seek concealment, easily traversed terrain, and their next waypoint while maintaining dispersion, this is a weighted value in the movement equation.

Time Critical Target vulnerability frequency is a measure of how often TCTs leave their hide site to move or engage targets, for example. Similarly, TCT vulnerability duration is how long they leave their hide site for these activities. These factors are controlled with the various agent state changes that are available in the MANA set up. In its hide site, a TCT has a high stealth value ensuring that the probability of detection is extremely small. When the TCT is out of its hide site, it is vulnerable to detection.

A base set up for a typical enemy infantry squad is displayed in Figure 13. The agent is given a negative weight for "uninjured friends" to provide the appropriate dispersion. Positive weights for other factors ensure the agent moves toward its intended objective considering concealment, without working too hard, and integrating with neutrals.

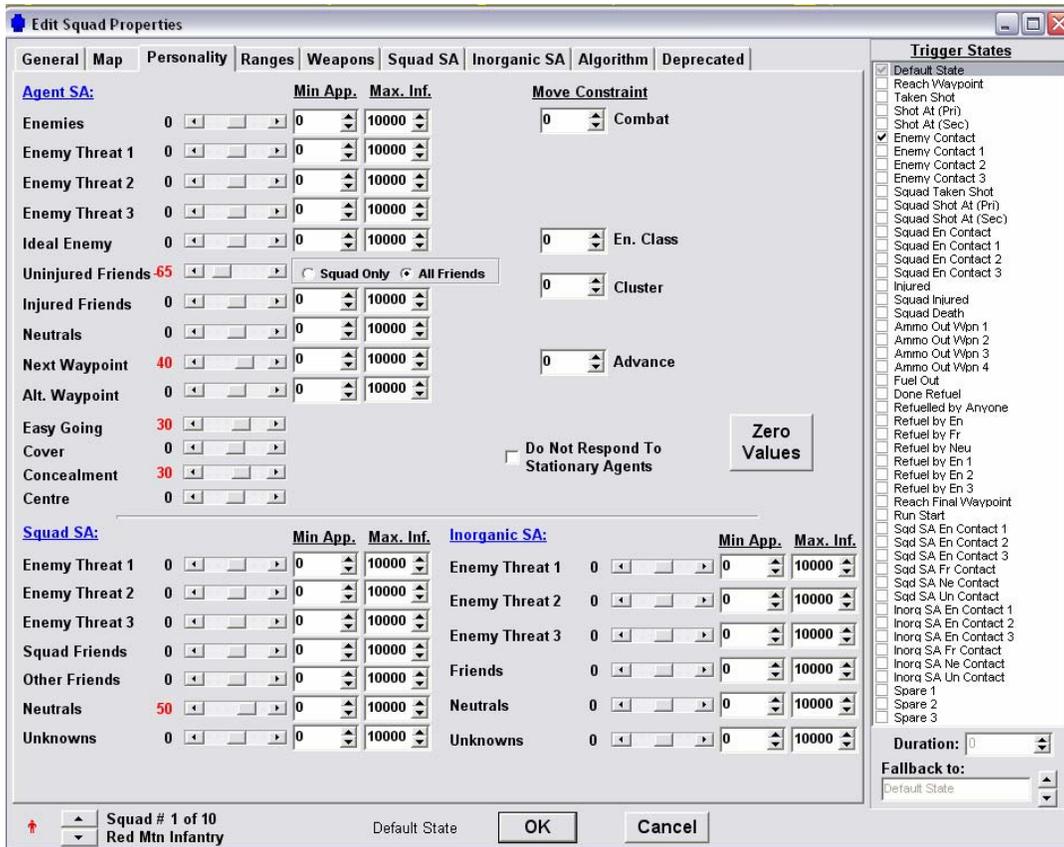


Figure 13. Red Mountain Infantry squad basic personality configuration. Values are manipulated to control dispersion, provide a mission, effect movement propensities, and manipulate cohesion with neutrals.

D. ORTHOGONAL LATIN HYPERCUBES

There are a large number of factors worthy of consideration between the controllable and uncontrollable factors. A problem arises in attempting to effectively vary these factors across a wide range of possible levels. A traditional factorial experimental design tests only a few factors at two or perhaps three levels each. To utilize this approach, some factors would have to be left out of the experimental design and linear relationships assumed. A smarter design is required.

An Orthogonal Latin hypercube (OLH) design is chosen for its excellent space filling properties, the resulting low correlation between factor inputs, and ability to identify nonlinear relationships. (Cioppa, 2002) OLHs can be used to design an experiment evaluating up to seven factors at 17 levels each in an efficient and effective manner. Nearly orthogonal Latin hypercubes (NOLHs) have nearly the same properties

with slightly higher, but negligible, correlation between factors. NOLHs can be utilized to evaluate from 8 to 22 factors at up to 129 levels.

Figure 14 plots each design point derived from an eight factor NOLH with 33 levels for each factor. This NOLH is then crossed with a two-factor factorial design. The factor names are presented down the diagonal. Each point on the plot represents the corresponding factor levels for a design point. The NOLH's space filling properties are demonstrated by the plots in contrast to the factorial design factors, #UAVs and Routing, compared to any of the other factors whose design points were obtained from a NOLH implementation. This design allows for the exploration of many variables (in this preliminary case, ten) over a large range while evaluating many points within the range for each appropriate variable. This ensures the ability to identify nonlinear relationships and interactions.

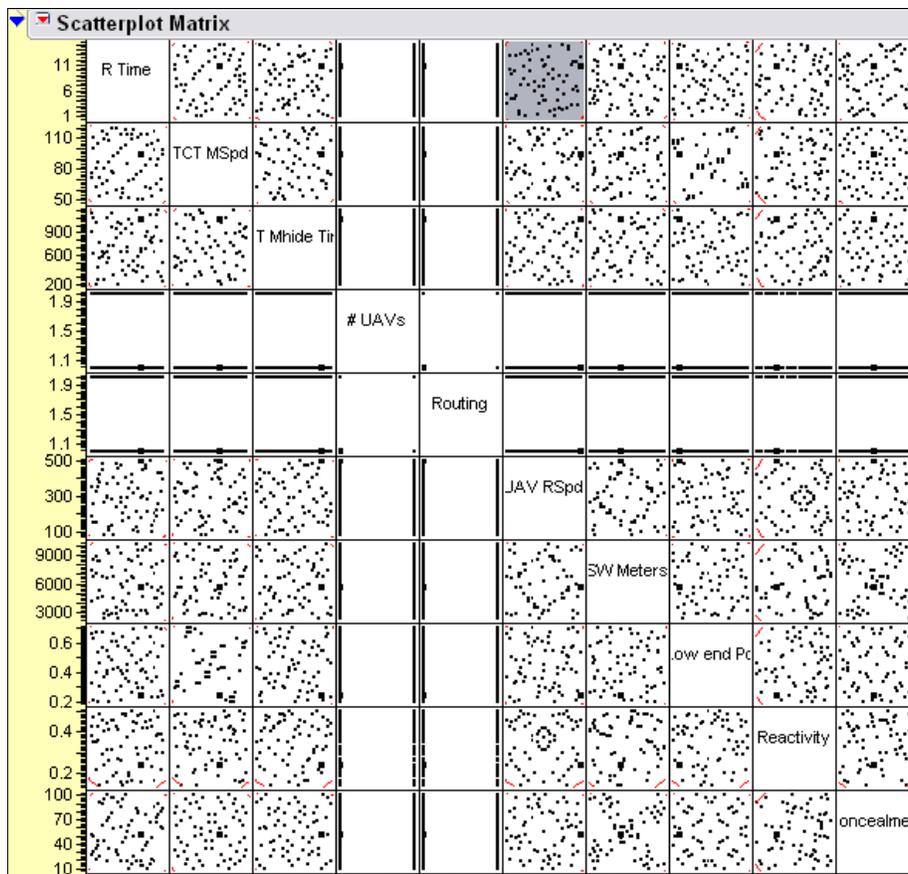


Figure 14. Pairwise scatter plot of design points utilizing a nearly orthogonal Latin hypercube crossed with a factorial design. Factor names appear along the diagonal. Each dot represents a design point for the corresponding factors.

The orthogonal nature of the design results in no significant design-imposed correlation. This provides the ability to look at the effects of each variable independently as well as interactions during analysis. Through optimal chaining of OLHs or NOLHs, the space filling characteristics can be increased while maintaining the orthogonal nature of the design and no significant design point correlations. (Cioppa, 2002) This provides a greater ability to analyze multidimensional data.

