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THESIS

EMPLOYMENT OF INTELLIGENCE, SURVEILLANCE, AND RECONNAISSANCE DRONE SWARMS TO ENHANCE GROUND COMBAT OPERATIONS

by

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On August 27, 2015, the Naval Postgraduate School's (NPS) Advanced Robotic Systems Engineering Laboratory flew 50 autonomous drones simultaneously. This demonstration proved that autonomous drone swarm technology is evolving at a daunting pace and drone deployment and control can now be done en mass. As academia, industry, and defense sectors continue to miniaturize sensors and enhance swarm operating systems, the transition from demonstrations to tactical employment will occur quickly. Doing so efficiently requires dedicated efforts to determine swarm sensor requirements and employment tactics, techniques, and procedures. This thesis uses agent-based simulation, cutting-edge design of experiments, and parallel computing to thoroughly explore drone swarm employment in support of a Marine infantry company. The scenario is a deliberate clearing mission, based on real events, in which an infantry company fights a peer enemy in restricted terrain. Analysis of the data obtained from 30,000 simulated missions reveals that, on average, the drone swarms enable the fire support team to target and engage twice as many enemy combatants when compared to the current ISR drone available at the company level. For the hierarchical swarm, this results in up to 50% fewer U.S. casualties. Data analysis and visual study of the emergent swarm also shows that the volume of the swarm, coupled with inherent sensor overlap, results in the largest reduction in sensor requirements.

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EMPLOYMENT OF INTELLIGENCE, SURVEILLANCE, AND RECONNAISSANCE DRONE SWARMS TO ENHANCE GROUND COMBAT OPERATIONS

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ABSTRACT

On August 27, 2015, the Naval Postgraduate School's (NPS) Advanced Robotic Systems Engineering Laboratory flew 50 autonomous drones simultaneously. This demonstration proved that autonomous drone swarm technology is evolving at a daunting pace and drone deployment and control can now be done en mass. As academia, industry, and defense sectors continue to miniaturize sensors and enhance swarm operating systems, the transition from demonstrations to tactical employment will occur quickly. Doing so efficiently requires dedicated efforts to determine swarm sensor requirements and employment tactics, techniques, and procedures. This thesis uses agent-based simulation, cutting-edge design of experiments, and parallel computing to thoroughly explore drone swarm employment in support of a Marine infantry company. The scenario is a deliberate clearing mission, based on real events, in which an infantry company fights a peer enemy in restricted terrain. Analysis of the data obtained from 30,000 simulated missions reveals that, on average, the drone swarms enable the fire support team to target and engage twice as many enemy combatants when compared to the current ISR drone available at the company level. For the hierarchical swarm, this results in up to 50% fewer U.S. casualties. Data analysis and visual study of the emergent swarm also shows that the volume of the swarm, coupled with inherent sensor overlap, results in the largest reduction in sensor requirements.

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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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LIST OF ACRONYMS AND ABBREVIATIONS

A2AD	Anti-Access and Area Denial
ABS	Agent-Based Simulation
ADP	Army Doctrine Publication
AGL	Above Ground Level
AIC	Akaike Information Criterion
ARSENL	Advanced Robotic Systems Engineering Laboratory
AV	Aerial Vehicle
C2	Command and Control
COTS	Commercial Off-the-Shelf
DoD	Department of Defense
DOE	Design of Experiment
DP	Design Point
EO	Electro-Optic
FiST	Fire Support Team
FOV	Field of View
GCS	Ground Control Station
GP	General Purpose
HQ	Headquarters
IAR	Infantry Automatic Rifle
IDF	Indirect Fire
IED	Improvised Explosive Device
ISR	Intelligence, Surveillance, and Reconnaissance
JCS	Joint Chiefs of Staff
MANA	Map Aware Non-Uniform Automata
MANA-V	Map Aware Non-Uniform Automata Version V
MARSS	Multi-Agent Robot Swarm Simulation
MCDP	Marine Corps Doctrinal Publication
MCWP	Marine Corps Warfighting Publication
MOC	Marine Corps Operating Concept
MOE	Measure of Effectiveness

MQ-1	Predator Drone
MQ-9	Reaper Drone
M&S	Modeling and Simulation
NCW	Net Centric Warfare
NOLH	Nearly Orthogonal Latin Hypercube
NPS	Naval Postgraduate School
NSS	National Security Strategy
RC	Radio Control
SA	Situational Awareness
SCUD	Western Name for Early Soviet Missile Series
TTP	Tactics, Techniques, and Procedures
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle
U.S.	United States
USA	United States Army
UV	Uninhabited Vehicle
VTOL	Vertical Take-Off Landing

EXECUTIVE SUMMARY

For the last thirty years, the United States (U.S.) military enjoyed unchallenged supremacy as the world's most technologically advanced fighting force. During conflicts in Iraq and Afghanistan, the U.S. military employed net centric warfare with devastating effect and efficiency (Scharre, 2014). However, after sixteen years of sustained combat operations, geo-political competitors and belligerent non-state actors are challenging the U.S. military's ability to maintain "all domain access" within the global commons (Trump, 2017).

As the world community shifts from a unipolar paradigm to a multipolar system, future operating environments promise to be even more complex and chaotic. The 2016 Marine Corps Operating Concept (MOC) warns that the nation's adversaries are taking advantage of technology proliferation, deploying hybrid forces, and using robust anti-access and area denial (A2/AD) capabilities to challenge the U.S. military at all levels of warfare. Further complicating matters, improvised explosive devices (IEDs), commercial drone systems, and cyber tools continue to become more affordable and are improving at an alarming rate. As the nation's enemies become more proficient with these technologies, they will seek to gain leverage over local populations and engage in urban conflicts to mitigate U.S. advantages in mounted maneuver and firepower (United States Marine Corps [MOC], 2016).

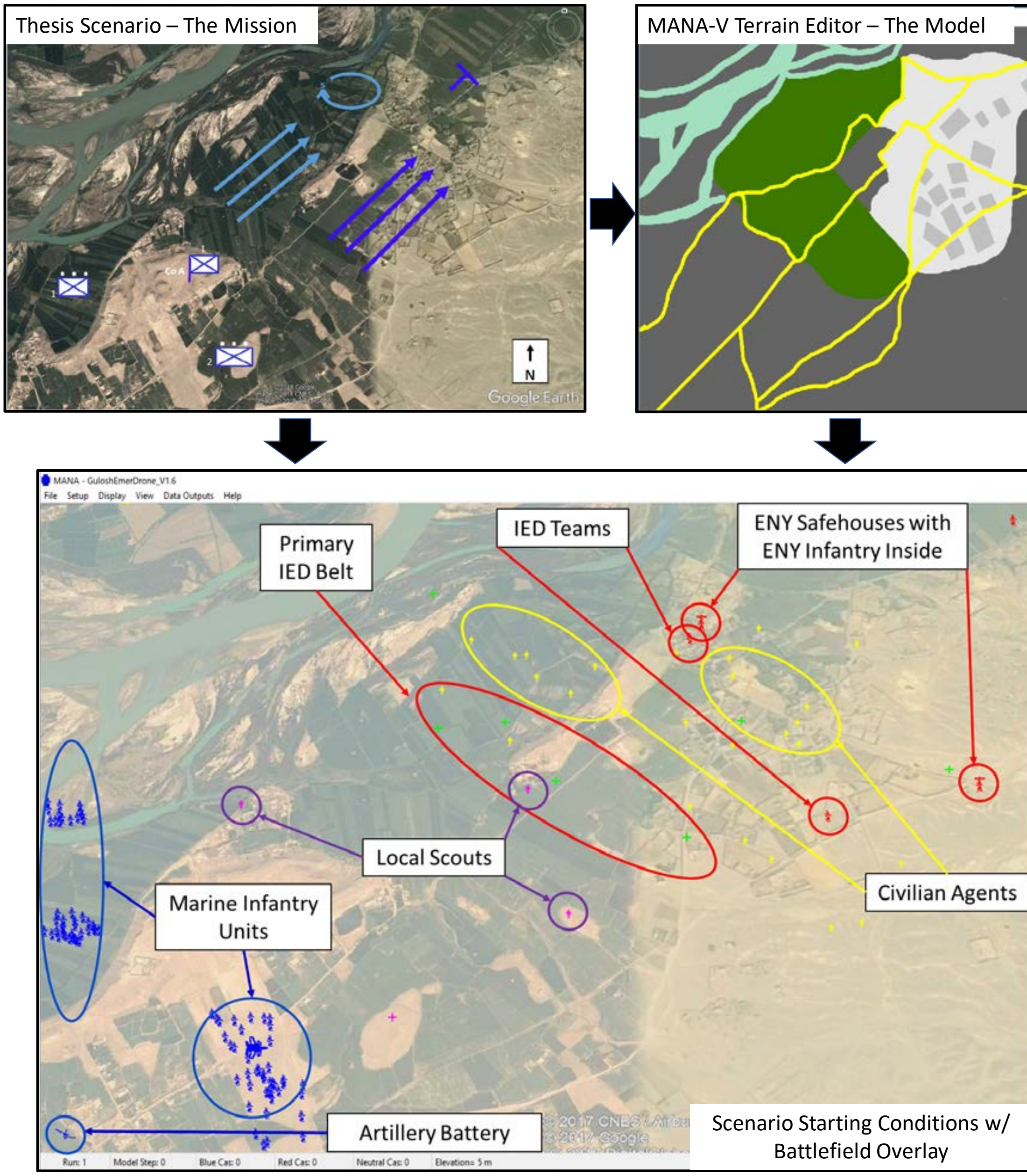
To prepare for the future operating environment and ensure access across the range of military operations, the U.S. needs to seek new and innovative ways to regain the tactical advantage (Trump, 2017). Although the Department of Defense (DoD) will need many technologies to combat these emerging threats, autonomous swarms are maturing at a rapid pace and offer viable solutions for gaining access to areas either unreachable or too dangerous to send military personnel (Scharre, 2014). Over the last ten years, significant efforts in the robotics research community have progressed autonomous swarm technologies from mere concept to reality.

Currently, the Naval Postgraduate School (NPS) is at the forefront of autonomous drone swarm technology. On August 27, 2015, NPS's Advanced Robotic Systems Engineering Laboratory (ARSENL) set a record by flying 50 commercial-off-the-shelf (COTS) autonomous drones simultaneously (Chung et al., 2016). Since this ground-breaking event, other national laboratories have built upon this technology and deployed nearly twice that number. Thus, as ARSENL and other peer programs continue to enhance drone hardware and swarm operating systems, the transition from experimentation to employment may occur quickly. Undoubtedly, simulation and experimentation will define how 21st Century forces employ swarms on future battlefields.

This thesis uses agent-based simulation (ABS), cutting-edge design of experiments (DOE), and parallel computing to thoroughly explore drone swarm employment in support of a Marine infantry company. Through the execution of 30,000 simulated battles, the thesis quantifies swarm system performance under combat conditions. The primary thesis questions focus on how command and control (C2) configurations, system operational thresholds, and swarm scaling affect overall unit performance. Collectively, the research seeks to inform decision makers on how different control strategies affect swarm performance and sensor requirements.

The author uses the ABS modeling environment MANA-V to create a realistic battlefield and appropriately capture the complexity and autonomous nature of the swarm. The thesis scenario is a real-world mission set experienced by the author while deployed in support of Operation Enduring Freedom. The simulation realistically depicts a challenging hybrid threat that seeks to deny U.S. forces access to an enemy stronghold. Furthermore, the drone swarm is modeled after the ARSENL C2 architecture. The ARSENL architecture and the author's combat experiences serve as the basis for this study.

MANA-V is an agent-based, time stepped, stochastic modeling environment intended for "quick turn," mission-level analysis (Lucas, 2015). For a decision maker or lead analyst, MANA-V provides mission visualization, valuable insight into an evolving battle, and intuition on sensor employment (McIntosh, Galligan, Anderson, & Lauren, 2007). As an analytic tool, MANA-V provides an intuitive interface to efficiently build scenarios and a data farming capability which allows a research team to run multiple experiments over a broad range of factors (Zappa, 2009). Figure ES-1 shows a simplified version of how a real operational environment is converted into a MANA-V terrain map and built into a combat model.



(Map chip is adapted from Google Maps 2018) [Best viewed in color]

Figure ES-1. Translating the Real World into a Model. Initial Starting Conditions for the Thesis Scenario

The conclusions for this thesis are grounded in a realistic model, efficient design of experiments, and the rigorous analysis of three experiment sets that produced unique results for 30,000 simulated battles. The thesis findings show that different unmanned aerial vehicle (UAV) control strategies have a profound effect on sensor coverage, indirect fire employment, and unit casualties. Six primary findings include:

- The hierarchical swarm demonstrates the greatest potential for casualty reduction and can do so with fewer UAVs than the emergent swarm. When implementing the preferred swarm configuration, Blue force casualties can potentially be reduced by 50 percent.

- On average, both drone swarms enabled the FiST to target and engage two to three times more enemy targets than the singular ISR drone.

- Data analysis and visual study of the emergent swarm show that the volume of the swarm, coupled with inherent sensor overlap, results in the largest reduction in sensor requirements.

- The preferred employment strategy for the hierarchical swarm calls for two subswarms of six drones. Each subswarm consists of two verification and four seeker drones. Under scenario conditions, 48 UAVs are needed to provide ISR for the company during the 2.5-hour battle.

- The preferred employment strategy for the emergent swarm recommends deploying a 15-drone swarm consisting of three verification and 12 seeker drones. Under scenario conditions, 60 UAVs are needed to provide ISR for the company during the 2.5-hour battle.

- ISR planners must be aware of swarm scaling and its implications on combat service support. Although the preferred employment configurations for the swarms only differ by three drones, the overall mission requirement differs by 12 UAVs. This fundamental concept will be important when developing swarm delivery/launcher platforms.

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I. INTRODUCTION

> A significant advantage can be gained by being first to exploit a development in the art and science of war. A military that is slow to exploit technological advances and adapt new ways of fighting opens itself to catastrophic defeat.
>
> —*The Marine Corps Operating Concept: How an Expeditionary Force Operates in the 21st Century*

A. GAINING ACCESS IN CURRENT AND FUTURE OPERATING ENVIRONMENTS

For the last thirty years, the United States (U.S.) military enjoyed unchallenged supremacy as the world's most technologically advanced fighting force. During conflicts in Iraq and Afghanistan, the U.S. military employed net centric warfare with devastating effect and efficiency (Scharre, 2014). However, after sixteen years of sustained combat operations, peer competitors and belligerent non-state actors are challenging the U.S. military's ability to maintain "all domain access" within the global commons (Trump, 2017). As commercial research and development efforts continue to outpace the military's acquisitions process, "standoff weapons such as surface to air missiles, precision-guided munitions, and armed unmanned aerial systems (UAS) are becoming commonplace" (Marine Corps Operating Concept [MOC], 2016, p. 5)." Adversaries are rapidly taking advantage of this access and establishing robust anti-access and area denial (A2/AD) capabilities across the spectrum of conflict.

With an increase in technology proliferation, the future operating environment promises to be even more complex and chaotic. Rather than facing uniformed enemies in conventional, open conflict, it is likely that U.S. ground forces will fight hybrid threats in challenging, urban terrain (MOC, 2016). Army Doctrine Publication (ADRP) 3–0 defines a hybrid threat as, "the diverse and dynamic combination of regular forces, irregular forces, terrorist forces, criminal elements, or a combination of these forces and elements all unified to achieve mutually benefitting effects" (p. 1–3). Further complicating matters, improvised explosive devices (IEDs), commercial drone systems, and cyber tools will continue to improve and be employed with greater expertise and lethality at low cost. Adversaries will seek to leverage the local population and fight in urban terrain to mitigate U.S. advantages in mounted maneuver and firepower (MOC 2016).

To prepare for the future operating environment and ensure access across the range of military operations, the U.S. needs to seek new and innovative ways to regain the tactical advantage (Trump, 2017). Although many technologies will assist in this effort, advancements in automation, manufacturing, and uninhabited vehicles (UV) offer viable solutions for gaining access to areas either unreachable or too dangerous to send military personnel (Scharre, 2014). Uninhabited vehicles will continue to play a critical role in collecting intelligence, reconnoitering the battlefield, and prosecuting targets; however, as they become more common, the substantial benefits once enjoyed by U.S. forces may be less pronounced.

B. BACKGROUND AND MOTIVATION

Conflicts in Iraq and Afghanistan resulted in a distinct change in the employment of unmanned aerial vehicles (UAVs). Over the two decades, military UAVs conducted long range reconnaissance missions and provided commanders a "real time" picture of the battlefield during mission execution (Newcome, 2004). Following the terrorist attacks on September 11, 2001, the demand for UAVs increased dramatically (Fuhrmann & Horowitz, 2017, p. 1). With mass production of precision guided munitions and the miniaturization of advanced sensors, UAVs transitioned from their traditional reconnaissance role to become premier, strategic strike platforms (Fuhrmann & Horowitz, 2017, p. 1). The undeniable success of platforms like the MQ-1 Predator and the MQ-9 Reaper changed how warfighters view UAS employment and procurement.