This study uses two, optimally appended, orthogonal Latin hypercubes for each group of factors, controlled and uncontrolled. This provides 33 design points for each group optimized for greatest space filling. The two sets of 33 design points each are then crossed to ensure each of the controllable factor design points are evaluated at the maximal range of possible combinations of uncontrollable factors as the robust design section discusses above. This results in 33 times 33 = 1089 design points which are each run for the three factorial cases of one, two, or three UAVs. Finally, these 3267 design points are each run for 40 iterations to take advantage of the stochastic nature of MANA and provide a look into the variation that may be expected. This results in 130,680 total MANA runs of the scenario. Conducting this many runs with a typical, physics-based combat model, such as JCATS or Combined Arms and Support Task Force Evaluation Model (CASTFOREM) would take years. This advanced level of experimental design with typical combat models is undesirable due to the resources required.

The ranges for the controllable and uncontrollable factors in both the real world and the MANA environment are displayed in Figure 15. On the right is a sample of the orthogonal Latin hypercube for the controllable factors presenting the first 20 design points. In addition to the 40 replications run for this design, a separate set of runs of 5 repetitions each is available to be used as a test set for verifying the models.

IV. DATA ANALYSIS

Orthogonal Latin Hypercubes (OLHs)/Nearly-Orthogonal Latin Hypercubes (NOLHs) and MANA output facilitate post processing and data analysis. A quick review of the collection and preparation of data for analysis begins this chapter. Next is a discussion of the statistical modeling techniques utilized to gain an understanding of the relationship between the Measure of Effectiveness (MOE) and the predictor variables and the results they produce.

A. DATA COLLECTION AND POST PROCESSING

MITRE Corporation in Woodbridge, VA coordinated over 150,000 total production runs for this analysis. MANA iterations run on site produced the preliminary data. The second data set was completed during Project Albert International Workshop 8 (PAIW 8) in Singapore. The final set of runs was completed utilizing the assets at the Maui High Performance Computing Center (MHPCC). MITRE facilitated the execution of each experimental design ensuring proper implementation at the appropriate site.

Each experiment returned a comma delimited file easily converted into an Excel spreadsheet or JMP statistical discovery software format. Both programs, from Microsoft and the SAS institute respectively, are commonly used for data manipulation and analysis. (JMP User's Manual, 2002) The output from each run includes the variable levels, duration of the run, and the number of killed agents, classified by type. The number recorded in each run is equivalent to the number classified, as previously described in Chapter II. Spreadsheet calculations easily turn the MANA units back into real world values for effective analysis in a user friendly format.

The MOE is expected enemy classification proportion per hour. This value is computed for each MANA run from the output as follows. First, the number of enemy classified in that run is divided by the total number of enemy in the scenario. This is done to provide the proportion classified for all 130,680 runs. The proportion classified is divided by the actual run time for each run to yield the proportion classified per hour. The last computation is average classification proportion per hour across the 40 runs at all

3267 design points. This number provides the average proportion of enemy classified per hour for the given factor levels in that design point—including controllable and uncontrollable factors.

The statistics of the aggregated data over all controllable factors for the one UAV scenario are displayed in Figure 17. The average proportion of enemy classified per hour over all runs is 0.0293.

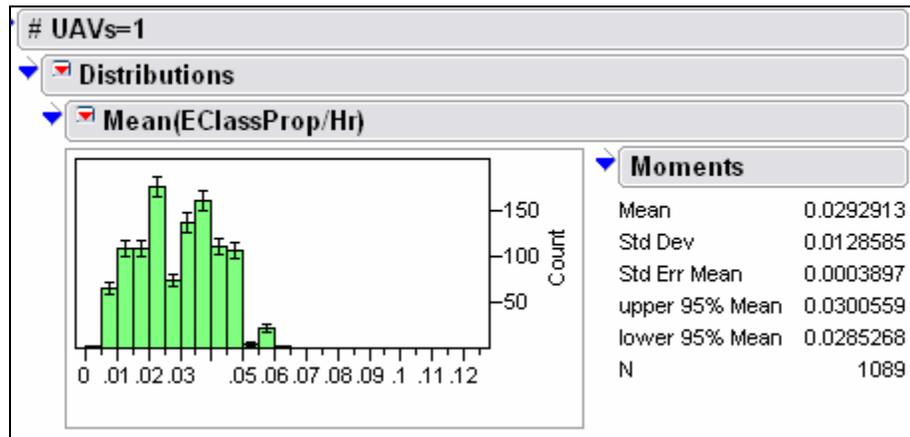


Figure 17. Distribution of the MOE, mean proportion of enemy classified per hour, for the one UAV scenario. Notice the mean is 2.93% of the enemy classified per hour.

Using 40 iterations at each design point ensures that the distribution function for the random variable (mean proportion detected per hour) representing the MOE for a particular data point is approximately normal, as stated in the Central Limit Theorem. This ensures the data meets one of the general assumptions for regression analysis. Randomly selected design points evaluated using the Shapiro-Wilk Test for Normality verify normality of the response and its use as our estimator of the true effects of the particular parameter settings. (Conover, 1999)

Figure 18 is a Normal Quantile Plot of the data for a randomly selected design point. Data that is normally distributed tends to fall on the diagonal line. Data contained within the confidence interval bounds is said to be distributed normally with 95% confidence. (JMP User’s Manual, 2000) Notice that this data falls almost entirely on the

line and is all contained within the confidence intervals. Thus, at this typical design point, the MOE fits well to a normal distribution.

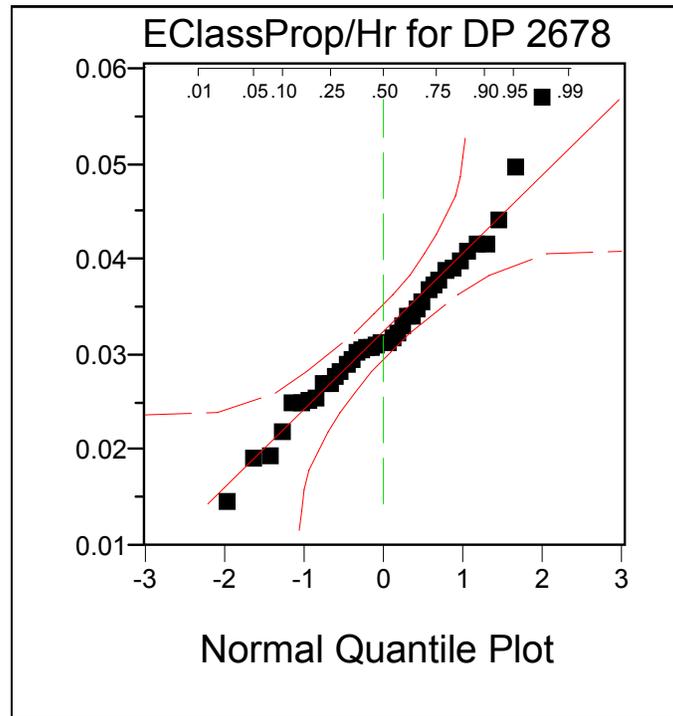


Figure 18. Normal Quantile Plot of resulting enemy classification proportion per hour from a randomly selected design point, number 2678. Most of the data fall on the diagonal and all fall within the 95% confidence interval indicating the normality of the measure of effectiveness for a typical design point.

After data post-processing, the resulting spreadsheet includes a row for each design point listing the factor levels and the associated mean enemy classification proportion per hour. The data are now ready for multiple regression and decision tree analysis.

B. MULTIPLE REGRESSION ANALYSIS

Multiple regression is a common technique for determining the effect of various factors on a response variable. It involves applying linear combinations of the coefficients of the factors that predict the response variable by minimizing error. Minimizing the error term produces an accurate fit of the response based on the factors.

Various statistical packages are available for facilitating multiple regression analysis. JMP Statistical Discovery Software version 5.0.1a (JMP User's Manual, 2002) is utilized for this work.

A detailed description of the data analysis process follows for the one UAV scenario and is similar for each model. The details of the models developed for the two and three UAV scenarios can be found in Appendix B. Due to anomalies with the multi-UAV runs requiring further iterations and time constraints on this study, further analysis is recommended for the multi-UAV scenarios.

The single UAV model utilizes 1089 responses to regress the controllable and uncontrollable variables on the MOE, mean classification proportion per hour. This first considers all main effects, two-way interaction terms, and main effects quadratic terms resulting in a total of 76 candidate terms for consideration in the model. Stepwise regression pairs down the parameter space to only those factors with a specified significance level by incrementally adding and deleting terms to the regression model. Once the statistically significant factors are identified, to obtain a parsimonious model, additional factors may be removed if they provide minimal improvement to the fit. (JMP User's Manual, 2000)

During the development of the model, performing stepwise regression on the factors eliminates those factors below the 0.01 level of significance. The resulting model provides parameter estimates for the significant factors and an R-squared value for the entire model. The R-squared value is the proportion of the variation in the MOE explained by the model. An R-squared value of 1.0 means that the model perfectly fits the data. At this point, an iterative process of removing the term with the least significance, reconstructing the model, and evaluating the resulting fit of the model provides a means for selecting a preferred model. The preferred model provides a balance between simplicity and goodness of fit.