Currently, all U.S. military services are seeking to enhance UAV employment by incorporating autonomous operating systems. In 2010, the Department of Defense restated autonomy as the "single greatest theme" for today's unmanned systems (Barry, 2014). More recently, in the Marine Corps' Capstone Operating Concept (MOC) 2016, the Commandant of the Marine Corps, expressed the need to incorporate autonomy into the Fleet stating:

> As we continue to reap the benefits of technological progress in many warfighting areas, we must capture the full potential inherent in automation. Automation can mitigate risk, reducing the exposure of humans to harm, and reduce the workload on personnel…The challenge, as machines become more capable and autonomous, is how to put people and things together in the most effective pairings for the mission at hand (MOC 2016, p. 16).

Just as the airplane circumvented traditional forms of combat power and changed the tactics used to prosecute missions, campaigns, and wars, so too will autonomous drone swarms. Autonomous warfare is “an operational concept that exploits the advantages of unmanned, autonomous, and robotic systems to increase autonomy and freedom for the human warfighter” (Barry, 2014, p.45). In effect, this “produces a comparatively faster tempo for tactical and operational decision-making” (Barry, 2014, p. 45).

Swarming can take on several distinct meanings, but this thesis will use a definition based in a military context. Swarming is a “network of uninhabited vehicles that autonomously coordinate their actions to accomplish a task. The assigned task must be under some degree of mission-level human direction” (Scharre, 2014, p. 29).

Currently, the Naval Postgraduate School (NPS) is at the forefront of autonomous drone swarm technology. On August 27th, 2015, NPS’s Advanced Robotic Systems Engineering Laboratory (ARSENL) set a record by flying 50 commercial off-the-shelf (COTS) autonomous drones simultaneously (Chung et al., 2016). This demonstration proved that not only is drone swarm technology evolving at a daunting pace, but it can now be done in mass.

Since this ground-breaking event, other national laboratories have built upon this technology and deployed even greater numbers. For example, on 16 October 2016, Massachusetts Institute of Technology’s Lincoln Laboratory deployed 103 micro drones from three FA-18 Fighter jets. (Department of Defense [DoD] Press Operations 2017). Thus, as ARSENL and other peer programs continue to enhance drone hardware and swarm operating systems, the transition from demonstrations to experimentation will occur quickly. More importantly, this research and experimentation will define how 21st Century forces employ swarms on future battlefields. In fact, ground forces are already gaining exposure to swarm systems. According to Dr. Kevin Jones, an ARSENL team member, ARSENL swarms are currently used as training aids in the Marine Corps' premier training event, the Integrated Training Exercise (personal communication, November 30, 2017).

In a restrictive fiscal environment, the military needs efficient ways to conduct experimentation and showcase program improvements (Trump, 2017). Now more than ever, program sponsors are challenging innovators to demonstrate their technology's worth and meet the requirements outlined by the Department of Defense (DoD). Simulation serves as the logical tool for showcasing UAV capabilities and tactics in a cost-effective manner. This thesis uses agent-based simulation (ABS) to model the current ARSENL drone swarm architecture and apply the swarm in a combat scenario. Conclusions from the model's outputs can be used to inform drone swarm sensor development, enhancement, and employment in future live-fly field experiments.

C. SCOPE

1. Military Concepts Defined

The following terms explain common military concepts important to understanding the context of this thesis research and the scope of the problem statement:

- Anti-Access (A2) – "An attempt to prevent or degrade the ability to enter an operational area. These challenges can be geographic, military, or diplomatic" (Gordon & Matsumura, 2013, p. xi).

- Area Denial (AD) – "Threats to forces within the operational area. As they relate to U.S. ground forces (the Army and Marine Corps), AD threats are characterized by the opponent's ability to obstruct the actions of U.S. forces once they have deployed" (Gordon & Matsumura, 2013, p. xi).

- Autonomous Warfare – "An operational concept that exploits the advantages of unmanned, autonomous, and robotic systems to increase autonomy and freedom for the human warfighter." (Barry, 2014, p. 45).

- Intelligence, Surveillance, and Reconnaissance (ISR) – "An integrated operations and intelligence activity that synchronizes and integrates the planning and operation of sensors, assets, and processing, exploitation, and dissemination systems in direct support of current and future operations" (Joint Chiefs of Staff [JCS], 2017, p. GL-10).

- Net Centric Warfare (NCW) – "An information superiority-enabled concept of operations that generates increased combat power by networking sensors, decision makers, and shooters to achieve shared awareness, increased speed of command, higher tempo of operations, greater lethality, increased survivability, and a degree of self-synchronization" (Alberts et al., 1999, p. 2).

- Swarming – A "network of uninhabited vehicles that autonomously coordinate their actions to accomplish a task under some degree of mission-level human direction" (Scharre, 2014, p. 29).

- Tactical Level of Warfare – "The level of war at which battles and engagements are planned and executed to accomplish military objectives assigned to tactical units or task forces. Activities at this level focus on the ordered arrangement and maneuver of combat elements in relation to each other and to the enemy to achieve combat objectives" (United States Marine Corps [USMC], 1997, p. 101).

- Unmanned Aerial Vehicle – "Military aircraft that is guided autonomously, by remote control, or both and that carries sensors, target designators, offensive ordnance, or electronic transmitters designed to interfere with or destroy enemy targets" (Unmanned Aerial Vehicle, n.d.).

- Unmanned Aerial System – "A UAS is comprised of an unmanned aircraft, payload, human element, weapons systems platform, display, communication architecture, life cycle logistics, and includes supported troops" (United States Army [USA], 2010, p. 8).

2. The Scope of the Military Problem

Anti-access and area denial (A2/AD) are not new military concepts. To the contrary, past conflicts provide countless examples of adversaries using different types of tactics and technologies to prevent an enemy from gaining access to areas of advantage. This thesis explores the use of autonomous drone swarms to defeat A2/AD technologies at the tactical level. More specifically, the model scenario represents combat experiences from Iraq and Afghanistan, modified to reflect potential threats in the future operating environment.

D. PROBLEM STATEMENT

While A2/AD is not a new phenomenon, emerging technologies and innovative TTPs are allowing adversaries to challenge U.S. interests across the spectrum of conflict. As technology proliferation accelerates and adversaries adapt their strategies to mitigate U.S. advantages in maneuver and firepower, autonomous drone systems will be critical in ensuring U.S. forces can physically access any location, at any time. Whether it is ground troops trying to seize a heavily defended urban objective or naval forces trying to seize a contested port, UASs allow U.S. forces to circumvent physical barriers such as mines, IEDs, or well-developed defensive belts and minimize human exposure to enemy fire.

As experimentation continues and swarms are considered for integration into ground units, many questions need to be answered to ensure that these systems do not inhibit the mobility or effectiveness of a fighting force. This thesis seeks to answer questions in the following two areas:

1. **Integration and Deployment of Swarm Technology**: What capabilities or characteristics do reconnaissance drone swarms need to outperform current ISR capabilities available at the company level? Does the command and control (C2) method used in deploying the drone swarm affect overall measures of effectiveness? Understanding how different control strategies affects swarm performance will enable decision makers to identify which type of swarm they need to accomplish the mission.

2. **System Requirements**: How many drones are needed to support a Marine infantry company conducting clearing operations in complex terrain? Identifying the number of drones needed to support a specific mission type will assist planners in identifying swarm delivery requirements. What sensor parameters are critical to swarm performance? What sensor thresholds make a swarm viable in this scenario? Determining key performance parameters for future sensors will assist program sponsors in specifying system requirements.

E. METHODOLOGY

Swarming networks, microdrone technology, and miniaturized sensors are still in their infancy. This thesis uses ABS to model current drone swarm capabilities and apply them to a real-world mission set experienced in Afghanistan. Through an extensive literature review and conversations with subject matter experts located at NPS, drone swarm agents are modeled after existing drone platforms and ARSENL's swarm C2 architecture. The following research process was implemented to answer the thesis problem statement (modified from Treml, 2013, p. 7):

1. Define Measures of Effectiveness (MOEs) for the different ISR capabilities (i.e., individual drone or drone swarms).

2. Develop and program a real-world scenario in MANA-V to study likely drone swarm employment.

3. Apply design of experiments (DOE) and data farming techniques to establish factor ranges for sensitivity analysis of swarm performance parameters.

4. Run simulations and organize data collection.

5. Identify the most influential model factors affecting the defined MOEs.

6. Apply data analysis techniques to develop metamodels. The metamodels are used to explain factor relationships observed through thousands of simulation battles.

F. THESIS ORGANIZATION

Chapter II is devoted to familiarizing the reader to the major concepts and tools used in this thesis. The chapter reviews drone platforms, defines swarm theory and potential control methods, and discusses Modeling and Simulation (M&S) approaches. Chapter III informs the reader on model methodology and development. The author presents the thesis scenario, covers agent characteristics, and discusses key model assumptions. Chapter IV discusses factor selection, the implementation of the design of experiments (DOE), and the use of the nearly orthogonal Latin hypercube (NOLH) to efficiently and effectively select input combinations to run. Chapter V discusses data collection, post processing, and the data analysis derived from model outputs. Chapter VI presents thesis conclusions and recommendations for future research.

II. APPLICATIONS OF SWARM THEORY, AN INTRODUCTION TO UAS, AND THE MODELING ENVIRONMENT

This chapter discusses concepts used to develop the thesis model. Section 2.A covers swarm theory and how the military seeks to harness the advantages of collective behavior. Section 2.B explains the basic elements of unmanned aerial systems (UAS) and introduces unmanned aerial vehicle (UAV) characteristics. Section 2.C defines modeling and simulation (M&S) and how the military uses M&S to study complex systems. Section 2.D discusses agent-based simulation (ABS) and reviews some previous ABS studies applied to military problems.

A. FROM NATURE TO ROBOTICS: SWARM APPLICATIONS

1. Swarm Theory and General Use

With technological revolutions in computing, robotics, and artificial intelligence, multiple disciplines are pursuing ways to transition swarm behavior from the natural environment to artificial systems. The word "swarm" is a derivative of the Old English term *swearm*, meaning a group of bees (Dickie, 2002, p. 6). In a modern context, biologists and naturalists commonly use the term *swarm* to describe a collective of social insects. Although not an exhaustive list, specific swarm behaviors "include path planning, nest construction, architectural engineering, and task allocation." (Ilachinski, 2017, p.107).

The attraction of swarm behavior is rooted in the idea that a network of insects can efficiently work together to accomplish a common task. Often the swarm is managed by an exchange of information between members of the swarm without any reliance on information from the global environment (Ilanchinki, 2017, p. 107). This idea naturally applies to modern concepts such as algorithm development, network design, and the employment of robotic systems. Currently, the academic community is effectively using swarm behavior in algorithm development to solve complex optimization or network problems (Bonabeau, Dorigo, & Theraulaz, 1999, p. 8). In the cyber realm, swarming programs are used to attack and defend critical information networks. Within the commercial industry, collective behaviors are being applied in many areas ranging from pollution detection to search and rescue (Barca & Sekercioglu, 2012, p. 346).

2. Military Application 1: Swarm Theory as a Form of Engagement

The military is beginning to view swarming as both a form of engagement and a capability set. Historically, military studies focused on three traditional forms of engagement: melee, massing, and maneuver. In 2000, Arquilla and Ronfeldt convincingly argued that developments in information systems, communications, intelligence gathering platforms, and precision munitions justified the addition of swarming as a fourth option.

Melee, the most primitive of the forms, represents duels between individual soldiers. Historically, battles started in linear formations, but quickly devolved into clashes between chaotic masses, absent of any command or control (Arquilla & Ronfeldt, 2000). Improvements in communications and the establishment of military drilling enabled commanders to fight forces in mass. Massing allowed a commander to more effectively command and control his force and direct combat power during the battle to exploit enemy weaknesses. Maneuver warfare is representative of current military doctrine and serves as the preferable form of modern combat. In maneuver warfare, a commander moves to a position of advantage and then rapidly masses combat power at a decisive point, overwhelming the enemy's ability to respond (Arquilla & Ronfeldt, 2000).

As a form of engagement, Arquilla and Ronfeldt (2000) define swarming as "a seemingly amorphous, but deliberately structured, coordinated, and strategic way to strike from all directions, by means of a sustainable pulsing of force and/or fire" (p. 45). Critical components to this swarming approach are a robust communications network, "internetted" sensor capabilities, and flexible C2 organization (Edwards, 2000, p.75). Small, dispersed maneuver units use these components to develop a collective understanding of the battlefield, coordinate targeting, attack in mass, and then redistribute to avoid detection or counter-attack (Arquilla & Ronfeldt, 2000).

In the future operating environment, multi-UAV systems may be critical to achieving collective situational awareness and massing lethal capabilities due to large military formations being susceptible to standoff, precision fires. The recent use of

Network Centric Warfare (NCW) in Iraq and Afghanistan shows that swarming is transitioning from concept to reality. Table 1 briefly summarizes information covered in this section and provides historic examples for greater context.

Table 1. Forms of Engagement

Form of Engagement	Basic Characteristics	Historical Cases
Melee (Traditional)	- Linear face offs, easily dissolved formations - Command and control nearly impossible during battle	- Ancient and feudal warfare - World War I aerial combat
Massing (Traditional)	- Established formations for set-piece battles, with a front, rear, and "waves" - Doctrines for maintaining hierarchy, shape, and thrust	- Greek phalanxes vs. Persian hordes - Napoleonic Wars - WWII Bombing Campaigns
Maneuver Warfare (Traditional)	- Complex, synchronized, fast tempo, multi-linear operations designed to surprise, penetrate, and flank - Application of mobile mass at "decisive point"	- Employment of German panzers in WW II - Operation Iraqi Freedom I
Swarming (Conceptual)	- Autonomous or semi-autonomous units engaging in convergent assault on a common target - Amorphous but coordinated way to strike from all directions – "sustainable pulsing" of force of fire - Many small, dispersed, networked maneuver units - Integrated surveillance, sensors, and C4I - Stand-off and close in capabilities	- Mongol approach to war - Mao's concept of "People's War" - Battle of the Atlantic

Table constructed with data from Arquilla and Ronfeldt (2000) and Edwards (2000).

3. Military Application 2: Swarms as a Capability Set

Currently, UAVs are synonymous with ISR. Premier UAVs, such as the Predator and Reaper, provide multiple capabilities in one platform (e.g., ISR, jamming, strike) and have enhanced our ISR capabilities immensely. However, these singular systems are typically theater or operational level assets, rarely accessible to front line, ground units. Deploying these systems in mass is impractical due to excessive costs. Additionally, in the author's experience, smaller UAVs, currently employed by ground units (i.e., infantry companies and below), can become manpower intensive. Most tactical level UAVs are launched while a unit is conducting a mission. If the UAV operator is not located in a secure location, additional personnel must protect the pilot during flight execution. While units gain some situational awareness, it often comes at the expense of combat power.

Multi-system UAVs and swarms seek to alleviate both shortfalls. Significant developments in automation, sensor miniaturization, and commercial-off-the-shelf (COTS) alternatives are changing the way the defense sector thinks about UAV employment. Instead of trying to build one high cost platform that performs many tasks, multi-UAV systems can be organized as a distributed capability set accomplishing the same mission, but with greater mass and survivability (Abatti, 2005). This is a revolutionary concept.

Currently, a single UAV can only address a singular battlefield event. To the contrary, a UAV swarm can be distributed across the battlefield, further developing a commander's situational awareness and response potential. In the future operating environment, particularly in a near peer conflict, swarms offer two distinct advantages. At the tactical level, ground forces can deploy autonomous swarms without significantly reducing combat power. Second, the smaller, more cost-effective systems can be deployed in mass, thereby enhancing system survivability, adding multiple system redundancies, and presenting a reduced or distributed signature (Abatti, 2005, p.175). Ultimately, a swarm forces an adversary to deploy more resources to locate and defeat the threat.

Drawing upon the definitions and concepts discussed in this section, this thesis studies swarming from the military perspective, with a focus on multiple UAVs being deployed as a capability set. Formally, swarming is defined as a "network of uninhabited vehicles that autonomously coordinate their actions to accomplish a task under some degree of mission-level human direction" (Scharre, 2014, p. 29).

The thesis scenario explores the deployment of two heterogeneous swarms working together to autonomously conduct ISR in support of a Marine infantry company. One UAV swarm consists of seeker drones responsible for locating possible hostiles. The other swarm is comprised of more sophisticated observation drones that aid the human supervisor in positively identifying a target and collecting information that can be passed to an indirect firing agency. For more information on swarm theory and multi-UAV concepts, see references: (Bamberger et al., 2006), (Barca & Sekercioglu, 2012), (Chung et al., 2013), (Davis et al., 2016), (Scharre, 2014) and (Valavanis, 2015).

B. UNMANNED AERIAL SYSTEMS: AN INTRODUCTION

1. Components of an Unmanned Aerial System

Although UASs vary in mission set and scope, they include the same basic components. Military variants are comprised of an air vehicle, payload, communication architecture, ground control station (GCS), launch and recovery equipment, and troop support (Fahlstrom, Gerin, & Gleason, 2012, p. 8), (USA, 2010, p. 8). The air vehicle (AV) is the airborne part of the system that transports the payload to a desired location for mission execution (Falhstrom et al., 2012, p.8). The payload provides a capability to a user and serves as the ultimate reason for choosing a UAS for a given task (Fahlstrom et al., 2012, p.10). Common military payloads are ISR sensors, communication relays, jammers, and weapons packages.