Figure 19 demonstrates this process for the single UAV scenario. The R-squared value, or proportion of explained variation in the MOE, is plotted as a function of the terms indicated along the X-axis. The line with diamonds represents the values obtained from a regression of controllable and uncontrollable factors, interactions, and squared

loss of information. The remaining analysis considers the mean enemy classification proportion per hour for the 40 times $33 = 1320$ runs at each controllable factor design point.

Figure 19 also displays the distinct point of diminishing returns as factors are added to the model. This typical characteristic of regression models is useful in determining the difference between statistical significance and practical significance. While all the terms listed at the bottom of the graph are statistically significance at the 0.01 level, they provide minimal additional explanation of the response after the first seven or eight terms. The first eight terms listed along the bottom of the graph explain over 90% of the variability in mean enemy classification proportion per hour across all the levels explored in this scenario.

Another way of looking at the effects of each term is to add them into the model in reverse order. Figure 20 shows the incremental predictive power each term on the horizontal X-axis contributes to the model in terms of R-squared in the response variable on the vertical Y-axis. The model from all the factors is the line with diamonds and the model obtained from the aggregated data for the controllable factors is the line with squares.

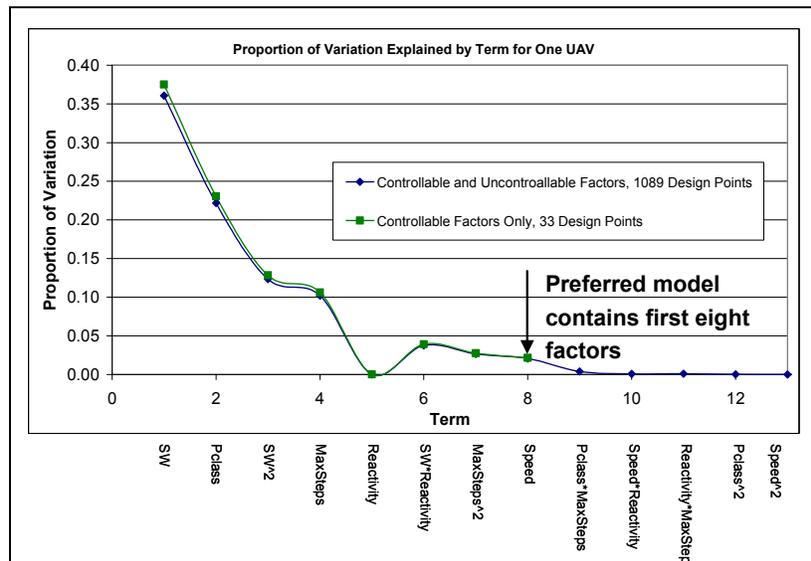


Figure 20. Proportion of variation in one UAV mean enemy classification proportion per hour across all scenario factor levels as each term is added to the model. There is a clear point of diminishing return and similarity between the models with all factors and the models aggregated over the uncontrollable factors. [Best viewed in color]

Again, the resemblance between the two plots clearly depicts the similarity between the two models. Using the simpler model developed from controllable factors and aggregated data produces no significant loss of information. In addition, this graph more clearly depicts the point of diminishing return. The value of adding the next most significant term after the eighth term is minimal. The arrow indicates the desired point of balance between goodness of fit and simplicity. The preferred eight term model contains the following terms for the single UAV scenario in order of importance:

1. UAV Sweep Width
2. UAV Probability of Classification
3. UAV Sweep Width Squared
4. Maximum Time Available
5. Reactivity
6. Interaction between UAV Sweep Width and Reactivity
7. Maximum Time Available Squared
8. UAV Speed

Note that all these terms are controllable factors.

UAV sweep width is the most significant predictor of the variability in the MOE across UAV capabilities in this scenario. Nearly 40% of the variance in the proportion of enemy classified per hour is explained by the UAV's sweep width alone. The first four terms explain over 80% of the variance in the MOE. UAV sweep width, probability of classification, sweep width squared, and maximum time available provide a good model—explaining the vast majority of the variability all by themselves.

There is a noticeable dip above the reactivity term in Figure 20, due to the fact that, on its own, reactivity does not explain a significant portion of the variability. However, the next term, an interaction between reactivity and the UAV's sweep width, is a significant predictor of the variability in the MOE. It is traditional to include the main effect term in any model where an interaction term is significant even if the main effect term is not. (Whittaker, 2003) Thus, reactivity is retained in this model even though it is

not mathematically required. The squared effects of maximum time available and UAV speed also have practical significance, although not as great as the previous terms.

Figure 21 is a visual representation of the preferred model. This plot of the predicted versus actual response displays how closely the model explains the MOE. Notice how well the data points follow the diagonal—indicating a nicely fit model. The residual plot on the right displays the homoscedasticity, or constant error variance, lack of influential cases, normal residual distribution, and linear relationship. (Hamilton, 1992) The associated statistics for this model are provided in Figure 22. The actual coefficients for each term in the model are listed. Also of note is the way in which the interaction terms and square terms are evaluated. The mean for each is subtracted off for each factor included in an interaction or squared term to ensure proper scaling.

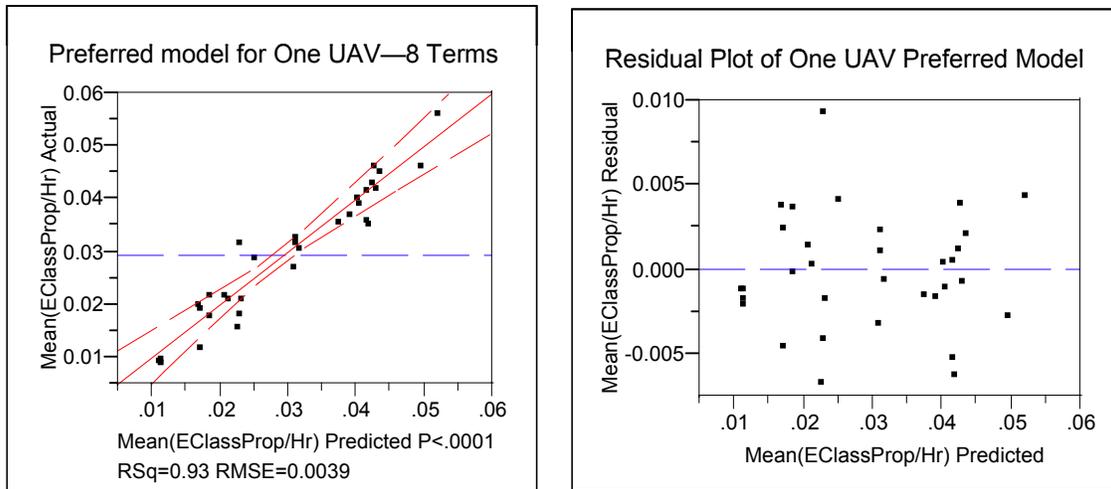


Figure 21. Predicted versus actual mean enemy classification proportion per hour displaying the good fit of the preferred single UAV model with eight terms and associated residual plot verifying the absence of pattern in the residuals.

Summary of Fit	
RSquare	0.928752
RSquare Adj	0.905003
Root Mean Square Error	0.003944
Mean of Response	0.029291
Observations (or Sum Wgts)	33

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	0.00486708	0.000608	39.1067
Error	24	0.00037337	0.000016	Prob > F
C. Total	32	0.00524045		<.0001

Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	0.0047896	0.003806	1.26	0.2203
UAVRSpeed	0.0000198	0.000007	2.69	0.0128
UAVRSW	0.0000031	2.764e-7	11.27	<.0001
UAVPClass	0.0243387	0.002762	8.81	<.0001
UAVUnkAttr	-0.000008	0.000028	-0.27	0.7876
MaxSteps	-0.001322	0.000221	-5.98	<.0001
(UAVRSW-6058.12)*(UAVUnkAttr-50)	-3.652e-8	1.138e-8	-3.21	0.0038
(UAVRSW-6058.12)*(UAVRSW-6058.12)	-7.03e-10	1.36e-10	-5.15	<.0001
(MaxSteps-7.00242)*(MaxSteps-7.00242)	0.0002559	0.000084	3.05	0.0056

Figure 22. Preferred one UAV model. The R-squared value for this model is above 90%. The display shows the coefficients for each term and the significance of each of the terms as well as the overall model.