The communications architecture is the subsystem that links the ground operator with the AVs. Through a two-way datalink, an operator can control the AVs and payloads while collecting sensor data and status information from the AV (Fahlstrom et al., 2012, p. 10–11). The GCS serves as the "nucleus" of the UAS. It allows a human operator to interface with the AVs and payload, while managing incoming UAS telemetry data (Fahlstrom et al., 2012, p. 8–9; Bürkle, Segor, & Kollman, 2011, p. 344). Launch and recovery equipment assists a ground unit in deploying and retrieving a UAS. Methods range from hand launched micro systems to more sophisticated AV launchers and airstrips needed for the largest of platforms (Falhstrom et al., 2012, p. 9–10). Launch and recovery procedures become increasingly more important as a UAS grows from a singular AV to multiple AVs.

The final component of a UAS is troop support. Austere and unforgiving combat environments can quickly degrade a UAS's effectiveness. As UASs grow in sophistication and complexity, the personnel needed to C2, manage flight operations, and maintain these systems also increases. Like manned aircraft, UASs require logistical support to include transport, communication enablers, and sustainment (USA, 2010, p. 10). Figure 1 shows an example of a hypothetical UAS construct.

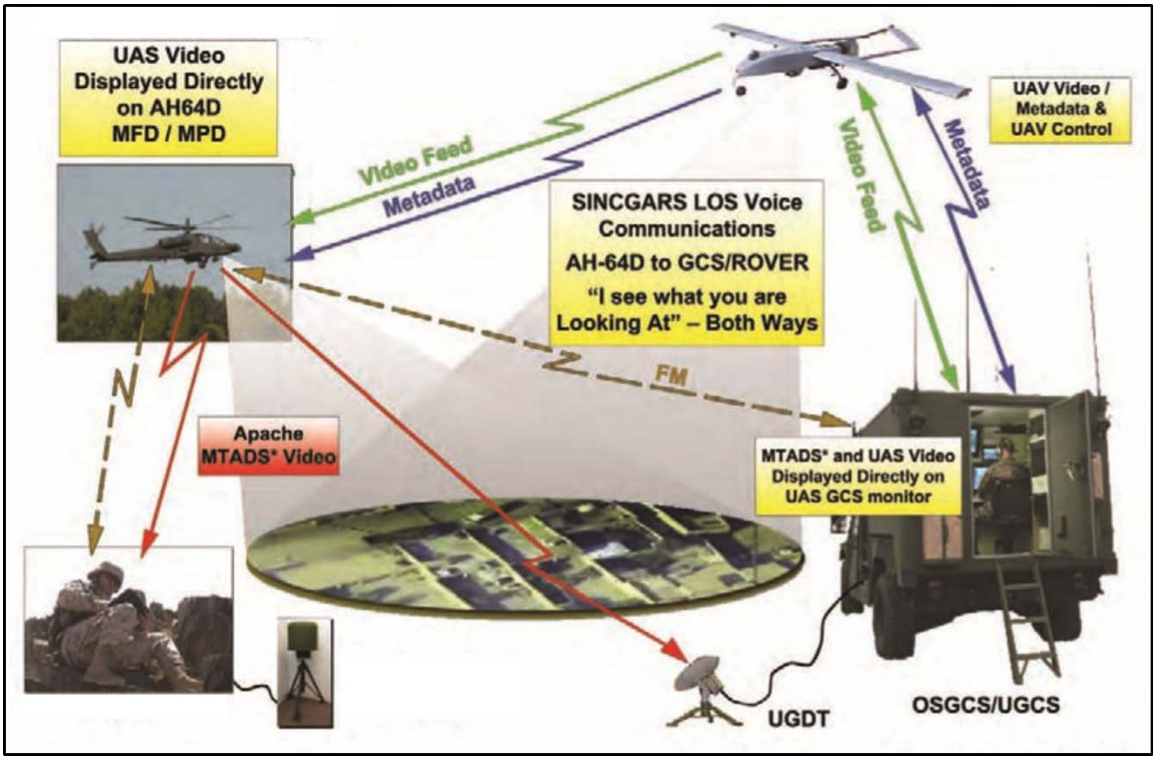

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Figure 1. Common UAS Construct. Source: USA (2010).

2. Types of UAVs

UAV design significantly affects mission profiles and performance factors, such as endurance, speed, and payload capacity. This thesis uses the following four descriptor types to orient the reader to the more common UAVs used in the military and civilian sectors.

The four UAV types are: fixed-wing, multi-rotor, single rotor helicopter, and fixed-wing hybrid Vertical Take-Off Landing (VTOL) (Chapman, 2017). Fixed-wing UAVs operate at higher speeds, which gives them enhanced endurance and greater area coverage. Unfortunately, fixed-wing UAVs are typically more expensive and require a more sophisticated launch and landing plan (Olson, 2017). Multi-rotor UAVs are easy to deploy and offer a controlled hover capability ideal for reconnaissance; however, the operating systems are inherently inefficient, resulting in limited endurance and payload capacity (Chapman, 2017).

Single rotor UAVs offer better on-station times and can carry heavier payloads when compared to multi-rotor systems, yet they are harder to control, and their heavy spinning blades can be dangerous (Olson, 2017). Finally, as the name implies, fixed-wing, hybrid UAVs offer a middle ground between fixed and rotor platforms. While the VTOL capability simplifies launch and landing plans, the hybrid design results in a lack of endurance compared to its fixed-wing counterpart and no hover capability. Table 2 provides a more comprehensive list of capabilities and limitations for each UAV type. Additionally, for more information regarding types of UAVs see references: Department of Defense (DoD), (2013), Fahlstrom et al. (2012), Newcome (2004), USA (2010), USMC (2015), and Valavanis (2015).

Table 2. UAV Characteristics and Limitations.
Adapted from Chapman (2016).

Type of UAV/Characteristics	**<u>Basic Characteristics</u>**	**<u>Limitations</u>**
Fixed Wing	- High Endurance - Longer Range - Large Area Coverage - The Fastest of the UAV Types	- Large launch and recovery requirement - No hover capability - More complex; Require more training - Expensive
Multi-Rotor	- Easy to use - Inexpensive - Hover capability - Can operate in confined spaces - Limited launch requirement; Vertical takeoff	- Short range - Short flight times - Small payload capacity
Single Rotor Helicopter	- Easy to use - Longer Endurance than Multi-Rotor (w/ gas power) - Can carry heavier payload	- Expensive - Require more training. - More dangerous due to heavy blade
Fixed-Wing Hybrid Vertical Take-Off Landing (VTOL)	- More endurance than rotor UAV's - Can operate in confined spaces - Limited launch requirement; Vertical takeoff	- Expensive - As a hybrid they don't outperform the other UAV's in speed or hovering capabilities - Unproven as many platforms are still in development

3. Military Group Classifications of UASs

In 2008, the DoD formally established five UAS classification groups to promote interoperability and a common understanding of UAS employment across the military services (MCWP 3–42.1, 2015, p. 1–4). The classification methodology focuses on a UAV's speed, weight, and altitude, instead of vehicle composition (USA, 2010, p. 12). Table 3 shows the group thresholds for each attribute.

Table 3. Unmanned Aircraft Group Categories. Adapted from MCWP 3–42.1 (2015).

<table>
<tr><th>UAS Category</th><th>Max Gross Weight</th><th>Normal Operating Altitude (Ft.)</th><th>Airspeed</th></tr>
<tr><td>Group 1</td><td>< 20 lbs.</td><td>< 1200 AGL</td><td>< 100 Knots</td></tr>
<tr><td>Group 2</td><td>21 – 55 lbs.</td><td>< 3500 AGL</td><td rowspan="2">< 250 Knots</td></tr>
<tr><td>Group 3</td><td>< 1320 lbs.</td><td rowspan="2">< 18,000 MSL</td></tr>
<tr><td>Group 4</td><td rowspan="2">> 1320 lbs.</td><td rowspan="2">Any Airspeed</td></tr>
<tr><td>Group 5</td><td>> 18,000 MSL</td></tr>
<tr><td colspan="4">Note: If a UAS has two characteristics in Group 1 and one characteristic in Group 2, it is a Group 2 UAS.

Acronym Key:
Lbs. = Pounds (U.S. Customary System); AGL = Above ground level; MSL = Mean sea level</td></tr>
</table>

Group 1 UASs are typically small, portable systems employed at the small unit level (USA, 2010, p. 12). Group 2 characteristics apply to medium-sized UAS which often require launching mechanisms, identified landing zones, and/or operator teams during mission execution. Group 2 UASs typically have a larger logistics requirement than Group 1 and are most commonly seen at the Regimental or Brigade level (USA, 2010, p. 12).

Group 3 UASs have greater endurance, fly at medium altitudes, and are large enough to be equipped with advanced sensor payloads and lethal capabilities (USA, 2010, p. 13).

Group 4 UASs are larger systems with greater endurance and payload capacity than the previous groups; however, improved areas are required to launch and recover the system as well as conduct high echelon maintenance (USA, 2010, p. 13). Group 5 UAS are the largest and most capable of the groups and they cover a much larger area. Improved surfaces are required for launch and recovery and the logistics footprint is similar to that of a manned aircraft (USA, 2010, p. 13). Figure 2 is a visual depiction of the military classification methodology and several joint UASs common to military operations since 2013.

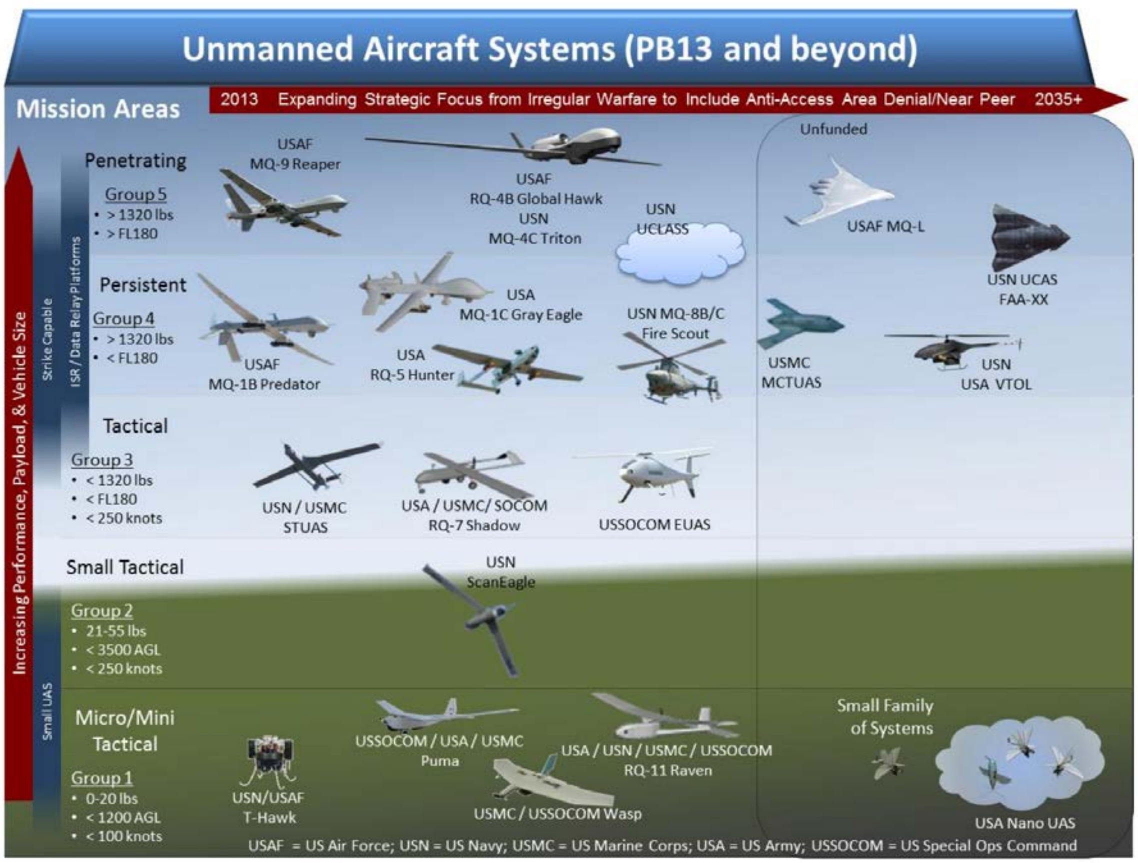

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Figure 2. Classification Groups and Unmanned Aircraft Systems. Source: DoD (2013).

4. Swarming from a Concept to Reality: Control Strategies

In robotic research, the advantages of swarming hinge upon mass, autonomy, and the idea of swarm intelligence. Swarm intelligence is "the collective intelligence that emerges from interactions among large groups of autonomous individuals" (Barca & Sekercioglu, 2012, p. 345). To the military, swarm intelligence naturally compliments ISR collection. A UAV swarm can rapidly deploy multiple sensors, in mass, to help build a collective understanding of the environment and inform or assist in future actions.

Autonomous action within a swarm allows a unit to maximize UAV employment while minimizing manpower requirements. Currently, most UASs, regardless of classification group, are controlled by a pilot from a GCS. Using this approach, "swarms of remotely controlled UAVs require as many skilled pilots as there are swarm UAVs. These pilots must be able to deconflict airspace demands, mission requirements, and situational changes in near real time" (Bamberger, Watson, Scheidt, & Moore, 2006, p. 41). Therefore, autonomy is essential to deploying many UAVs simultaneously as swarms quickly become unmanageable with respect to manning and C2.

Successfully incorporating all three traits, mass, autonomy, and collective intelligence, into a swarm is highly dependent upon the system communication architecture and software design (Barca & Sekercioglu, 2012; Chung et al., 2016). Just as UAV hardware defines the physical capabilities and limitations of a swarm (i.e., speed, altitude, endurance), communications and software design determine the control strategies available to deploy a swarm. A well-designed control strategy allows an operator to effectively deploy multiple UAVs while efficiently collecting mission critical information. The seminal literature addresses three broad categories for swarm control strategies.

a. Control Strategies

Control strategy defines how a swarm communicates both internally and externally. The three categories of control strategy are centralized, decentralized, and hybrid. In centralized systems, a central planner is responsible for managing a swarm's behavior at a global level (Valavanis, 2015, pp. 977–978). This means that the planner interacts with individual robots to direct flight paths, allocate payload distribution, and collect data (Barca

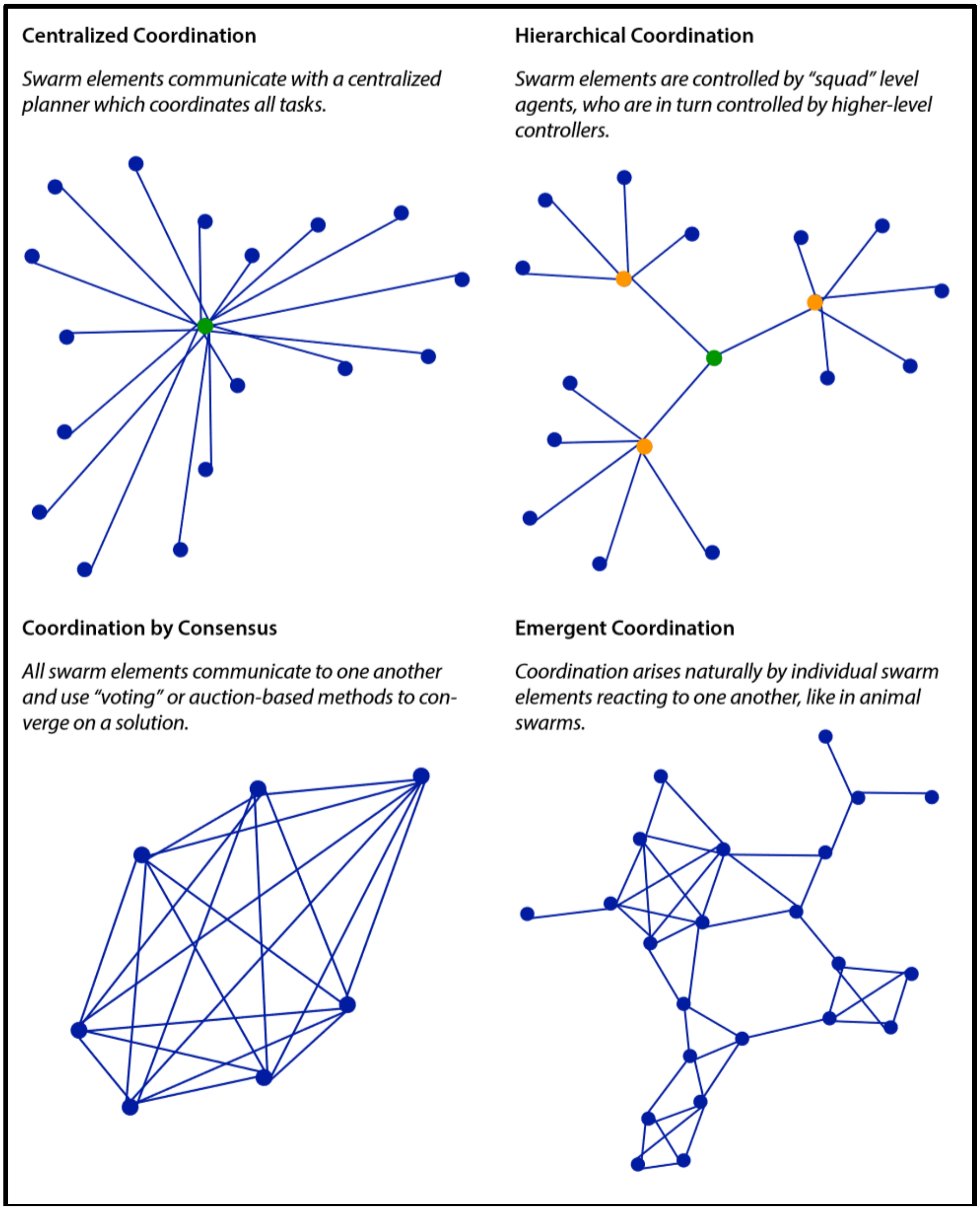
& Sekercioglu, 2012 p. 347). Because a planner can interact directly with any UAV in the system, the overall behavior of the swarm is more predictable and immediate corrective action can be initiated if a UAV deviates from the mission plan.

Unfortunately, superior control comes at a price. Centralized architectures do not scale well with additional UAVs (Barca & Sekercioglu, 2012, p. 347; Chung et al., 2016, p. 1256). As the number of UAVs increases, the system's bandwidth can be overwhelmed, resulting in missed information. Moreover, the central planner can experience task overload and fatigue. This breakdown in the system often results in a rapid loss of situational awareness and swarm control (Valavanis, 2015, pp. 977–978).

A decentralized system uses a distributed approach to reduce the complexity of deploying multiple UAVs simultaneously. Decentralized systems combine multiple UAVs to create subswarms that operate under a single leader drone. This allows the mission supervisor to interact with subswarm leaders that disseminate information to their subordinate UAVs. This reduces the stress that centralized systems place on their communications architecture and allows a mission planner to maintain control over a larger number of UAVs (Barca & Sekercioglu, 2012, p. 347; Valavanis, 2015, pp. 977–978).

The disadvantage to this approach is that the mission planner can no longer control the swarm at the individual level. Often, little information will be known about the subordinate drones' activities unless observed through the subswarm leader. This lack of global knowledge can result in either unpredictable or undesirable behavior that is neither observed nor known to the mission planner (Barca & Sekercioglu, 2012, p. 347).

Innovation in control strategy will continue to improve swarm capabilities and overall swarm behavior. Currently, many of the top performing control systems use a hybrid approach in which both centralized and decentralized methods are combined to minimize system limitations while maximizing swarm potential (i.e., deploying additional UAVs). Barca and Sekercioglu (2012) contend that maintaining a balance of centralized and decentralized characteristics is essential to future robotic swarm development. Hybrid control strategies allow a central planner to exert control over the swarm while reducing the complexity of trying to manage multiple UAVs simultaneously (p. 347). Figure 3 offers a brief description and visual depiction of the two traditional control strategies discussed and two theoretical, hybrid models.



[Best viewed in color]

Figure 3. Swarm Control Strategy. Source: Scharre (2014).

5. Transitioning the Swarm from Experimentation to the Tactical Edge: Advanced Robotic Systems Engineering Laboratory (ARSENL) Swarm Architecture

In 2011, the Secretary of the Navy authorized the Naval Postgraduate School to host the Consortium for Robotics and Unmanned Systems Education and Research (CRUSER), (Work, 2011). Six years later, CRUSER is a diverse program that promotes research, education, concept design, and experimentation in the maritime application of automation, robotics, and the deployment of unmanned systems (Work, 2017). More specifically, CRUSER is at the forefront of human robotic interfacing and autonomous networks.

The Advanced Robotic Systems Engineering Laboratory (ARSENL), a subset of CRUSER, represents a multi-disciplinary research group dedicated to designing robotic and unmanned systems of the future. The ARSENL team combines cutting-edge research with student military experiences to create materiel solutions ideally suited for the military's most daunting capability gaps. It is ARSENL's research in UAV drone swarms that serves as the foundation and enabler for this thesis.

In August 2015, ARSENL conducted the world's largest autonomous live-fly experiment (at that time), successfully controlling 50 fixed-winged UAVs simultaneously (Chung et al., 2016). Within two years, MIT's Lincoln Laboratory doubled this feat by deploying 103 nano-UAVs from two F-18 fighter attack aircraft (DoD Press Operations, 2017). Although aerial swarms are still in a demonstration phase, the military's focus on swarms will quickly shift from engineering and technology-based exploration to tactical employment and sustainment.

ARSENL's groundbreaking experiment was profound in two ways. The experiment proved that a large number of fixed-wing UAVs could be deployed and controlled in mass. Additionally, ARSENL's demonstration marked the need to consider other factors external to the swarm. The ARSENL team highlighted new research challenges to include efficient human-swarm interaction, maintainability of the swarm, protecting the swarm against jamming and cyber technologies, and the need to consider logistics support for operating large numbers of robots (Chung et al., 2016, p. 1255).

6. Modeling the ARSENL Swarm Architecture

This thesis uses modeling and simulation (M&S) to gain insight into deploying an ISR swarm in a combat environment. The swarm in the model is grounded in the current control strategies and hardware configuration successfully used by ARSENL. The swarm UAS consists of a ground control station, the air vehicles, a three-component communication system, two robotic launchers, and a support team of six personnel.

The most common air vehicle used by ARSENL is the Zephyr II fixed-wing UAV. The Zephyr II is a cost effective and capable commercial off-the-shelf (COTS) system that allows the team to leverage open-source components (Chung et al., 2016, p. 1256). This acquisition approach is necessary as the cost of a swarm UAS can increase drastically as the number of UAVs increases. Additionally, ARSENL has proven that their swarm architecture design can be used on different air vehicles. Currently, ARSENL is deploying small quad-copter swarms in support of Marine Corps training in 29 Palms, California. This thesis does not focus on a specific UAV platform, rather exploratory analysis is used to gain insight into the preferred characteristics of a swarm UAV.

For communications, ARSENL uses a three-component communication system on each UAV. The system contains an 802.11 wireless radio, a radio control receiver (RC), and a serial "telemetry" radio (Chung et al., 2016, p. 1258). The 802.11 serves as the primary communications system used to command and control the swarm. The wireless radio allows air vehicles to communicate with other aircraft and ground stations (Chung et al., 2016, p.1257-1258). This configuration can be deployed as a mesh network between aircraft. The radio control receiver allows the central planner to assume manual control of the AV and the "telemetry" link serves an auxiliary way of communicating with individual vehicles during emergency situations (Chung et al., 2016, pp.1257–1258).

The ARSENL swarm uses a central planner, hybrid control strategy. Due to limited bandwidth, orders from the central planner are disseminated to sub-swarm leaders who are responsible for managing the air vehicles under their hierarchy. Recall the hierarchical coordination strategy shown in Figure 3. Taking advantage of parallelism, a central control method using sub-swarm leaders maximizes both C2 and scaling within the swarm.

This thesis investigates both the hierarchical and emergent coordination strategies. As defined by Scharre (2014), in a hierarchical swarm, “swarm elements are controlled by “squad” level agents, who are in turn controlled by higher-level controllers” (p. 39). In an emergent swarm, “coordination arises naturally by individual swarm elements reacting to one another” (p. 39). Due to the complexity of the swarm, this thesis only focuses on the swarming system. Other details such as launch devices and ground support are not directly studied. For more information on ARSENL efforts and swarm configurations see references: Bamberger et al. (2006), Barca and Sekercioglu (2012), Chung et al. (2013), Chung et al. (2016), Davis et al. (2016), Scharre (2014), and Valavanis (2015).

C. MODELING AND SIMULATION (M&S)

A “system” is defined as a collection of entities that act and interact to accomplish some logical end (Law, 2007, p. 3). Modern warfare is a complex set of integrated systems designed to identify and exploit an adversary’s weaknesses. Weapons systems, force organization, and operational battle plans contain so many variables that analytical solutions have difficulty in providing comprehensive insight into a system’s behavior. By combining mathematical models with modern computing resources, M&S is becoming a viable and powerful tool for exploring future combat systems, their effects on the battlefield, and optimal employment techniques.

The Department of Defense defines a model as “a physical, mathematical, or otherwise logical representation of a system, entity, phenomenon, or process” (DoD, 1998, p. 136). A simulation is the “method of applying a model over time” (DoD, 1998, p. 57). Due to the size, scope, and complexity of military systems, traditional experiments are becoming constrained, infeasible, and costly (Lucas, Kelton, Sanchez, Sanchez, & Anderson, 2015). Modeling and simulation is a practical and cost-effective way of gaining insight into complex problems. The military uses M&S to develop models of the real-world, define system performance parameters, generate data, and perform data analytics to gain insight into operational, managerial, and technical systems (DoD, 1998, p. 136).

The military M&S process begins with developing a model of a real-world system and identifying the experiment measures of effectiveness (MOEs). A MOE is a metric used to quantify mission performance under specified conditions (Zappa, 2009). Next, an analyst identifies UAV performance characteristics or factors (e.g., system speed, range, or probability of detection) and builds a design of experiment to study how these characteristics effect overall mission effectiveness. Once the desired measurement space is defined, computers and other technologies are used to run simulated experiments of the model. Analytic techniques are applied to simulation outputs, creating quantitative insight into mission performance. These insights help drive military decisions, seeking to ensure that service members have the equipment they need to fight and win the nation's wars. See Figure 4 for a visual representation of the M&S process taught at the Naval Postgraduate School.

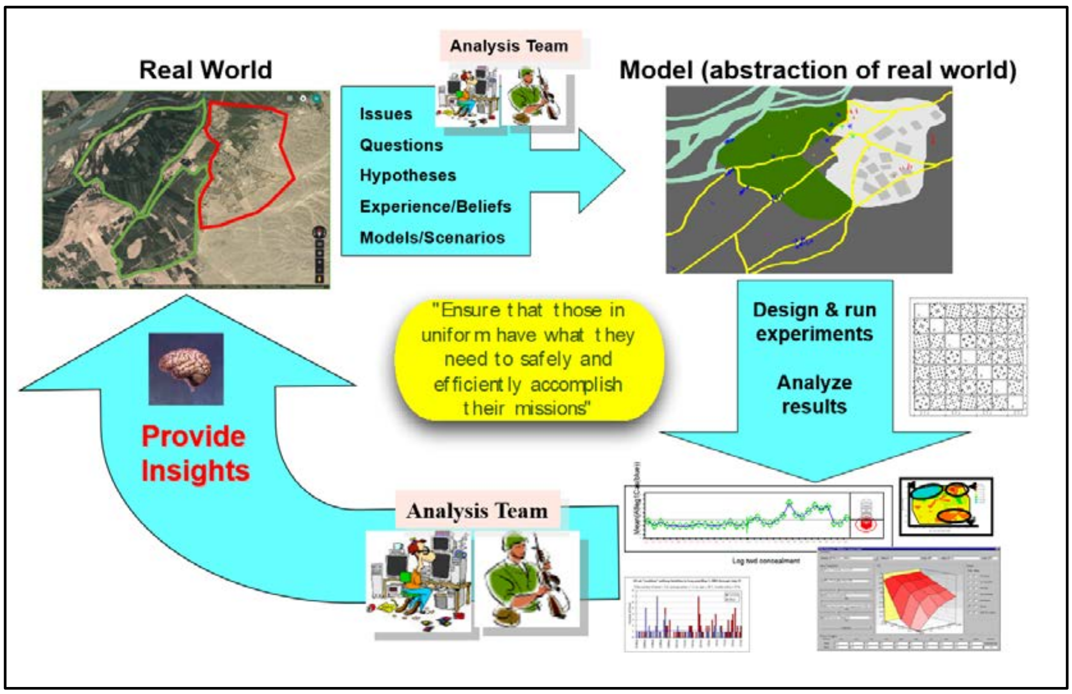


Figure 4. M&S Process. Adapted from Lucas (2017).

D. AGENT-BASED SIMULATION (ABS)

1. ABS Defined

An agent is an autonomous decision making entity that can assess its situation and act based upon established rules (Kuiken, 2009, p. 8). Furthermore, agents typically possess the ability to communicate with other agents, possess their own resources (e.g., energy source, sensing capability), and maintain a partial knowledge of a model scenario (Kuiken, 2009, p. 8). An agent's ability to sense, maneuver, and act are only a subset of the larger system being explored.

Agent-based simulation is a type of computer-based modeling that seeks to study how individual entities act and interact within a larger, real-world system. Examining agent actions allows analysts and decision makers to gain valuable insight into emerging system behavior and individual agent properties. Due to the complexity of robotic swarms and their tactical role on future battlefields, ABS is the most appropriate modeling environment for studying ISR swarms at the combat mission level.

2. Using ABS to Study Military Robotic Swarms

The author's literature review uncovered that the majority of swarm research focuses on the technical and engineering aspects of swarming. While the defense community relies heavily on M&S for drone development and procurement, simulation efforts to investigate the tactical employment of drone swarms is still in its infancy. Gaudiano, Shargel, Bonabeau, and Clough developed an agent-based model to simulate different types of control strategies for a swarm of UAVs (Gaudiano et al., 2003, p. 1). Their study provided a strong argument for developing a quantitative, analytic approach when developing TTPs for swarm ISR deployment.

Dickie developed the Multi-Agent Robot Swarm Simulation (MARSS) which enables an analyst to explore the effects that agent behavioral factors have on swarm performance during search missions. His research showed that swarm performance is dependent on the level of communication between fellow UAVs. Additionally, he highlighted the importance of how drones react to information, both good and bad. He discovered that swarm performance reduces drastically if the swarm begins to react to global information in the wrong way (Dickie, 2002, p. 91).

Kuiken (2009) used agent-based simulation to explore the effects of deploying multiple UAVs in different configurations to search for SCUD missile sites. Kuiken compared individual drone employment to a multi-UAS variant. He concluded that formation configurations play a significant role in search and detection missions and that target confirmation rules can reduce the effectiveness of deploying multiple UAVs simultaneously.

Building on the efforts described above, this thesis uses MANA-V, an agent-based model, to study the employment of ISR swarms in support of a Marine infantry company. Over the last 16 years of war, many promising technologies proved too burdensome for use at the tactical edge. Undoubtedly, robotic integration will enhance unit lethality; however, many questions remain with respect to swarm integration at lower levels. ABS offers a unique modeling environment for exploring the complex nature of robotic swarms and their use in locating and prosecuting enemy targets.

III. THE MODEL: TRANSITIONING CONCEPTS AND CHARACTERISTICS INTO AN AGENT-BASED SIMULATION

All models are wrong, but some are useful.

—George Box

This chapter describes the thesis model and discusses model development. Section 3.A provides a brief introduction to Map Aware Non-Uniform Automata (MANA-V), the simulation software package used for this study. Section 3.B describes the thesis model scenario and explains the tactical distribution of allied and enemy forces. Section 3.C discusses building the terrain in MANA-V. Section 3.D discusses agent behaviors and characteristics, applying Chapter II concepts and Unmanned Aerial Vehicle (UAV) specifications to agent types. Section 3.E identifies the limitations of MANA-V and recommends enhancements to future software editions.

A. MAP AWARE NON-UNIFORM AUTOMATA (MANA-V)

Three distinct characteristics reinforced the author's decision to use MANA-V to explore the internal and external interactions of an ISR drone swarm.

1. MANA-V Is Designed to Run Advanced Designs of Experiments to Explore Combat Interactions

In 2000, the New Zealand Defense Agency created the Map Aware Non-Uniform Automata (MANA) agent-based model environment to explore the behavior of entities in real-world combat (McIntosh, Galligan, Anderson, & Lauren, 2007). Currently, MANA-V is an agent-based, time stepped, stochastic modeling environment intended for "quick turn," mission-level analysis (Lucas, 2015, p. 2). For a decision maker or lead analyst, MANA-V provides mission visualization, valuable insight into an evolving battle, and intuition on sensor employment (McIntosh et al., 2007, p. 5). As an analytic tool, MANA-V provides an intuitive interface to efficiently build scenarios and a data farming capability which allows a research team to run multiple experiments over a broad range of factors (Zappa, 2009, p. 19).

MANA-V is designed to support operations analysts. The data farming capability allows an analyst to apply advanced design of experiments (DOE) techniques which can populate thousands of unique experiments in a relatively short period of time. This thesis uses MANA-V to create a realistic simulated environment and then study drone swarm employment in support of a Marine infantry company. Multiple DOEs were run to identify influential factors, interactions, and thresholds that effect swarm performance.

2. MANA-V Measures and Tracks Situational Awareness (SA)

MANA-V uses agents, also referred to as agent squads, to represent autonomous military units. An agent squad is a set of homogenous elements with the same characteristics. Agents are modified with sensors and personality traits which govern how an agent senses and interacts within the simulated environment (Zappa, 2009, p. 19). Agent sensors detect and classify other agents in the scenario. Personality traits dictate how an agent responds to friendly, enemy, and neutral entities in terms of movement, communications, and aggression. As a scenario unfolds, different sensors and behaviors begin to develop an agent's individual SA. This SA is tracked by two distinct "awareness maps" (Zappa, 2009).

The two types of SA maps used in MANA-V are organic and inorganic. An organic map holds direct contacts, interactions, and knowledge experienced by an individual agent. The inorganic SA map captures shared information between agents of the same force. Through established communication links, agents begin to develop a shared understanding of the battlefield (McIntosh et al., 2007, p 5). Combining these two features results in each agent having a unique understanding of the unfolding scenario (Zappa, 2009).

Measuring and tracking situational awareness is essential to understanding the effectiveness of a drone swarm ISR platform. Taking advantage of MANA-V's unique data farming capability, this thesis investigates how sensor and behavior manipulation effect swarm performance in support of a Marine infantry company.