This model makes sense. As UAV speed, sweep width, and sensor capability increase, the proportion of enemy classified per hour increases. These effects are intuitive, as capabilities increase, so does performance, lending credibility to the model. Conversely, as the time the UAV spends in the area increases, the proportion of enemy classified per hour decreases, requiring slightly more contemplation but also making sense. The longer the UAV searches, new contacts become sparse. Additionally, the target rich environments are visited first, providing more opportunity for classifications. This also makes tactical sense since it is quite reasonable to send a search asset to survey the most likely enemy sites first. The rate at which classifications occur decreases over time.

The interaction term indicates the significant relationship between sweep width and reactivity. It may seem better to have a wide sweep width. However, when the sweep width is high and the UAV is employed with a propensity to follow unidentified

contacts until classified, the greater sweep width can accumulate too many unknown contacts. This has a negative effect on the proportion classified per hour due to a conflict of interests. The UAV cannot follow all unidentified contacts in this case and performs poorly.

Figure 23 displays this interaction in the top-middle and left-center row plots. For two different levels of reactivity, 10 and 90 for example, varying the sweep width has a different effect. This is depicted in the left center plot by the non-parallel curves. The red curved line, with a value of 10, indicates minimal desire to chase unclassified contacts and a desire to stay on the route. In this case, as sweep width is increased, the point of diminishing return is reached later than in the case depicted by the blue line. The blue line, with a value of 90, indicates a high propensity to follow unclassified contacts vice follow routing. When the UAV is more inclined to follow the unclassified contacts, a point of diminishing return is reached more quickly because it develops too many competing interests more quickly.

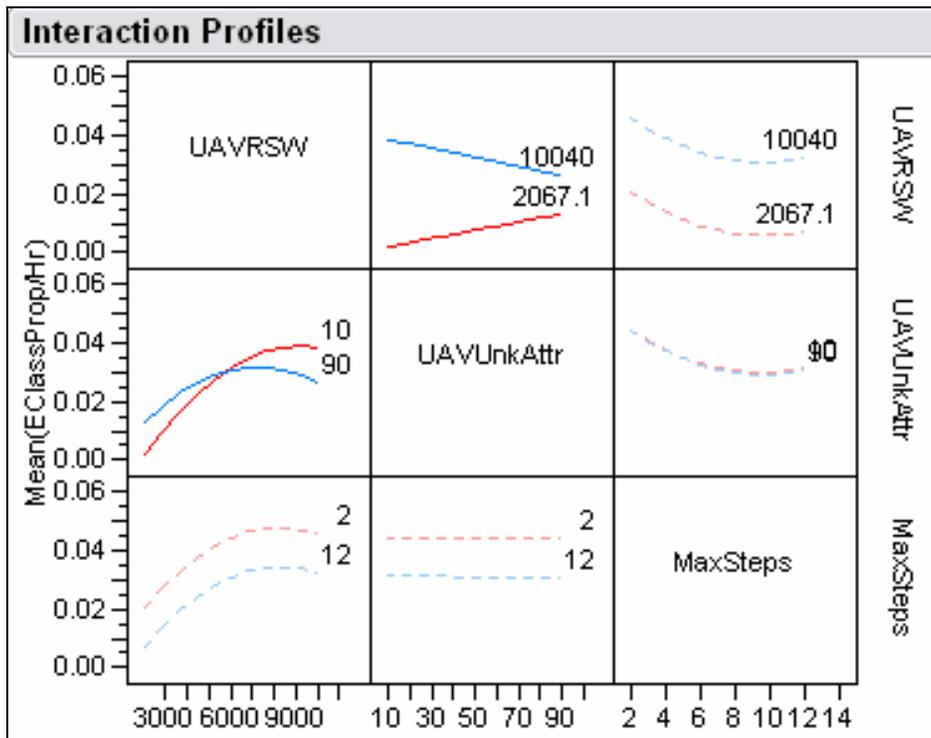


Figure 23. Interaction plots between UAV sweep width, UAV probability of classification, and max steps. The display shows the presence of an interaction between SW and PClass and the nonlinear effects of SW and time. [Best viewed in color]

In the top middle plot, the effect of varying reactivity is different for a sweep width of 2,067 meters, in red, compared to a sweep width of 10,040 meters, in blue. The difference in slopes between the two lines is clear. Increasing the reactivity of the UAV with the large sweep width has a negative effect. The wider the sweep width becomes, the more unclassified contacts the UAV detects, and the harder it is to classify each. The UAV is overtasked. Conversely, when the sweep width is low, increasing the reactivity helps the under tasked UAV find more enemy contacts.

The sweep-width-squared term indicates a point of diminishing returns for sweep width. As sweep width increases, holding all other factors constant, the mean enemy proportion classified per hour increases up to a certain point. This makes intuitive sense. As discussed in the previous chapter, increasing the sweep width without increasing the capability of the sensor to achieve the equivalent single glimpse probability of classification may result in a decrease in performance at some point.

The squared term for time the UAV is on station, indicates that there is not just a simple linear relationship explained by the main effect term, but that endurance has a point of diminishing return as well. Figure 23 displays the interactions of endurance as dashed lines indicating no significant interaction with the other variables. Each plot runs parallel with respect to the interaction term. However, the nonlinear effect of “max steps” can clearly be seen. In both plots on the right side of Figure 23, as max steps varies, the mean classification proportion per hour decreases in a curvilinear fashion. Although the mean proportion of enemy classified per hour decreases over time, the rate of decrease diminishes as well. It appears that about seven hours is the point at which the curve levels off.

The significance of each of these factors can be visualized using leverage plots. The leverage plot shows for each point what the residual would be with and without that effect in the model. (JMP User’s Manual, 2002) Figure 24 displays the effect each term has on mean proportion of enemy classified per hour. As the factor level is varied across the bottom, while holding all other terms constant, the effect on the MOE can be referenced on the left. The terms with a greater effect have a line with a steeper slope. Sweep width has the largest impact and appears with the greatest slope. Probability of

classification, the second most significant factor, is very close in significance, as the associated plot in Figure 24 is nearly as steep as the sweep width plot. In this manner, relative significance can be visualized for each of the effects.