3. MANA-V Models Internal and External Communications

In MANA-V, communication links control the flow of SA internal and external to an agent. Internal squad communication parameters control SA flow within an agent squad. Control parameters include communication range, time to disseminate information within the squad, and contact persistence (McIntosh et al., 2007). External squad communication parameters, also referred to as inter-communications, "determine how information is treated once it arrives at the squad via a communications link" (McIntosh et al., 2007, p. 68). External squad communication parameters allow for a more detailed exploration of the communication network between agents. Parameter examples include communication net latency, accuracy of information passed between agents, and link capacities. For more details on how communications are modeled in MANA, see the MANA 4 User's Manual, pages 68–71.

As discussed in Chapter II, swarm communication architecture directly affects control strategy and information collection. Due to the intricacies of swarm communication networks, it was crucial to find simulation software that could accurately model the ARSENL communication architecture. Although MANA-V does not provide engineer level detail for communication links, it is well suited to study communication networks at the mission level and the effects of varying that capability. MANA-V's basic approach, coupled with an easy to use interface, allows the user to accurately model multiple ISR control strategies, a swarm ground control element, and the fires agencies needed to prosecute enemy targets identified by the swarm. Section 3.E discusses individual agent characteristics and modeling approaches in greater detail.

B. THE SCENARIO

This section discusses the scenario, force locations, and how the author built the modeling environment in MANA-V. An abbreviated version of a company operations order is used to succinctly introduce the reader to the scenario. The author intentionally simplifies the scenario and avoids using complex military terminology. For additional resources on military tactical tasks and vocabulary see Marine Corps Warfighting Publication (MCWP) 3–11.1: Infantry Company Operations.

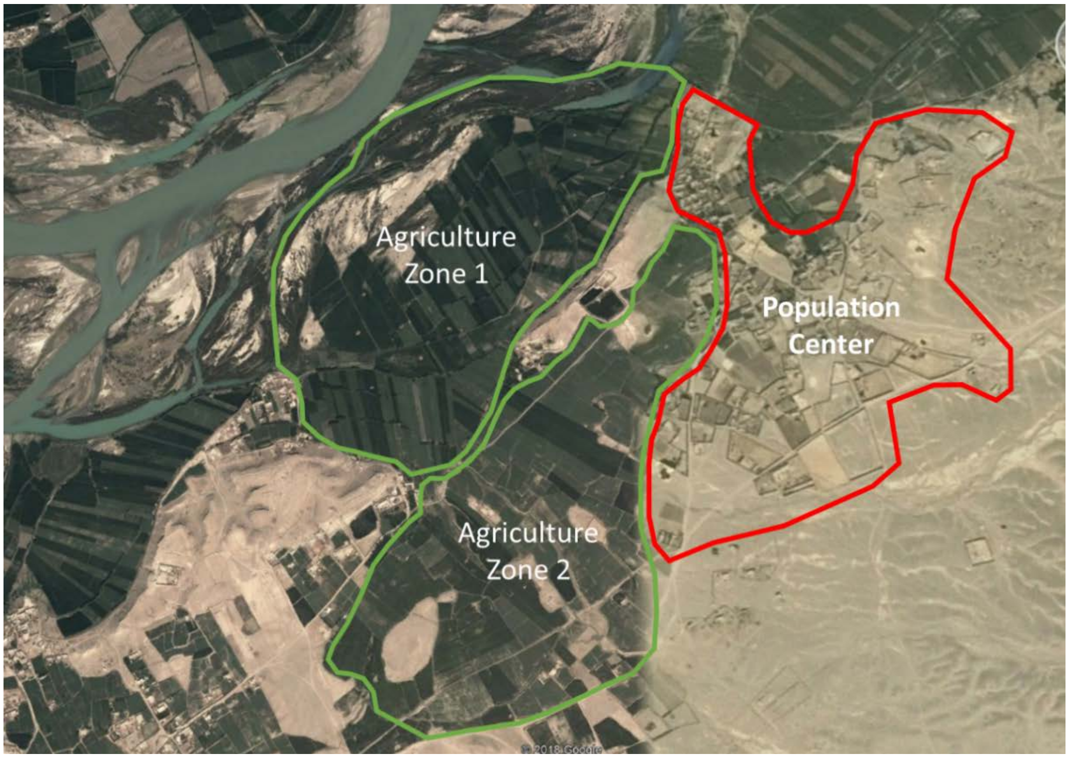
1. Selection Criteria

Scenario selection for this thesis was challenging. Initially, stakeholders wanted to explore swarm employment in larger tactical scenarios, such as clearing maneuver corridors or targeting enemy in support of amphibious operations. Accomplishing this task requires making large assumptions and amplifying current swarm capabilities. To avoid making unsubstantiated claims, the author chose a personally familiar scenario experienced in Afghanistan compatible with current ARSENL swarm performance. Additionally, the following matters were considered:

- It must be grounded in a real, military mission set.
- The terrain should represent a realistic battlefield that Blue forces are likely to encounter in future operating environments.
- The battlefield should challenge the Blue force's ability to develop situational awareness and employ ISR assets.
- The scenario should be designed to demonstrate swarm performance against a challenging adversary with similar fighting capabilities. Casualties should be indicative of fighting in a high intensity conflict. This is one of the few ways to gain insight into system improvement (Treml, 2013, p. 35).
- The number of agents must not become excessive, otherwise runtimes for MANA-V become excessive. It was identified that exploring units above the company level starts to add too many agents, which inhibits data collection efforts (Treml, 2013, p. 35).

2. The Battlefield

For the thesis model scenario, the author chose a mission personally experienced while deployed to Afghanistan. During the seven-month deployment, coalition forces fought to defeat a robust "hybrid force" consisting of local criminal elements, hardened Taliban fighters, and foreign military advisers. Additionally, the battlefield was a complex environment along the Helmand River characterized by primitive towns surrounded by agricultural zones. Figure 5 provides a satellite view of the scenario battlefield.



[Best viewed in color]

Figure 5. Scenario Battlefield: Southern Afghanistan. Adapted from Google Earth (2018).

The agricultural areas are a mixture of open fields, irrigation ditches, poppy crops, and corn fields. The towns consist of narrow alleyways, livestock pens, and compounds surrounded by 6- to 8-foot mud walls. Population centers typically house 250–500 people. This unique area stressed the company's organic ISR assets as the enemy used the terrain and local population to conceal their actions and conduct attacks to their advantage. Figures 6 and 7 provide pictures representative of the local terrain.

[Best viewed in color]

Figure 6. Corn Fields in the Agricultural Zone. Source: Steele (2010).

[Best viewed in color]

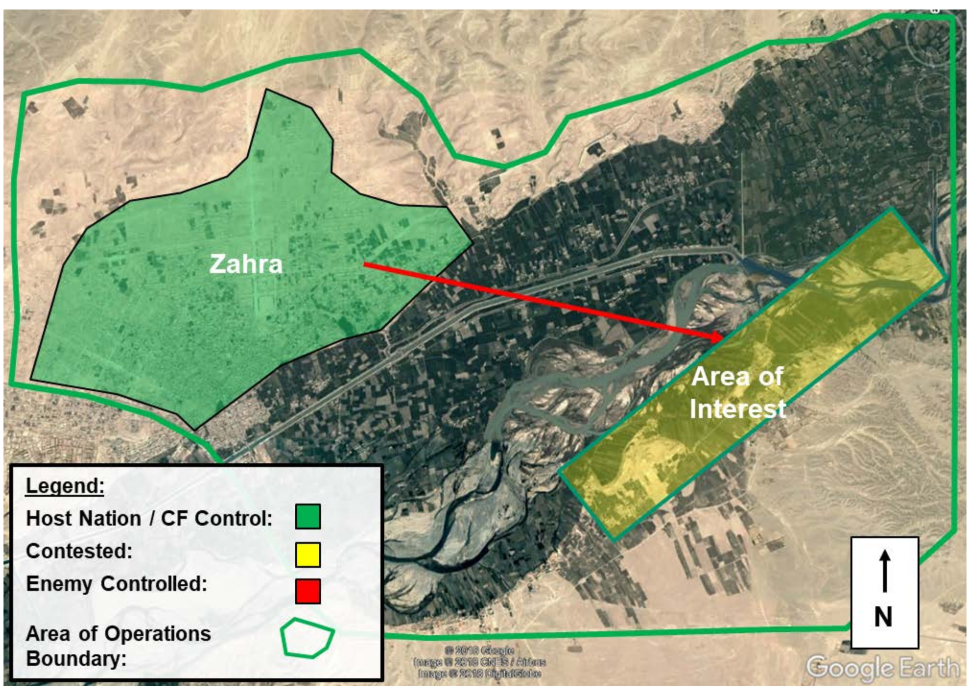
Figure 7. Typical Urban Infrastructure. Source: Stancati (2014).

3. The Operations Order: Introducing the Scenario

a. Orientation: The Scenario Story and Events Leading to the Mission

A successful allied offensive in southern Helmand Province resulted in the defeat of a sizeable Taliban force. Within the past three months, sources report that mid-level Taliban leaders fled north to the Helmand River Valley to consolidate their soldiers and gain access to a reliable revenue source. As attacks on Afghan Army outposts and local police stations increase, there is a fear that the Taliban are trying to gain control of the opium market fueled by local poppy crops.

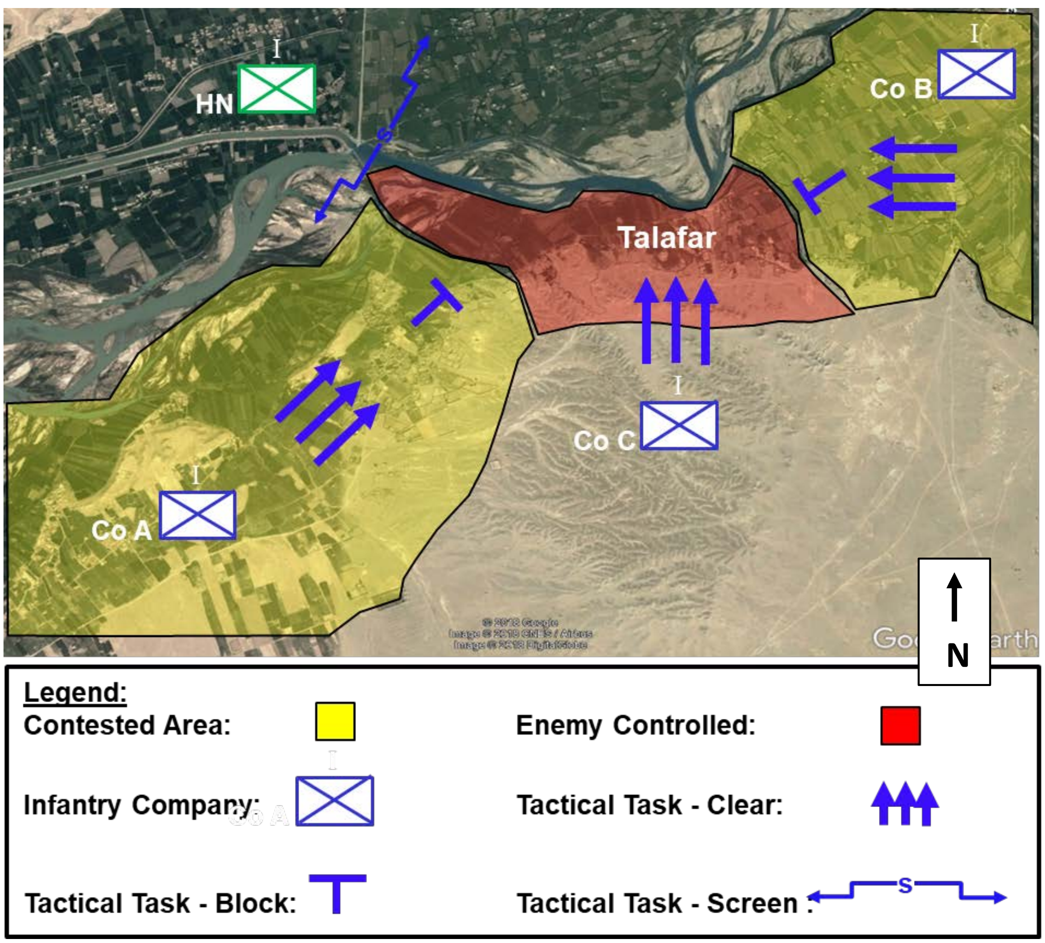
The U.S. regional command recently sent a Marine Infantry Regiment (Blue force) to secure the town of Zahra, the largest population center in the area. While in Zahra, the Marines discovered through reliable intelligence that mid-level Taliban leadership is hiding in the farming communities at the outskirts of the city. Figure 8 shows the Regimental Area of Operations and Area of Interest where the Taliban are attempting to establish a stronghold.



[Best viewed in color]

Figure 8. Regimental Area of Operations and Contested Area. Adapted from Google Earth (2018).

Recognizing that the Taliban's influence continues to grow, allied forces identify that decisive action is needed to thwart enemy momentum. A local informant reported that key Taliban leaders are hiding in Talafar, a village sympathetic to the insurgency. Within the next 72 hours, a Marine infantry battalion will conduct combat operations in the area of interest. Companies A and B will establish blocking positions to the southwest and northeast of Talafar to prevent the Taliban from fleeing the area. Company C is tasked with clearing the enemy stronghold and capturing Taliban leaders and weapon stockpiles. Ultimately, the regimental command wants to prevent the Taliban from gaining control of the poppy trade. Figure 9 shows a military depiction of the infantry battalion's operational plan.



[Best viewed in color]

Figure 9. Battalion's Operations Plan to Capture Taliban Leaders in Talafar. Adapted from Google Earth (2018).

The remainder of the modified operations order discusses the forces and actions located within Company A's battlespace, the geographical region outlined on the left in Figure 9.

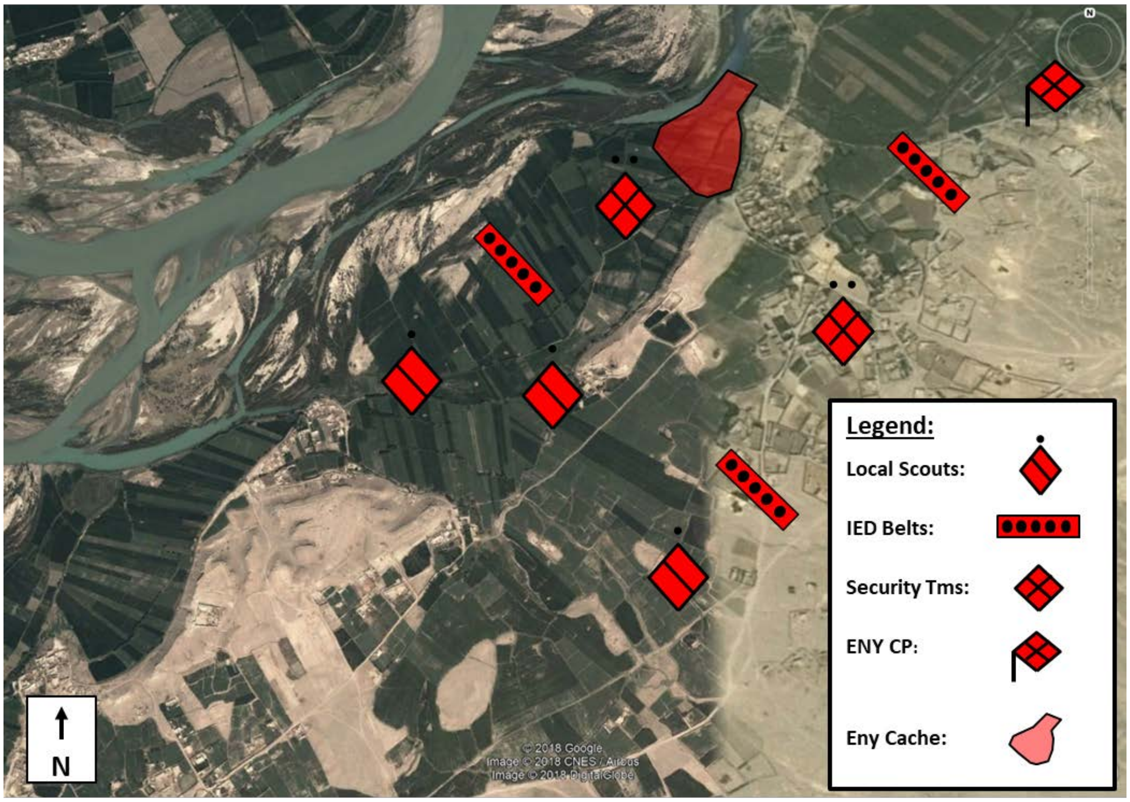
4. Situation: The Units Involved in the Company Fight

a. Enemy Forces

Intelligence reports that 10–20 enemy fighters are operating in Company A's area southwest of Talafar. The enemy force consists of IED teams, several rifle squads, and a local command element. The IED teams are using explosive devices to murder local leaders aligned with U.S. forces. The rifle squads are intimidating the local population and demanding tax payments to expand their drug smuggling operation. A local informant reports that the enemy is stockpiling weapons and explosives in an orchard just outside the village.

The enemy is armed with small arms to include: AK-47 assault rifles, general purpose (GP)—40mm grenade launchers, rocket propelled grenades, and medium machine guns (RPK). Improvised explosive devices typically contain homemade explosive materials; however, military grade items such as anti-tank mines, anti-personnel devices, and artillery shells are growing in frequency. Due to a tenuous relationship with the locals and several instances where children were killed by pressure plate IEDs, the IED teams shifted from remote controlled bombs to command wire devices.

The most likely course of action is that the enemy delays U.S. forces until Taliban leaders depart Talafar. To accomplish this task the enemy will defend in depth. This means that local scouts will be deployed forward to report U.S. positions to enemy units. IED teams and rifle squads will use the civilian population to move into positions of advantage. They will then initiate complex attacks using command wire IEDs and small arms to induce a high number of casualties. U.S. forces can expect enemy fighters to fight to the death until the local commander confirms that the Taliban leadership is clear of the area. See Figure 10 for the proposed enemy's situation template, a military document used to visualize how an enemy force will fight.



[Best viewed in color]

Figure 10. Enemy Situation Template. Proposed Distribution of Forces. Adapted from Google Earth (2018).

b. Civilian Population

The arrival of the Marines prompted the departure of women and children as locals expect a clash between U.S. and Taliban forces. Unfortunately, many of the farmers and their sons remained behind to protect their homes, making it difficult to distinguish Taliban fighters from the civilian population. The enemy uses this to their advantage by wearing local garb and using civilian traffic to mask their movements. Currently, the enemy can move freely within the area, allowing them to choose when and where to strike.

Of note, this thesis does not seek to evaluate civilian casualties or civilian behavior. The focus of the thesis is to identify how many drones are needed in this operation and determine which factors are most important in enhancing swarm performance. Since target selection and engagement is a function of the company fire support team, no effort was included in the model to track civilian casualties. However, a civilian agent squad was added to stress the search and detection capabilities of the ISR swarm.

c. Friendly Forces

The Marine infantry battalion consists of three infantry line companies, one Afghan infantry company, and a UAV company. Additionally, one M777 Lightweight Howitzer battery is in direct support of the battalion.

The battalion's mission is to defeat enemy forces in the vicinity of Talafar in order to deny the Taliban safe haven and a source of revenue.

5. Mission: Company A

Company A will kill or capture enemy fighters and seize weapon caches in order to deny Taliban forces safe haven in the vicinity of Talafar. The company must be prepared to establish blocking positions southwest of Talafar in support of Company C's mission.

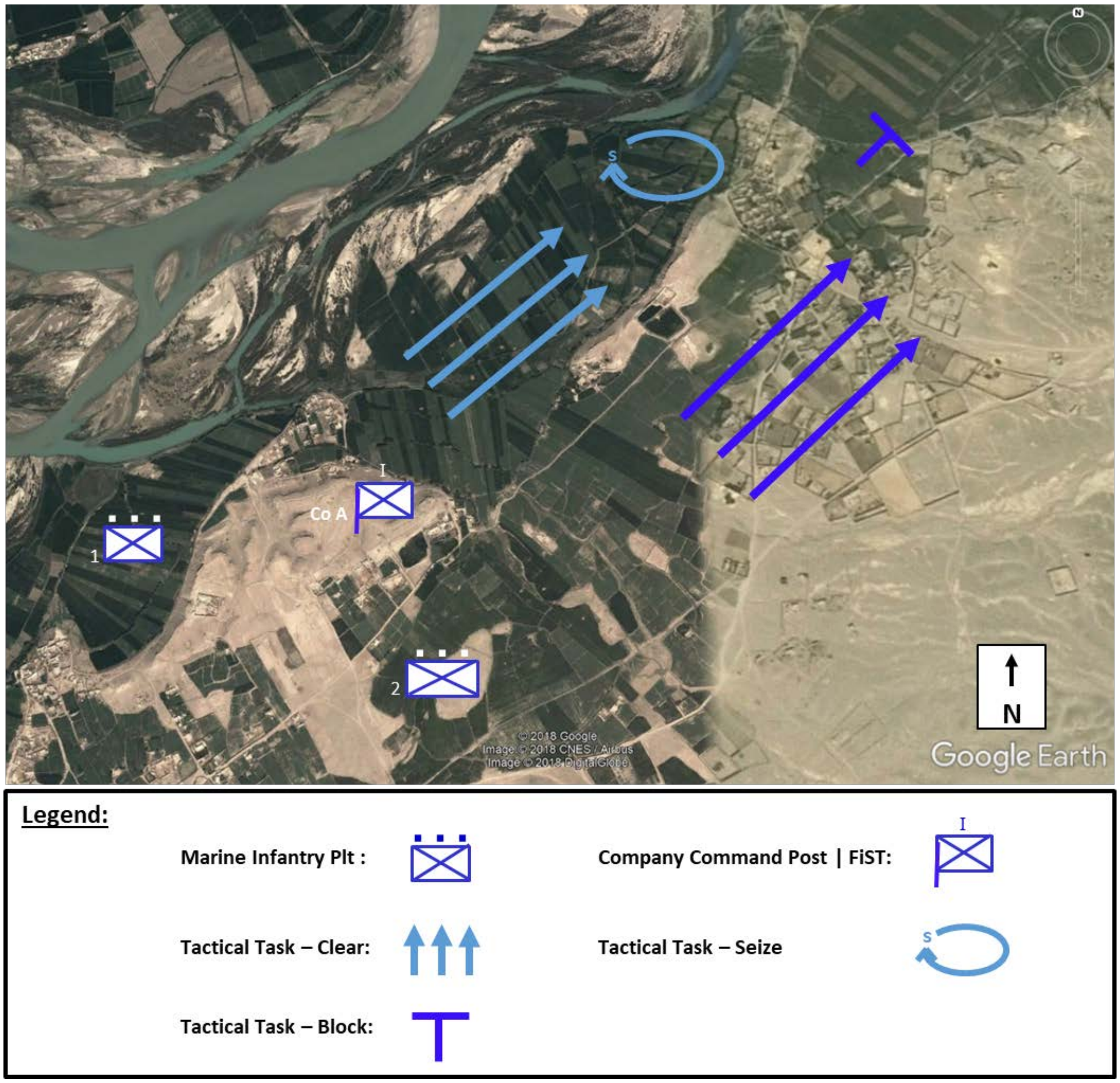
6. Execution: Company A

a. Commander's Intent: Company A's role in the Battalion Operation

The purpose of this operation is to defeat enemy forces and prevent enemy leadership from escaping the area. The company will conduct a clear in zone and seize a weapons cache located in the agriculture zone. Additionally, the company will establish blocking positions southwest of Talafar to ensure that the enemy does not evade Company C. At end state, enemy forces are killed or captured, the weapons cache is destroyed, and the company blocking positions effectively prevent the enemy from egressing the area.

b. Concept of the Operations: How Company A Will Accomplish the Mission

See Figure 11 for a visual depiction of Company A's mission.



[Best viewed in color]

Figure 11. Company Scheme of Maneuver. Adapted from Google Earth (2018).

c. Tasks: What Company A Units are Doing during the Operation

First platoon will clear the agricultural zone of enemy fighters and seize the weapons cache. After the weapons cache is collected or destroyed, the platoon will reinforce company blocking positions. Second platoon will clear the primary routes running through the local village and establish the company's primary blocking positions. Local homes will only be entered or fired upon if enemy fighters use the structures to initiate ambushes. Forces must apply proportional response when using either direct or indirect fires against targets located in the village. Although forces have the right to self-defense, civilians must be considered when applying lethal force. First squad, third platoon is the company's reserve.

The company fire support team (FiST) controls all indirect and aerial fires during the mission. External units attached to the company include an 81mm mortar section and a UAV team, equipped with an ISR swarm system. The 81mm mortar section will provide immediate fire support during the mission. The UAV team will assist the FiST in locating and targeting enemy combatants. At the beginning of the operation, the artillery battery will be in direct support of the company. This means that the company FiST will have priority.

This ends the operations order. The admin and logistics and command and signal paragraphs are intentionally omitted as they do not play a role in this thesis model scenario.

C. BUILDING THE VIRTUAL ENVIRONMENT: TERRAIN IN MANA-V

In MANA-V, the model environment is comprised of three-layers. The first layer is an elevation map which uses greyscale colors ranging from 0 to 255 to represent terrain elevations (McIntosh et al., 2007). The color black depicts low areas of elevation. Lighter areas represent an increase in elevation, with white being the highest point on the map. For this thesis model scenario, the map elevation ranges from 0 to 20 meters in height.

Any terrain map can be converted to bitmap, greyscale and uploaded into the MANA-V software. The elevation map effects agent movement, weapons effects, and sensor line-of-sight calculations. The author used data from the National Imagery and Mapping Agency to develop Figure 12, the elevation map for this scenario.

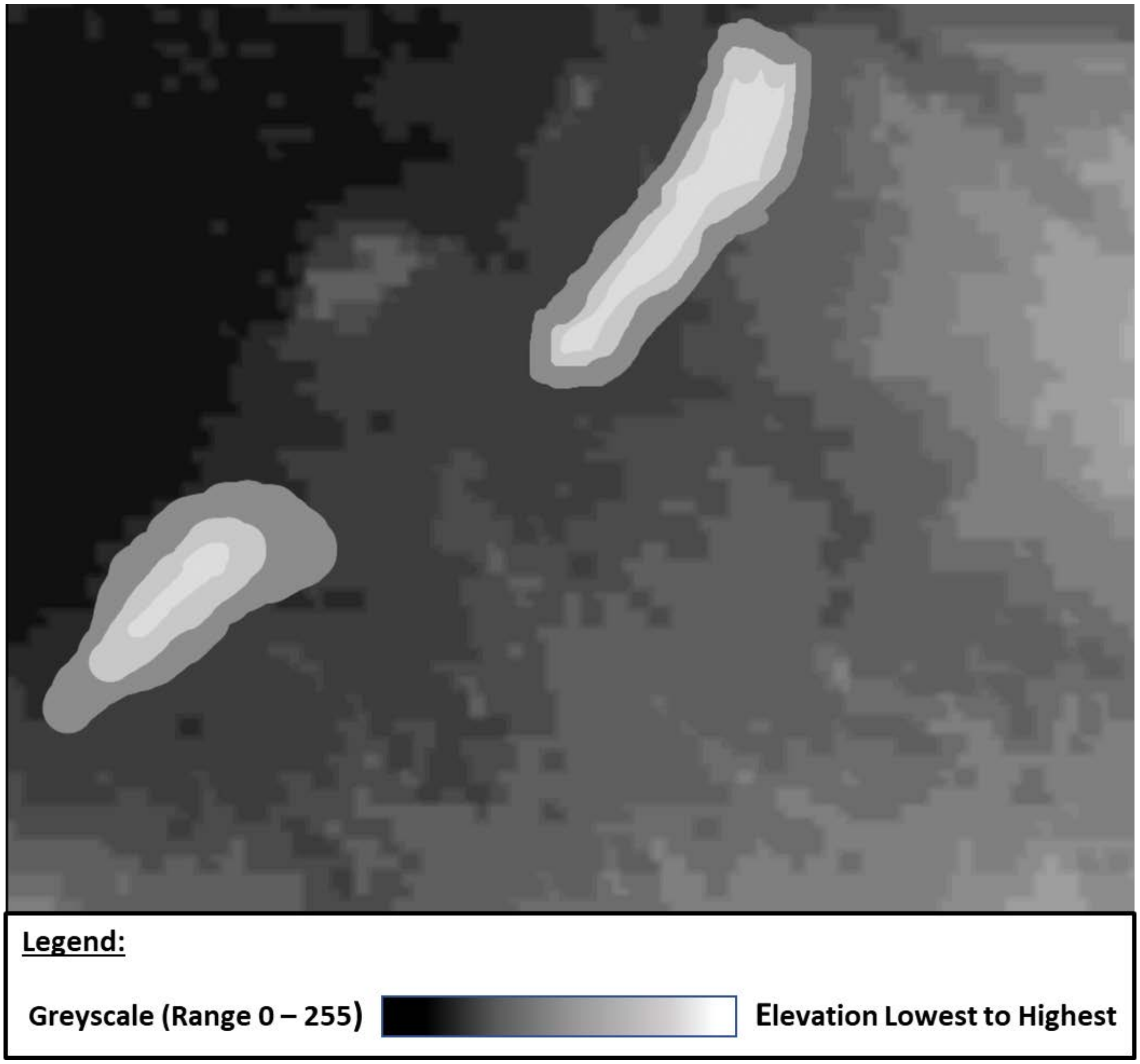


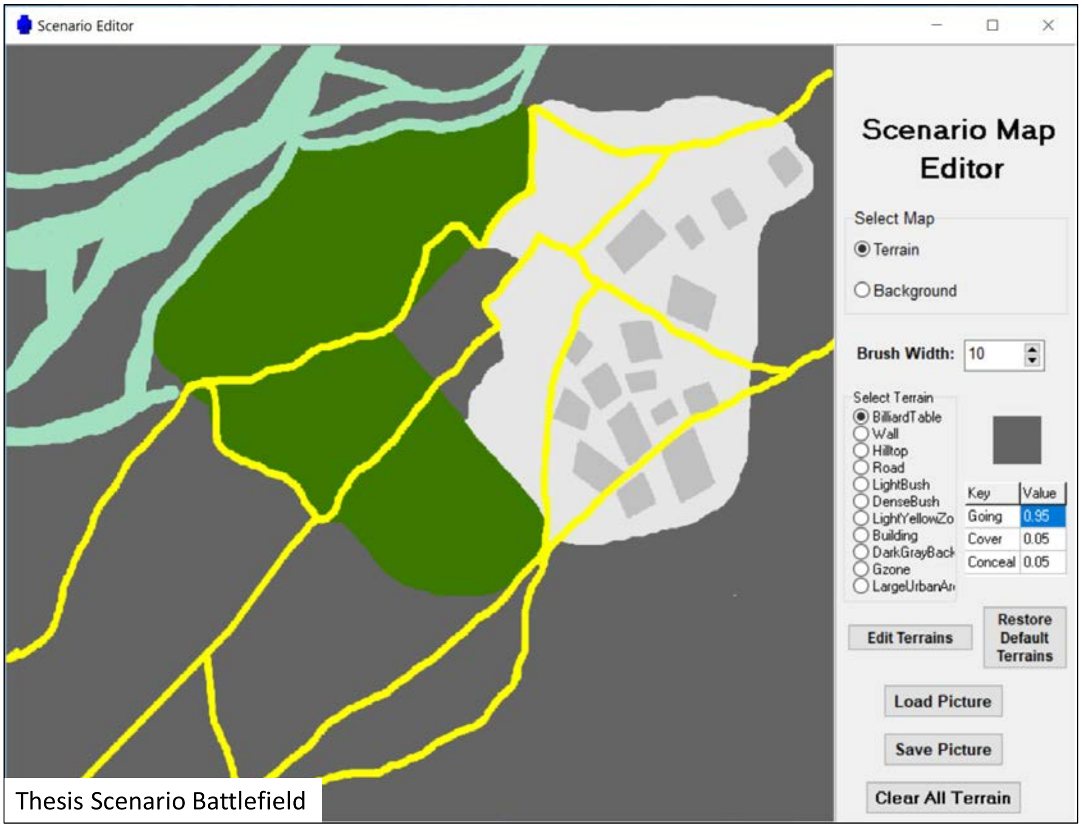
Figure 12. Scenario Elevation Map

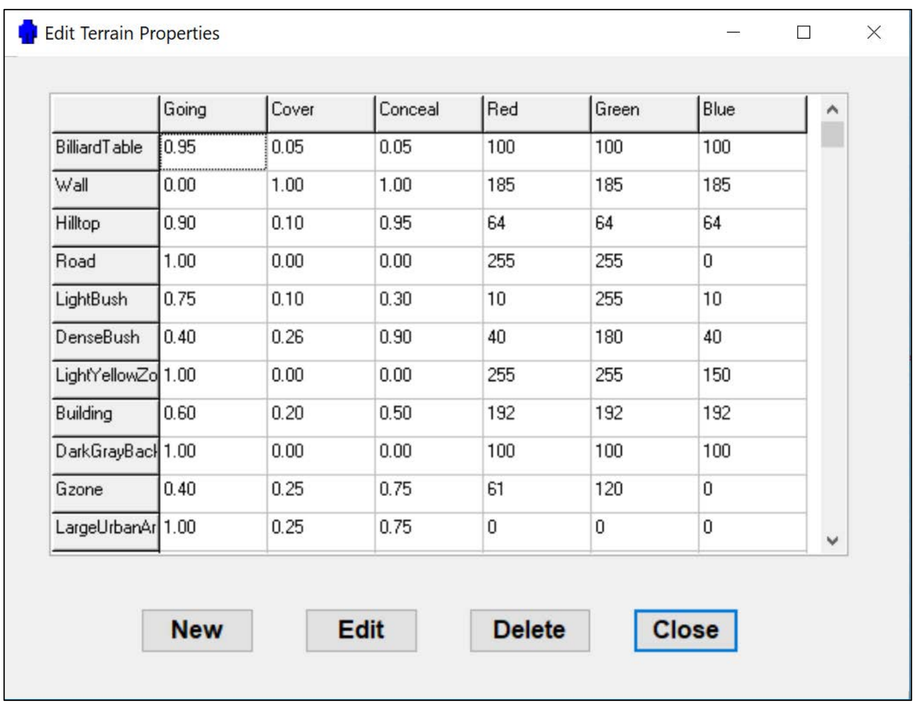
The second and more complex layer is the terrain map. Using a red, green, blue color scale, a user can build the geographical characteristics that define their battlefield. The MANA-V Terrain Editor requires several parameter inputs. On a scale from zero to one, users weight three terrain characteristics: terrain trafficability, referred to as “Going,” “Cover,” and “Concealment.”