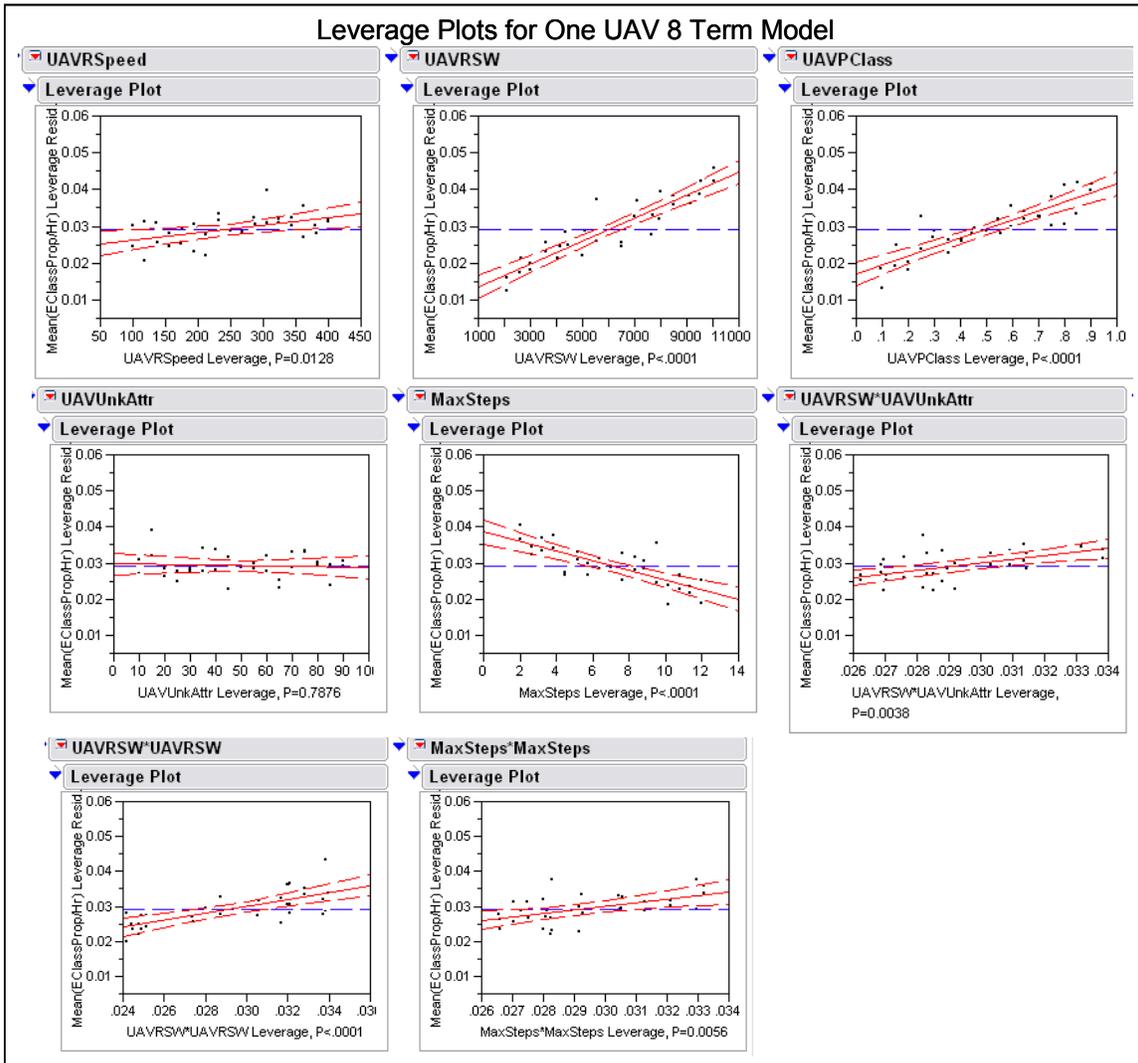


Figure 24. Leverage plots of one UAV preferred model terms indicating degree to which each term affects the MOE, mean proportion of enemy classified per hour.

C. CLASSIFICATION AND REGRESSION TREES

Classification and Regression Trees (CRTs) are good tools for creating decision trees and provide another way to analyze the relationship between factors and the MOE. A regression tree is a recursive partition of the raw data into sets of inputs containing

similar responses. Partitioning of the data occurs successively according to the optimal splitting value determined from all possible values of each available variable. The optimal splitting value is the value of the predictor variable that minimizes sum of square error amongst all predictors. After each split, the next optimal split is determined within each partition. This may be the same variable as the initial split or a different variable obtained from all available factors and can be different for each partition. Considering each partition independently of the previous splits automatically accounts for interactions. This continues until the improvement in fit falls below user specified levels. Again, we must balance fit with parsimony. The concept is complex, but the resulting model is easy to understand.

Figure 25 displays a recursive split of the raw data from all 43,560 MANA runs on all controllable factors and uncontrollable factors for the one UAV scenario. As partitioning of the data proceeds, the most significant factors produce the first categories. The splitting point for a factor range suggests an upper or lower limit for that factor capability producing significant improvement in the MOE. Each box indicates the optimal factor and the optimal level to divide upon. Details within the box include the number of data points within the split, the mean enemy classification proportion per hour and the standard deviation within the split.

This analysis complements the regression analysis in the previous section. Again, all of the terms in the tree are controllable factors. The first split is made on UAV sweep width. This is the single most significant factor in this scenario. The decision tree also provides the optimal split point at about 4,430 meters. Based on the analysis for this Sea Viking scenario, over the ranges examined, a system with a sweep width greater than 4,430 meters can be expected to provide a rate of enemy proportion classified over two times greater, on average, than a system with sweep width below 4,430 meters, 0.0348 and 0.0166 respectively.

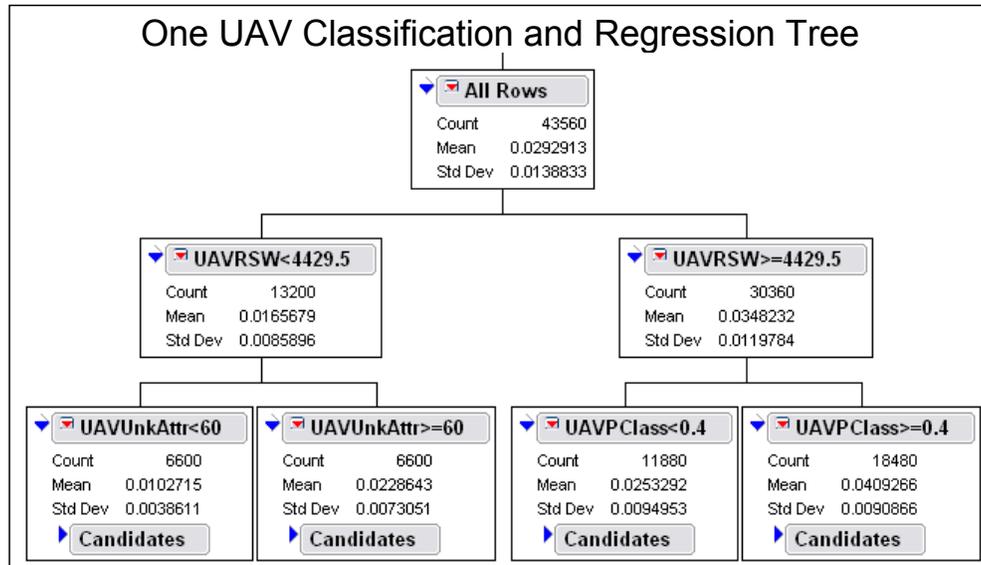


Figure 25. Decision tree split on the raw data by proportion of enemy classified per hour for each MANA run of the one UAV scenario, considering controllable and uncontrollable factors. The tree indicates the overall significance of sweep width and probability of classification, and the interaction with reactivity.

The next most important factor is probability of classification. If sweep width is above the optimal minimum of 4,430 meters, ensuring the sensor capability provides at least a 40% probability of classification for the expected environmental and geographic conditions will provide over a 60% increase in the expected proportion of enemy classified per hour.

The next significant factor explaining performance is reactivity when the UAV sweep width is less than 4,430 meters. In this case, employing a more reactive UAV will increase the proportion of enemy classified per hour. The additional information gained from following unclassified contacts may be acted upon and provides an increase in performance.

Two factors are noticeably missing from the CRT: UAV Speed and Time. These factors appeared in the regression analysis, but even when this CRT extends several more levels, these factors do not show up as might be expected. Their significance is substantially less than the primary factors brought out by the decision tree.

This brings up the possibility of another MOE, namely proportion of enemy classified per mission. This MOE captures the effect of the entire mission whereas the original MOE captures the time effect as a rate. By considering the total enemy classified during a mission, the effect of time may become more apparent.

With this new MOE, or MOE 2, proportion of enemy classified per mission, a new CRT tree is developed and appears in Figure 26 below. As expected, time, in this case max time, is the primary factor when considering the total amount of enemy classified during a mission. A UAV on station at least seven hours will classify nearly twice the proportion of the enemy than a UAV with fewer than seven hours on station time when averaged over all the other variables. Additionally, given seven hours to search, much greater probability of classification is required to produce a significant increase in classifications. This suggests endurance may make up for short comings in sensor capability.

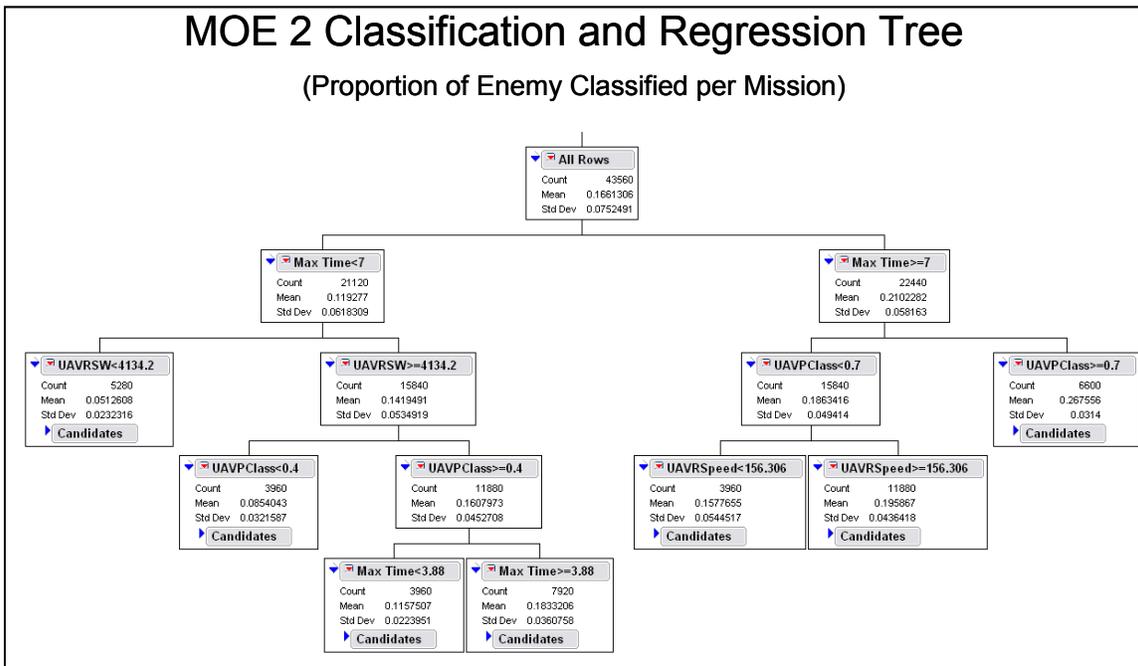


Figure 26. CRT split on the raw data by proportion of enemy classified per mission for each MANA run of the one UAV scenario, considering controllable and uncontrollable factors. The tree indicates the significant time effect and the appearance of speed while retaining previous decision factors.

The effect of sensor capability, namely sweep width and probability of classification, appear similarly in this model as they did in the previous CRT. A brief study of the second decision tree in Figure 26 reveals that, on average, a UAV with a sweep width greater than 4,200 meters and a probability of classification of 0.4 or more can classify approximately 18% of the enemy in this scenario in about four hours. This provides a good reference point in determining factor effects.

Speed appears in Figure 26 when the UAV is going for over seven hours and has a probability of classification less than 0.7. Compared to the other splits, the effect is minimal making it the sixth, and last, one to appear. At speeds over 160 knots the proportion of enemy classified increases by less than 30% on average. A sweep width greater than about 4,200 meters with fewer than seven hours available nearly triples the expected proportion of enemy classified.

V. CONCLUSIONS

The purpose of computing is insight, not numbers.

-Richard Hamming

A. ANALYSIS SUMMARY

The data obtained from the design of experiments and the Sea Viking scenario implemented in MANA for this study provide normally distributed data points from which to conduct statistical analysis. The uncontrollable factors, or noise, imposed in this scenario produce statistically significant effects on the MOE, but not practical effects. This allows for simplification of the data into aggregated points over the noise and further analysis which focuses on the controllable variables.

This study uses two analysis techniques to look at the proportion of enemy classified per hour: multiple regression analysis and Classification and Regression trees. The two analyses complement each other. Each analysis identifies similar factors of greatest importance, key interactions, and provides similar insights. In contrast, the regression analysis yields formulae for predicting UAV performance for capability combinations not explicitly modeled in the simulation. Additionally, relative effects of one capability set can be compared to others using the information from regression analysis. The Classification and Regression Tree analysis provides a hierarchical view of the factors. The splits define factor levels as a minimum or maximum goal to keep in mind.

The regression analysis on this aggregate data produces a good fitting model for the single UAV scenario. Sweep width and probability of classification have dramatically more significant effects on the proportion of enemy classified per hour than the other factors for the ranges and factors considered. This makes sense and lends credibility to the modeling. Interactions between the factors indicate the degree to which the factors must be considered together. As expected, sweep width, probability of classification or sensor capability, and reactivity or employment philosophy are related and insight is provided regarding these relations.

Decision points for primary factors are indicated. A sweep width above about 4,500 meters provides a significant increase in the proportion of enemy classified per hour. A sensor package providing at least 0.4 probability of classification per glimpse for contacts within its intended environment will significantly improve performance with regard to the proportion of enemy classified per hour.

The absence of time and speed in the CRT led to the value of a second performance measure: proportion of enemy classified per mission. The decision tree based on this MOE brings to light the value of having a UAV with an on station time of at least seven hours. The significance of speed is once again revealed as minimal in this scenario.

Using the analytical model obtained from this analysis, predictions of the relative performance expected for other capability sets in this scenario can be evaluated. The decision points provide a threshold value to keep in mind in the development of systems with regard to relative expected performance in this scenario. By decomposing the data according to the decision points, further analysis can provide a more accurate picture of the effects of the factors on the MOE.

Minor anomalies are present in the two and three UAV scenario which warrant additional analysis and iterations. Models based on the current information are in Appendix B. They are consistent with the insights for the single UAV scenario.

B. KEY TACTICAL INSIGHTS

The most important factor when considering time sensitive Intelligence Preparation of the Battlespace in the Sea Viking Scenario is the sweep width of the UAV. In general, wider sweep widths yield higher expected proportions of enemy classified each hour—often more than twice as much. This is qualified by the assumption that the sensor package can maintain a fairly high probability of classification as the sweep width increases. In less than seven hours, a UAV/sensor package capable of producing a probability of classification of at least 0.4 over a 4,500 meter sweep width may be expected to produce rate of enemy classification nearly three times greater, on average,

than a UAV that does not meet these standards for the scenario detailed in this study. This may be crucial in a time constrained situation.

In consideration of mission success, or classifying the largest proportion of the enemy during the course of a mission, a UAV on station at least seven hours is most valuable in this scenario. This time on station may mitigate many of the shortcomings in sensor capability or speed of the UAV. On the other hand, with fewer than seven hours time on station, the factors discussed above for time sensitive gathering of intelligence provide the greatest proportion of enemy classified per mission in the Sea Viking scenario.

Whether considering a rate of classification or the proportion classified for an entire mission, use of tactical routing is more effective than traditional search patterns. This makes tactical sense and lends credibility to the model. For employment considerations, the more intelligence that is available the more important it is to follow routing as opposed to chasing unclassified contacts. The balance between reactivity and strictly following a route is difficult to quantify. With that caveat, reserving about one-third of the on station time for chasing unknowns and using the remainder to follow a tactical route appears to be the best combination for the Sea Viking scenario. A large sweep width and low probability of classification may result in too much wasted time if reactivity is high. Conversely, high reactivity can be effective if the sweep width is low.

C. ADDITIONAL INSIGHTS

Many insights have been realized in the course of this analysis. The most significant appear in the previous section. The following is a list of additional insights surfacing during this work.

- Speed has a positive effect on UAV classification performance. However, speeds greater than 200 knots provide little improvement in ability to classify enemy. Certainly there are other important reasons to have a fast UAV which should be considered, for example dash speed.
- Increasing sweep width when minimal enemy intelligence is available will increase the proportion of enemy classified. However, there is a point of diminishing return when task saturation becomes an issue. This is especially true if the probability of classification is too low.

- Two UAVs do not provide twice the classification ability; however there is improvement over a single UAV. Three UAVs seems to have a more synergistic effect, doubling the expected proportion classified with two UAVs in this scenario given the routes examined.
- Agent-based models and data farming techniques provide an efficient means to view the effects of a variety of parameters. Unknown values may be farmed to provide insights to parameter effects without explicit modeling of capabilities which may be unknown and previously guessed.
- Creative modeling is required in Agent-based Modeling. The point is quick turnaround and insights into interactions and focusing further analysis. Using readily available MOEs in a particular ABM can enable more effective and capable analysis.

D. FOLLOW ON WORK

The following is a list of follow on research of value that could be accomplished utilizing this work:

- Analysis of factors effecting classification of time critical targets
- Analysis of effects of the terrain
- Data analysis on Multi-UAV data
- Further development and enhancement of the Excel tool for parameter exploration
- Focused analysis over the key parameters and ranges identified
- Analysis of the effect of a much larger neutral to enemy ratio
- Repeat analysis in an OIF based scenario

The following is a list of follow on research of value stemming from this research:

- Validation/comparison of the MANA Sea Viking scenario with a similarly developed scenario in Combat XXI
- Development of a model addressing the dynamic retasking issue
- Development of a model addressing the multiple concurrent operations issue
- Development of a model focusing on the Global Hawk Maritime Demonstration for the Maritime Patrol and Reconnaissance Force
- Analysis of the available sensor packages and development of expected probabilities of classification

- Reliability study determining the number of UAVs required to support a Sea Viking scenario
- Human factors study determining effective screening and classification techniques integrating the man and the machine
- Analysis of distributed communications flow for a network centric environment incorporating multiple UAVs for sensing and shooting

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APPENDIX A. SEA VIKING 04 SCENARIO DETAILS

The following slides are taken directly from the Sea Viking Scenario brief and describe the enemy situation for the scenario. (Marine Corps Warfighting Lab, 2003)

Game/Exercise Assumptions

- Play will remain at the JTF level and below, regional powers are not and will not become hostile
- Limited Host Nation Support, no port or airfield in JOA
- Very restricted basing in theater
- Timeframe: April or October? 2015
- Area of Play: SE Asia
- Classification: Unclassified
- Force Levels: MEB / ESF equivalent
- Game/Exercise play: Operational/Tactical
- Sea base minimum OTH (25nm at sea)

Red Objectives

- Goals: Gain independence
- Methodology:
 - Survive until Central Government collapses “Fait Accompli”
 - Avoid direct conflict with Coalition forces
 - Invite NGOs into conflict area
 - Invite international media, showcase civilian deaths
 - Repeatedly stress “Caliphate” does not desire hostilities
 - Ask for UN brokered cease fire
 - Promise to act decisively to end piracy within territorial waters
 - Offer to hold elections in 2 years
 - Portray self as small Muslim nation attacked unjustly by rich Christian crusaders
 - If conflict unavoidable, attempt to draw coalition forces into a MOUT/Jungle fight

Red Order of Battle

Air – IADS (mobile SA-10/20,13,8, & 6?). Adding Ships with increased AD cap (HQ-61).
 AAA – RBS-90 Bolide, 2S6M (SP 30mm/SA-19)

TBM – CSS-2 IRBM, 6 mobile launchers, 2 x reloads, 6 decoys.