For the “Going” parameter, a weight of zero inhibits any agent movement and a weight of one results in free maneuver. Values between zero and one limit an agent’s speed by that fraction. Overall, the “Going” parameter allows a user to accurately model how terrain and buildings effect unit maneuver and movement speed.

The “Cover” parameter represents the level to which terrain protects an agent against direct fire weapons. A weight of zero represents open terrain in which an agent is fully exposed to enemy fire. A weight of one means that the terrain protects the agent in total. Values between zero and one limit agent exposure by that fraction and play a key role in adjudicating kinetic exchanges between agents (McIntosh et al., 2007).

The “Concealment” parameter models an agent’s visibility in the terrain. A weight of zero infers that an agent is fully visible to all agent squads while a value of one means an agent is totally concealed (McIntosh et al., 2007). When combining all three parameters, a rich model environment begins to emerge. In a more practical sense, the MANA-V Terrain Editor allows a user to control traffic patterns, restrict agent movement, and capture realistic sensing and weapons effects based on terrain and structures. Figure 13 shows the terrain map for this scenario.





	Going	Cover	Conceal	Red	Green	Blue
BilliardTable	0.95	0.05	0.05	100	100	100
Wall	0.00	1.00	1.00	185	185	185
Hilltop	0.90	0.10	0.95	64	64	64
Road	1.00	0.00	0.00	255	255	0
LightBush	0.75	0.10	0.30	10	255	10
DenseBush	0.40	0.26	0.90	40	180	40
LightYellowZo	1.00	0.00	0.00	255	255	150
Building	0.60	0.20	0.50	192	192	192
DarkGrayBack	1.00	0.00	0.00	100	100	100
Gzone	0.40	0.25	0.75	61	120	0
LargeUrbanAr	1.00	0.25	0.75	0	0	0

[Best viewed in color]

Figure 13. Scenario Terrain Map with Terrain Characteristics

The final layer is a background bitmap. Unlike the first two maps, the background image is purely aesthetic. It allows the user to overlay a map chip that assists in orienting the audience to the real-world location the user is modelling. The background image does not affect agent movement or model calculations. Figure 14 is the full scenario modeled in MANA-V. The different captions describe how the scenario description translates into the model environment.

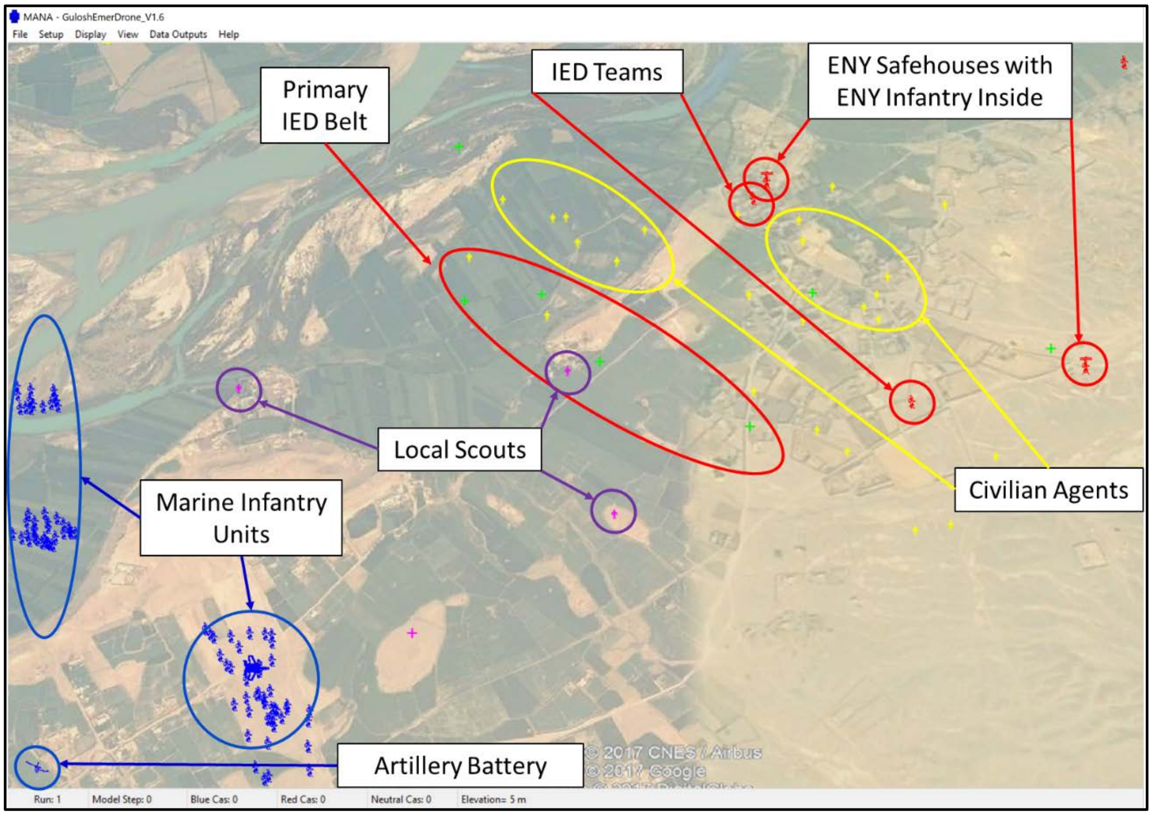


Figure 14. The Thesis Scenario in MANA-V

D. MODEL ASSUMPTIONS CRITICAL TO MODEL DESIGN

In modeling and simulation, assumptions are needed to frame the scenario and explain agent characteristics. The following assumptions are the main influencers that drove agent development and model design.

- This thesis seeks to gain insight into swarm performance, not ground unit proficiency. To focus on the swarm, Marine infantry and enemy security forces are modeled as near peer adversaries.

- The battlefield and mission set are appropriate for current swarm capabilities. While this makes the thesis scenario more believable, it forced the author to reduce weapon ranges and sensor distances to accurately reflect true battlefield conditions.

- The enemy fighters fight to the death to protect the notional Taliban leaders to the northeast of the battlefield. The battle stops when the model reaches 9,000 timesteps. One timestep represents one second in real time, which means that the longest the battle can last is 2.5 hours. The author is aware that it is unlikely that enemy forces fight to the death; however, the small map makes it difficult for the enemy fighters to escape to a safe area.

- Due to a small battlefield, high UAV speeds disproportionately affect swarm performance. Recognizing this modeling shortfall, speed considerations are not included in the design of experiment.

- Fire support planners and air controllers prefer Group 1 UAVs to operate below 500 feet above ground level (AGL). This constraint serves as the upper bound for all field of view and search area calculations.

- All UAVs are equipped with gimbal optics or sensors to allow the vehicle to sense in 360 degrees. None of the UAVs are modeled with fixed or directional sensor suites.

- UAVs are not subject to attrition. Enemy fighters are not programmed to attack the single UAV or AVs in the swarm.

- The UAV support section discussed in this thesis is a hypothetical construct and does not currently exist. Based on conversations with

ARSENL team members, it is recommended that the smallest UAV support section consist of six Marines: central planner, assistant central planner, two targeteers, and two launch and recovery specialists. The author uses this task organization and terminology throughout the thesis.

- ISR coverage is constant. During combat operations, the UAV support section is responsible for ensuring that there are no gaps in ISR employment. More specifically, this means that swarm deployment and recovery do not interfere with ISR coverage.

- No swarm launch or recovery platforms are modeled as part of the Blue force. Launch is assumed to be instantaneous once the company headquarters is established. Additionally, recovery actions are not factored into swarm employment due to limitations in the MANA software. The effect of this assumption is that the findings on drone swarm size represent an optimistic estimate.

E. THE AGENT SQUADS AND BASIC CHARACTERISTICS

This section provides a detailed description of the 16 different types of agent squads modeled for this scenario. The author used assumptions, combat experiences, input from subject matter experts, and open source publications to design each agent squad. Additionally, the author explored 100 simulated battles of the base scenario varying sensor and weapon parameters. This verification process assisted in fine tuning parameter inputs, verifying that simulation outputs were practical, and ensured that the scenario represented the author's experience when conducting a similar mission. The fixed weapon ranges and sensor values presented below are the results from the verification experiment. Unfortunately, all simulation packages are limited in their ability to precisely replicate the "real world." MANA is no different.

a. Drone Swarm Agents

For this thesis, an ISR drone swarm consists of two distinct types of UAVs. The seeker UAV serves as the swarm's contact sensor tasked with locating targets of interest.

Theoretically, the seeker UAV is cheap and expendable, allowing a UAV support section to launch seekers in mass to cover more of the battlefield and deny enemy forces a first strike advantage.

The verification UAV is an autonomous member of the swarm, outfitted with an enhanced camera system. Once the seekers locate a potential enemy target, they signal to the closest verification UAV. The verification UAV serves as the "eyes" of the UAV support section, providing the central planner with a live video feed of the target area. Theoretically, the central planner can manage the different feeds and a targeteer can extract targeting data from the ground control station. Ultimately, confirmed enemy targets are passed to the company's Fire Support Team (FiST) for prosecution. The agent descriptions below capture how the emergent and hierarchical swarms are modeled in MANA-V.

(1) Emergent_Seeker_Drones

This agent squad represents the seeker part of the swarm. Individual agents can detect contacts out to 100 meters but rely on the verification agent to classify a contact. The squad travels in a linear formation with heavy priority given to mission waypoints such as the known cache and village. If an agent locates a contact, a signal is sent to the closest verification drone for further investigation. Note that during experimentation, the DOE varies the seeker drone's sensor characteristics with the intent of identifying operational thresholds that enhance swarm performance.

The seeker agent is a blue fixed-wing icon. The icon jitters when investigating unknown contacts. Once a seeker drone detects an agent, the drone will continue to investigate the contact for up to 300 seconds or until the verification drone classifies the agent as hostile or neutral. After 300 seconds, the seeker drone moves on to the next agent or continues to the next predetermined waypoint. At the beginning of the scenario, the seeker squad moves to investigate the weapons cache in the agricultural zone and then shifts focus to the village.

(2) Emergent_Verification_Drones

For the emergent swarm, there is one verification drone per group of seeker drones. In the design of experiment (DOE), the number of verification drones is varied to gain insight into how many drones are required to support the company in this scenario. The verification drone agent cannot physically detect enemy contacts, rather it can only classify contacts. This action models the verification drone's relationship with its seeker counterpart. Ultimately, once a seeker identifies a potential target, the verification drone must move to the suspected target area to classify the agent as friendly, neutral, or hostile. A single verification drone can classify out to 200 meters, but the probability of accurately classifying a contact drops significantly outside of 50 meters. Similar to the number of drones, the DOE varies the verification drone's sensor characteristics with the intent of identifying operational thresholds that enhance swarm performance. The DOE is further discussed in Chapter IV.

The emergent verification agent is a blue UAV icon. The icon remains blue during mission transit. If a seeker drone locates an unidentified contact, a verification drone increases its speed and turns green. This action signifies that the verification drone is actively trying to classify an unknown contact. Once the drone classifies an enemy agent, the drone will continue to follow the hostile contact for up to 100 seconds or until the FiST destroys the enemy agent with indirect fires. The FiST engages enemy agents in the order they enter the queue for as long as the enemy agent remains visible on the SA map. If the hostile agent is still alive after 100 seconds, the verification drone must re-classify the target or the hostile agent will be removed from the SA map. Additionally, while the UAV icon is green, the agent's propensity to pursue enemy agents increases.

The verification agent travels in a dispersed, linear formation with heavy priority given to mission waypoints. If an agent locates a contact, it will attempt to classify the contact and report to the Company HQ agent. The Company HQ updates the inorganic situational map for all Blue forces. This action simulates the UAV support section confirming a contact's status and updating the company headquarters. Furthermore, if a contact is classified as hostile, the FiST sends a report to a firing agency to engage the enemy combatant.

(3) Hierarchical Seeker Drones, Hierarchical Verification Drones

These two agents have the exact same characteristics as their emergent counterparts. The only significant difference between the agents is their task organization. As discussed in Chapter II, the hierarchical swarm allows the central planner to divide the swarm into subswarms. Each subswarm contains its own seeker and verification drones. This approach allows the central planner to disperse his or her resources and sectorize the reconnaissance effort. In the thesis scenario, one subswarm is sent to investigate likely enemy locations in the agricultural zone while the second subswarm reconnoiters the village.

b. Friendly Forces

(1) Marine_Squad 1_1– 2_3

Each Marine infantry squad consists of 13 infantrymen. Individual agents have an "Eyes_Advanced Optic" sensor which allows them to detect and classify other agents out to 200 meters. Organic squad weapons include the M-4 assault rifle, the M-27 Infantry Automatic Rifle (IAR), and an M203: 40mm Grenade Launcher. While the two rifles are modeled as direct fire, point weapons, the M203 fires an indirect, explosive munition with a kill radius of five meters. Due to a small battlefield, the nature of the terrain, and the author's combat experiences, the engagement ranges for each weapon system are limited to 150 meters. Note that the sensor and weapons' ranges for this agent are fixed in accordance with the parameter thresholds identified in the verification experiment.

All squads move along predetermined tactical waypoints towards mission objectives. First platoon moves to seize the enemy weapons cache in the agricultural zone. Second platoon, clears a route through the urban zone to establish a blocking position on the north side of the village.

The default behavior for each squad is to patrol in a linear formation with priority given to mission waypoints. If a Marine squad locates an enemy agent, the friendly agents pursue the hostile element and engage with organic weapons. If agents locate an IED, they are programmed to report the device and avoid the area. When fired upon, the Marine squad icon changes to the prone position (an agent lying on the ground) to represent an agent seeking cover to reduce the probability of being hit by a bullet.

Squad communications follow doctrinal reporting procedures. Infantry Squads 1_2 and 2_2 represent the location of the platoon commander. Any information on enemy forces is reported to the squad's respective platoon commander via radio. In turn, the platoon commanders pass situation updates to the Company_Headquarters (HQ) agent for action.

(2) Company_HQ (FiST Capable)

The Company_HQ agent represents the location of the company commander, the FiST, and the UAV support section. This agent can sense out to a fixed distance of 500 meters; however, the probability of detecting enemy agents is extremely low. The agent's organic weapons are the same as those assigned to the Marine squads. Ultimately, the Company HQ can defend itself against close combat attacks; however, its primary function is to collect and disseminate information to the Blue force.

At the beginning of the scenario, the Company HQ moves into an elevated position overseeing the battlefield. Once in position, the agent remains static to exercise command and control of Blue's mission. The UAV support section is responsible for controlling ISR assets and locating enemy combatants. If an enemy is located, the UAV support section reports targeting information to the FiST. The FiST sends a concise report to either the M777 artillery battery or the 81mm mortar section to prosecute enemy combatants.

The Company_HQ agent serves as the communications hub for all Blue units. Marine squads report enemy contacts via radio. The UAV support section is co-located with the FiST, using a live video feed to assist fire supporters in locating and targeting enemy agents. To gain insight into the UAV support section's proficiency level, the author varied the communication latency parameter. Latency determines how quickly information is processed before updating the inorganic situational awareness map. Essentially, manipulating latency helps gain insight into how a central planner or UAV operator's level of proficiency affects the targeting process. Once the UAV support section confirms the target's location, the FiST uses radio communications to pass targeting data to the two firing agencies supporting the mission.

(3) RQ-11B_Raven_UAS (SingleUAS)

This agent models the Marine infantry company's organic ISR asset. The Raven UAS is a hand launched, fixed-wing drone with 90 minutes of endurance. Although the Raven can perform at higher altitudes, fire support coordinators prefer the UAV remain below 500 feet AGL to deconflict with manned aircraft and close air support missions. Coupling this constraint with the limitations of the Raven's electro-optic (EO) camera, the agent can sense out to 200 meters. In Experiment Set 1, this parameter value remains fixed.

The Raven agent follows waypoints to likely enemy positions in the vicinity of the weapons cache and the village. In its default state, the Raven is programmed to navigate to mission waypoints or investigate unknown entities with equal preference. In its contact state, the agent will aggressively seek out enemy infantry, IEDs, or IED triggermen.

(4) M777_155mm (M777)

The M777_155mm agent represents an artillery battery in direct support of a Marine infantry company. The M777 does not have any organic sensors and relies on information from the Company HQ to engage enemy targets. This communications link simulates how the FiST sends targeting data to the M777 artillery battery during a fire mission.

The M777 agent has a max effective range of 10,000 meters, which allows the battery to engage any target on the map. Additionally, the agent is modeled as an indirect weapon system with a kill radius of 25 meters per round. At the beginning of the scenario, the battery is equipped with 50 rounds. After firing all ammunition, it takes the battery 10 minutes to reload.

(5) 81mm_Mortar_Section

The 81mm_Mortar_Section agent serves as the second indirect firing agency available to prosecute enemy agents. Like the M777, the mortar section does not have any organic sensors and relies on information from the Company HQ to engage enemy targets.