Air Force: 72 – SU-27 Flanker, and 72 – SU-25 Frogfoot, 36 – Foxhounds, 2 B-727 AEW,
 3 KC-130 Refuelers

Land – 6 SPF Brigades. Mobile Artillery (VTT-322, 2S23) with smart sub-munitions and
 passive counter battery capability (SORAS). PT-76 upgraded thermals, shoot on move,
 90mm. Decentralized Infantry Operations (Fire and Forget Soldiers).

Local Constabulary and irregulars.(need to establish # & Loc)

Naval – 6 Kilo 636 (w ASCM), patrol craft/missile patrol craft, mines, and armed militia
 in small civilian craft.

Naval Air – 8 Fokler 27's Maritime Patrol Aircraft (Joint real-time targeting)

Naval Coastal Defense – 3 Batteries mobile ASCM's (YJ-82 ASCM) 1 Naval Inf Bde to
 protect ASCM and base.

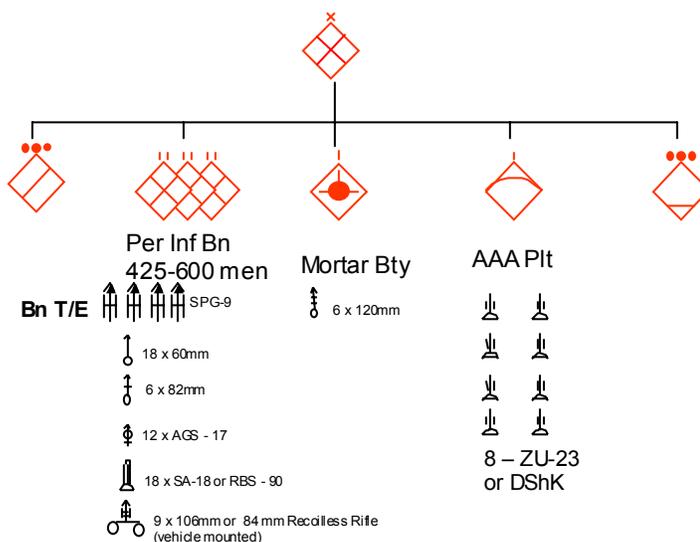
Electro-Magnetic – Jamming / spoofing capability (radio and GPS) Computer Network
 Attack?

Space – Access to commercial space assets. Controls major Green satellite terminal

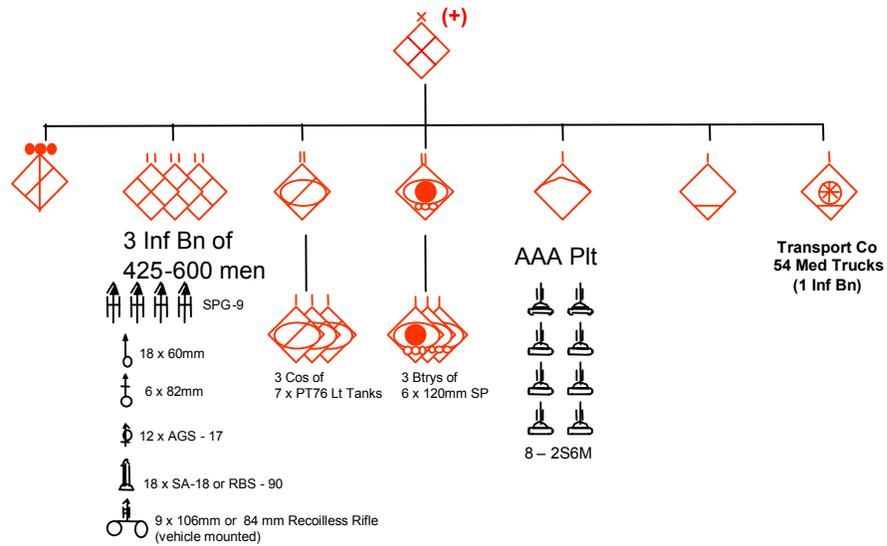
WME – Red commercial and research facilities are capable of make biological and
 chemical weapons.

The following force structure is for the enemy units portrayed in the Sea Viking
 04 scenario. (Marine Corps Warfighting Lab, 2003)

Light Brigade x 3

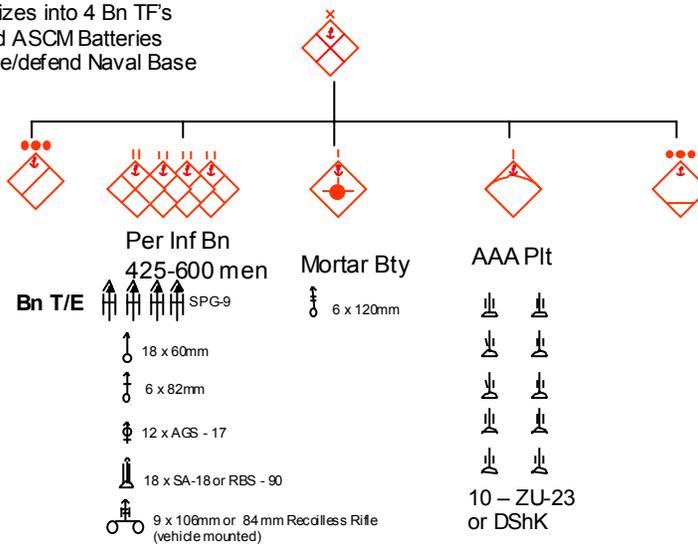


Reinforced Brigade x 3



Naval Infantry Brigade x 1

BDE mobilizes into 4 Bn TF's
 3 to defend ASCM Batteries
 1 in reserve/defend Naval Base

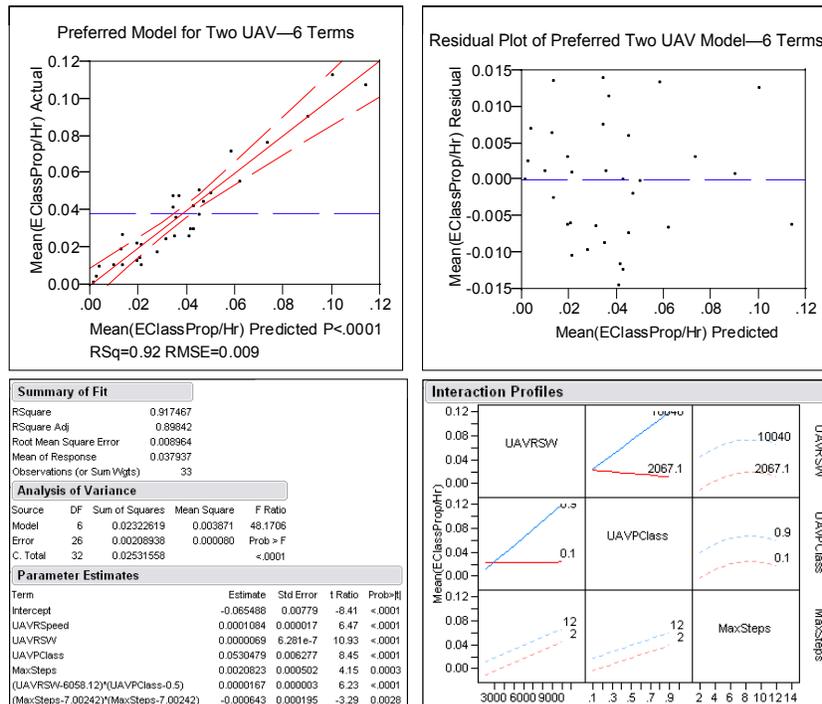


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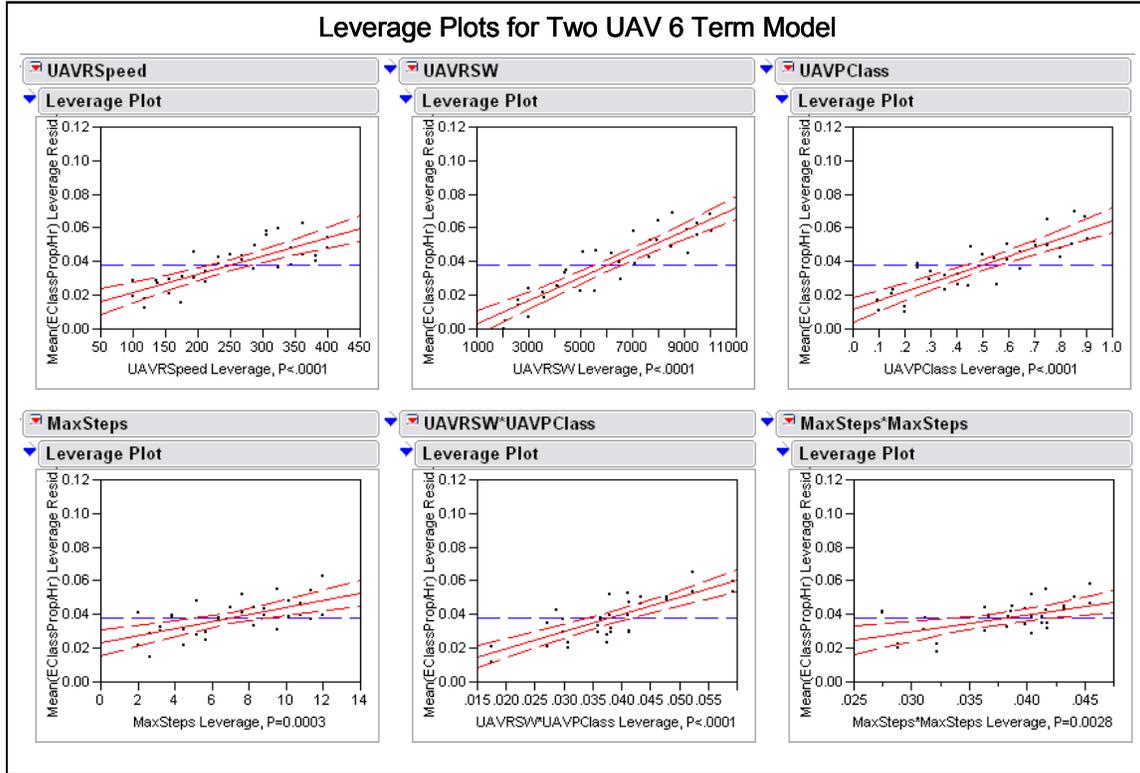
APPENDIX B. REGRESSION MODELS FOR MULTI-UAV SCENARIOS

Anomalies discovered during data analysis prompted additional iterations of various design points for the multi-UAV scenarios. Due to time constraints and the need for still more runs, detailed analysis of the multi-UAV scenarios is not presented in this work. Some insights from the data may be gained, but the statistical rigor to support them is lacking at this point. It is highly encouraged that further research investigates this data.

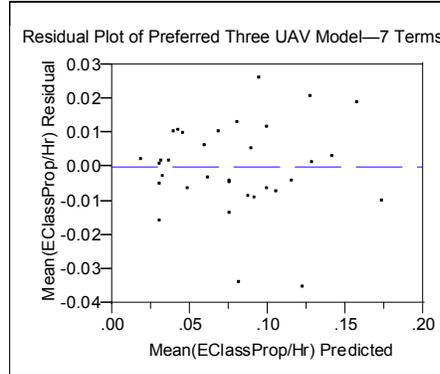
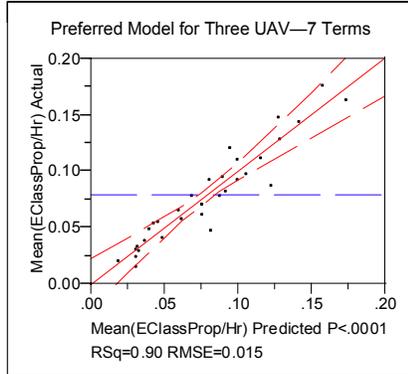
The model produced for the two UAV scenario, displayed below, is very similar to the model for the one UAV scenario, with a couple exceptions. The reactivity terms drop out earlier and are not included in the preferred model and a strong interaction between sweep width and probability of classification appears. The reactivity terms are statistically significant, and they could be included in the model, however they do not provide the level of practical significance seen in the single UAV case. The interaction between sweep width and probability of classification appears similarly in the decision tree analysis for the single UAV model.



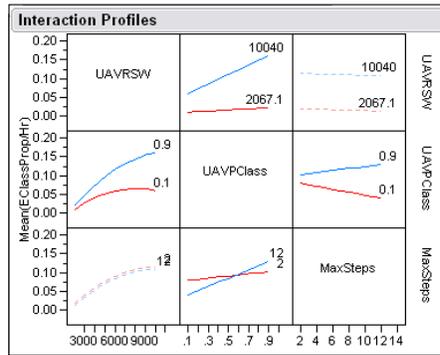
The leverage plots for the two UAV scenario, displayed below, show the relative effects of the terms in the preferred model. Time has a positive effect here as opposed to the negative effect seen in the single UAV model.



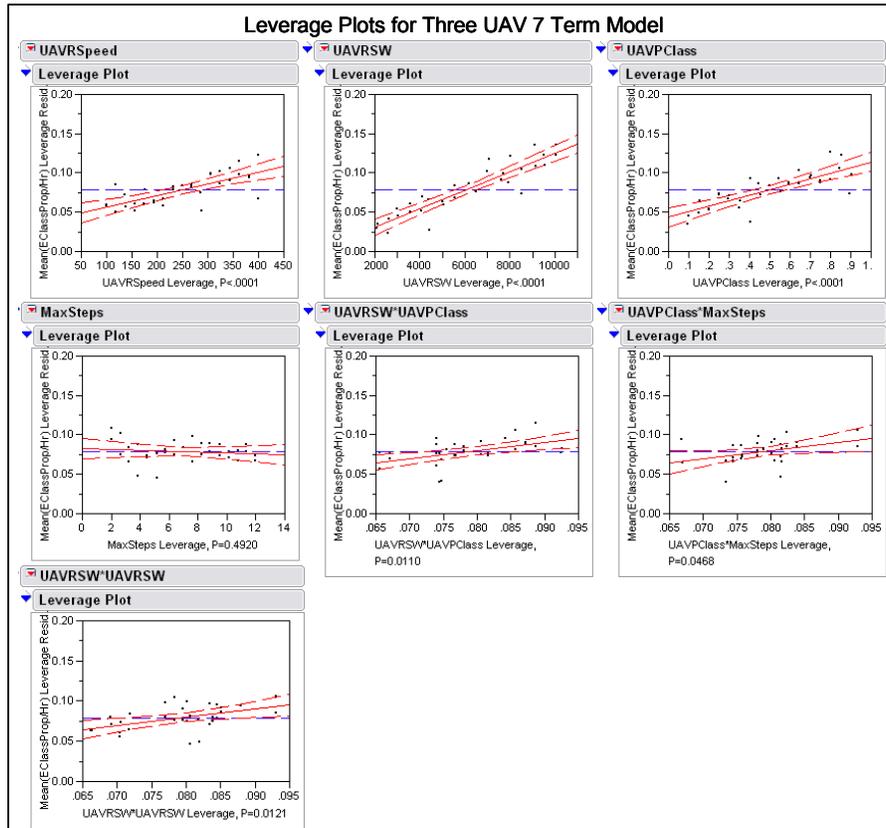
The model produced for the three UAV scenario, displayed below, is similar to the two UAV model with the addition of a sweep width squared term and an interaction between time and probability of classification.



Summary of Fit				
RSquare		0.90207		
RSquare Adj		0.87465		
Root Mean Square Error		0.014991		
Mean of Response		0.078766		
Observations (or Sum Wgts)		33		
Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	0.05175104	0.007393	32.8979
Error	25	0.00561814	0.000225	Prob > F
C. Total	32	0.05736918		<.0001
Parameter Estimates				
Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	-0.051468	0.013099	-3.93	0.0006
UAVRSpeed	0.0001505	0.000028	5.37	<.0001
UAVRSW	0.0000117	0.000001	11.16	<.0001
UAVPClass	0.0702681	0.010497	6.69	<.0001
MaxSteps	-0.000586	0.000084	-0.70	0.4920
(UAVRSW-6058.12)*(UAVPClass-0.5)	0.000014	0.000005	2.75	0.0110
(UAVPClass-0.5)*(MaxSteps-7.00242)	0.0083719	0.004003	2.09	0.0468
(UAVRSW-6058.12)*(UAVRSW-6058.12)	-1.505e-9	5.56e-10	-2.71	0.0121



The leverage plots for the three UAV scenario, displayed below, show the relative effects of the terms in the preferred model. Sweep width is most significant as displayed by the steep slope of the sweep width plot. Time has a negative effect on the rate of enemy proportion classified, similar to the effect seen in the one UAV model.



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