The mortar section has a max effective range of 5,600 meters and a shot kill radius of 10 meters per round. At the beginning of the scenario, the section moves into a firing position near the Company HQ and establishes its firing point. All fire missions are sent from the FiST to the mortar section via radio. The agent is equipped with 50 high explosive rounds. Due to the short duration of the mission, it is assumed that emergency resupply will not be needed, thus the mortar section cannot reload after expending its initial stockpile.

c. Enemy Forces

(1) Local Scout Agents: Local_Scouts_Scouts_Gzone, Local_Scouts_Uzone

The local scout agents represent the enemy's forward deployed reconnaissance element tasked with reporting Blue force movements. The scout agents are divided into zones with GZone representing those scouts in the agricultural area and the Uzone pertaining to those scouts in the urban sprawl. It is common for hybrid forces to recruit or pay locals to collect information on U.S. forces. Killing or detaining a local scout typically results in the population resisting allied efforts to bring security to the region. To accurately model this relationship, the Local Scouts' concealment parameter is set to 100%. This modeling technique simulates that the scouts can move freely on the battlefield and report Blue force locations without being targeted by Marine infantry or ISR assets. Furthermore, this agent is programmed to seek out, follow, and report Blue movements to the enemy commander via cell phone.

(2) ENY_Local_Commander

Like the Company HQ, this agent is static and serves as the communications hub for all Red units. Organic sensors and weapons are defensive in nature, allowing the agent to sense and engage Blue forces out to 200 meters. Upon receiving local scouting reports on Blue force movement, the ENY Local Commander radios to the safe houses, releasing enemy fighters to defend in sector. Ultimately, the commander's primary function is to identify Blue force locations and disseminate that information to the IED teams and security forces.

(3) Enemy Safehouse Agents: Safehouse_North, Safehouse_South

Safehouse agents determine the starting locations for the four enemy security squads. Safehouse_North applies to the enemy defending in the agricultural zone. Safehouse_South applies to the force defending in the village.

The safehouse agents are denoted by yellow mast icons. Using MANA's "homebox" feature, the safehouse locations are randomly placed at the beginning of each simulated run. This modeling technique simulates uncertainty prior to the battle and adds variability to the model.

At the beginning of the scenario, the enemy security forces are tethered to the starting location. Once Blue forces are located, the ENY Local Commander calls the safehouses via radio. This action releases enemy fighters from their respective safehouse to defend in sector. To verify that an enemy security force is properly released from the safehouse, the mast icon changes from yellow to red.

(4) Enemy Security Forces by Zone: Eny_Local_SecFor_Gzone1, Gzone2, Urban1, Urban2

Each security force (SecFor) consists of five well trained fighters. Individual agents have an "Eyes_Binos" sensor allowing them to detect and classify other agents out to 225 meters. This slight detection advantage models the disadvantage U.S. forces experience when operating in urban environments. Because the Marines cannot blend in with the local population, they can be detected at a greater distance. To the contrary, enemy fighters can hide within the civilian population and initiate attacks to their advantage. Organic squad weapons include the AK-47 assault rifle, the PKM medium machinegun, and a 40mm grenade launcher. Like the Marine infantry, the engagement ranges for each weapon system are limited to 150 meters and all sensors and weapons ranges for this type of agent are fixed in accordance with the parameter thresholds identified in the verification experiment.

Once activated, the SecFor teams move along predetermined waypoints towards their defensive positions. Once at their defensive position, they spread out to simulate a linear defense. The agents are programmed to stay close together to mass fires on the Marine infantry. If a SecFor agent takes fire from the Blue force, their icon changes to the prone position (an agent lying on the ground) to represent an agent seeking local cover. As addressed in the assumptions section, the SecFor agents fight to the death. The stopping condition for the simulation is based on time, not a defined stopping condition.

(5) ENY_IED_Tm1_(Uzone), ENY_IED_Tm2_(Gzone)

There are two enemy IED teams located on the battlefield. Both teams seek out and arm neutral IED agents. The agent's concealment parameter is 90%, simulating the triggerman's ability blend in with the population and detonate a device from a position of advantage. At the beginning of the scenario, each team is assigned to one of the seven IEDs. This means that only two IED agents can be active during an experiment run. When enemy scouts report Blue movements to the commander, the IED teams move to arm their assigned device. If an IED team gets within 150 meters of an IED, the team refuels the device. The refuel action changes the IED agent from its default state to armed. As long as the triggerman (IED Tm agent) is alive, the IED remains capable of attacking Blue forces.

(6) IED

There are seven IED agents on the battlefield. The IEDs represent an obstacle belt designed to inflict casualties and prevent Blue forces from achieving their mission. Green cross icons mark each IED location. At the beginning of the scenario, all IEDs are benign. When an IED team comes within 150 meters of the IED agent, the device is activated. This simulates a triggerman preparing the IED for detonation.

Two actions occur when an IED agent is activated. The IED icon changes from green to red and the agent's allegiance setting shifts from neutral to enemy. The allegiance shift allows Blue forces to see the device if in the right location. The location of all IED agents resets at the beginning of each simulation run to add variability to the model.

d. Neutral Forces

(1) Civilian NonHostile

This agent simulates civilian presence in both the village and agricultural zone. All civilian agents are randomly distributed across the battlefield and challenge the Blue force ISR assets in locating and identifying enemy forces.

F. MODEL LIMITATIONS

Recall that models are merely a representation of the "real world." No matter how sophisticated the software, models will be limited in their ability to capture every aspect of a complex operating environment. In order to understand the findings and conclusions of this thesis, readers must be aware of the model's shortcomings. The following points address software limitations that inhibited both model design and study conclusions.

1. Aerial Sensors and Sensor Characteristics

MANA is a low-resolution modeling environment. The elevation and terrain maps affect agent movement, line-of-sight calculations, and weapons affects at the ground level. Users may input an agent's sensor height or remove movement restrictions to simulate flight; however, the program does not provide advanced options for aerial platforms. To be more specific, MANA gives no consideration to air centric factors to include air delivered munitions (i.e., sensor frames per minute, sensor/camera angle, or sensor performance at different altitudes). Instead, a user must accept "work arounds" or parameter manipulations to model air vehicles. This approach limits MANA's utility in studying a platform's detailed technical specifications.

2. No Dynamic Re-tasking

During ISR missions, it is common for UAS operators to deviate from the initial flight plan to investigate possible enemy contacts in vicinity of the ground force. This process is called dynamic re-tasking. For swarms, this concept is even more important as a central planner can task subswarms to investigate unknown contacts as the rest of the swarm continues along its tactical route. While MANA does allow a user to assign very specific agent behaviors, none of the behavior settings replicate dynamic re-tasking. This limitation prevented the author for exploring the advantages and disadvantages of using subswarms during mission execution. Perhaps follow-on efforts can work with the MANA-V team to build in a dynamic re-tasking behavior or find a modelling technique that can more accurately model subswarm employment during mission execution.

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IV. DESIGN OF EXPERIMENT: EFFICIENTLY EXPLORING THE FACTOR SPACE TO GAIN INSIGHT INTO SWARM PERFORMANCE

Designing an experiment is both an art and a science. The art involves properly framing the problem, identifying factors related to the response, and determining experimental constraints. The science includes developing a well-balanced design that efficiently explores the factor space without confounding factor effects. While simulation is a cost effective and powerful tool for exploring complex systems, without a proper design of experiment (DOE), a simulation study can become unwieldy. To the contrary, when simulation and DOE are synchronized, the potential for studying the factor space increases dramatically.

This section discusses the thesis experiments and their associated DOE. Section 4.A. examines the measures of effectiveness (MOEs) used to analyze swarm performance during mission execution. Section 4.B presents the thesis experiments and identifies the factors used for each DOE. Section 4.C introduces the nearly orthogonal Latin hypercube (NOLH) and quantifies how this advanced DOE technique saves an analyst both time and computing resources.

A. THESIS EXPERIMENTS: QUANTIFYING MISSION SUCCESS

The Defense Acquisition University defines a measure of effectiveness as “the metric that measures the military effect that comes from using the system in its expected environment” (“Measure of Effectiveness,” n.d.). More simply, a MOE is a metric that quantifies mission performance under specified conditions (Zappa, 2009). In this thesis, ISR assets seek to locate and target enemy combatants before the enemy can initiate a complex attack. Company fire support personnel, to include UAV operators, accomplish this task by efficiently locating enemy fighters in zone and effectively prosecuting those targets with IDF assets. Ultimately, the FiST and UAV support section are responsible for denying the enemy freedom of maneuver and the element of surprise.

In this thesis, the author studies the Blue force's performance, as defined by thesis MOEs, by varying factors for unit lethality, ISR performance characteristics, and UAV employment. In each experiment set, the author uses advanced DOEs to vary factors with the intent of gaining insight into operational thresholds and unit performance measures. When combining MOEs and factors, a design of experiment begins to take form.

B. THESIS EXPERIMENTS

1. Experiment Set 1: Base Case—Current Company Configuration

The first experiment set studies the deployment of the RQ-11B Raven reconnaissance drone. The Raven is an organic company asset and uses a gimbal, stabilized camera with fields of view (FOV) ranging from 9–35 degrees. For this scenario, the Raven flies at 500 feet above ground level (AGL) with 90 minutes of endurance. Additionally, the UAV employs a sensor which is capable of viewing out to 200 meters.

The author used Experiment Set 1 to develop a baseline understanding of the thesis scenario when deploying current ISR assets. To efficiently explore the design space, the author chose an NOLH DOE consisting of 33 design points (DPs). The design was then stacked and rotated to create a combined DOE of 65 DPs. Each DP was replicated 100 times for a total of 6,500 simulated missions. See Tables 4 and 5 for the primary MOEs studied in this experiment and the eight factors used to explore the design space.

Table 4. Experiment Set 1 MOEs

Experiment Set 1: Baseline / Current TO	
Measures of Effectiveness	
MOE 1:1	How long does it take the Blue force to classify the first hostile agent? (A number between 0 and 9,000 seconds).
MOE 1:2	How many Blue casualties are sustained during mission execution?

Table 5. Experiment Set 1: Factors with Variable Type and Range

Factors for Drone Employment		
Factor List	Ranges	Type of Variable
1. Drone Sensor Range (m):	200 – 500	Continuous
2. Drone Sensor Mean Time Between Detections (sec)	10 – 300	Continuous
Factors for Ground Combat Element		
Factors	Ranges	Type of Variable
1. Movement Speed of Infantry Agents (m/sec)	0.3 – 1.0	Continuous
2. Blue Force Combat Proficiency (Phit)	0.25 – 0.75	Continuous
Factors for Supporting Arms		
Factors	Ranges	Type of Variable
1. M777 Combat Proficiency (Phit)	0.3 – 1	Continuous
2. M777 Reload Time (sec)	480 – 900	Continuous
3. 81mm Mortars Combat Proficiency (Phit)	0.25 – 0.90	Continuous
4. SUAS Operator's Proficiency (sec)	30 – 300	Continuous

2. Experiment Sets 2 and 3: Swarm Employment

The second and third experiment sets focus on the deployment of the ISR swarm. These experiment sets examine the impact of different control strategies on the MOEs as defined in the base case. Experiment Set 2 focuses on the emergent swarm in which the seeker and verification drones travel as one heterogenous flock during mission execution. Experiment Set 3 studies the hierarchical control strategy, deploying the swarm in two small subswarms that are assigned to patrol along parallel sectors. Both scenarios assume that the swarm flies at 500 feet AGL and that each drone type (verification and seeker) has 45 minutes of flight endurance.

The only difference between the two experiments is the control strategy used during mission execution. The author intentionally mirrored the DOE to address the thesis question of whether or not control strategy affects swarm performance. Additionally, the factors for each experiment pertain to only swarm capabilities. Concentrating solely on swarm performance parameters allows the author to answer the second thesis question by identifying performance measures that enhance swarm effectiveness.

Experiment Sets 2 and 3 each consist of seven factors. To efficiently study the design space, the author chose an NOLH DOE consisting of 65 design points. The design was then stacked and rotated to create a combined DOE of 129 DPs. Each DP was replicated 100 times for a total of 12,900 simulated missions per experiment set. Table 6 displays the MOEs and factors for the experiments.

Table 6. Swarm Experiment Set: MOEs and Factors with Variable Type and Range

Experiment Sets 2 and 3: Control Strategies		
Measures of Effectiveness		
MOE 1	How long does it take the Blue force to classify the first hostile agent? (A number between 0 and 9,000 seconds).	
MOE 2	How many Blue casualties are sustained during mission execution?	
Factors for Drone Employment		
Factor List	**Ranges**	**Type of Variable**
1. Number of Verification Drones	1 - 5	Discrete Numeric
2. Number of Seeker Drones per Verification Drone	1-5	Discrete Numeric
3. Seeker Drone Mean Time Between Detections (sec)	10 - 300	Continuous
4. Verification Drone Probability of Classification (Pclass)	0.10 – 0.90	Continuous
5. Dispersion b/t Seeker Drones (m)	10 – 300	Continuous
6. Dispersion b/t Verification Drones (m)	10 – 300	Continuous
7. Swarm Latency (sec)	30 - 300	Continuous

The first two factors affect the overall capacity of the swarm. The seeker drones scale off the verification drones. For example, if the design point in the DOE calls for three verification drones and two seeker drones per verification drone, then the total number of drones in the swarm equals six.

Factors three and four examine the technical aspects of the swarm. For probability of detection, MANA uses the inverse and allows a user to manipulate the mean time between detections. Thus, factor three addresses the seeker drone’s ability to detect enemy combatants based on a sensor with a detection range of 50 to 100 meters. As the distance increases towards 100 meters, the time to detect increases. Factor four is the key tactical employment factor of interest for the verification drone. The verification drone can classify out to 200 meters. As the classification distance increases, the probability of classification decreases.

Factors five and six manipulate the dispersion between drones within an agent squad. These parameters change the behavior settings in an agent squad, directing individual agents to maintain an approximate distance. MANA does offer a formations option consisting of traditional military movement patterns. Unfortunately, the thesis battlefield was too small to benefit from this feature.

The final factor, swarm latency, models the central planner and targeteer's ability to effectively manage the swarm, collect data from the ground control station, and pass the information to the FiST. More concisely, the latency parameter affects how quickly swarm agents process information and pass it to the FiST. In the author's experience, a support section's data management and battle drills are just as important as controlling the UAV. Well trained teams can quickly identify enemy combatants, position the UAV to collect targeting data, and accurately transmit that data to prosecute a target. This factor models the proficiency of the UAV support section and provides insight into the minimum skill level needed for the section to effectively support the ground force.

C. DOE METHODOLOGY: SPACE-FILLING NEARLY ORTHOGONAL LATIN HYPERCUBE (NOLH)

In simulation, the design space involves all combinatorial possibilities between input factors. To illustrate this concept, consider a full factorial design containing eight factors. Each factor is categorically divided into five settings (referred to as levels). Under these circumstances, the design space sampled for the experiment is comprised of 5^8 or 390,625 factor combinations.

On average, it takes 10 minutes to run one simulated attack on the author's Microsoft Surface 4 Laptop. Combining the full factorial DOE with the average simulation run time, it would take 7.43 years to complete one replication of the full factorial design.

While the full factorial approach explores the design space completely, the time and money needed to conduct such an experiment is untenable. A more efficient design is needed.

In 2002, Thomas Cioppa developed an advanced algorithm that generates nearly orthogonal Latin hypercubes (LHs) with good space-filling properties (Cioppa & Lucas, 2007). “A good space-filling design is one in which the design points are scattered throughout the experimental region with minimal unsampled regions” (Cioppa & Lucas, 2007, p. 45). Essentially, the NOLH allows a user to achieve the same insight as the full factorial design at a fraction of the cost. For more flexible or extended NOLHs, see references MacCalman, Vieira, and Lucas (2017) and Hernandez, Lucas, and Carlyle (2012).

D. SWARM DESIGN OF EXPERIMENT

The correlation and scatterplot matrices from Experiment Sets 2 and 3 demonstrate the characteristics of the NOLH DOE. Figure 15, the correlation matrix, shows that the correlation between any two factors is in the interval (-.04, .04). This confirms that the DOE maintained a nearly orthogonal structure which ensures that follow-on analysis should not be affected by multicollinearity (Zappa, 2009).

Correlations

	NumVerifDrones	NumSeekersPerObs	SeekerAvgTmBetwDet	VerifPClass	SeekerDisperse	VerifDisperse	FiST.Latency
NumVerifDrones	1.0000	0.0194	-0.0224	0.0089	-0.0085	-0.0263	-0.0346
NumSeekersPerObs	0.0194	1.0000	-0.0020	-0.0353	0.0276	-0.0282	-0.0071
SeekerAvgTmBetwDet	-0.0224	-0.0020	1.0000	0.0012	-0.0000	0.0059	0.0031
VerifPClass	0.0089	-0.0353	0.0012	1.0000	0.0007	-0.0027	0.0074
SeekerDisperse	-0.0085	0.0276	-0.0000	0.0007	1.0000	-0.0008	-0.0045
VerifDisperse	-0.0263	-0.0282	0.0059	-0.0027	-0.0008	1.0000	-0.0040
FiST.Latency	-0.0346	-0.0071	0.0031	0.0074	-0.0045	-0.0040	1.0000

Figure 15. Correlation Matrix for the NOLH DOE Consisting of 129 DPs.

Figure 16, the scatterplot matrix, is a visual representation of the space-filling power of the NOLH. Each point represents a unique design point. The matrix panes denote the various input combinations between pairs of factors (Zappa, 2009). Collectively, the scatterplots represent the combinatorial interactions between factors. Thus, with only seven factors and 129 DPs, the NOLH DOE explores a vast part of the design space. Additionally, the NOLH gives the analyst the ability to fit a diverse set of metamodels to multiple different MOEs.

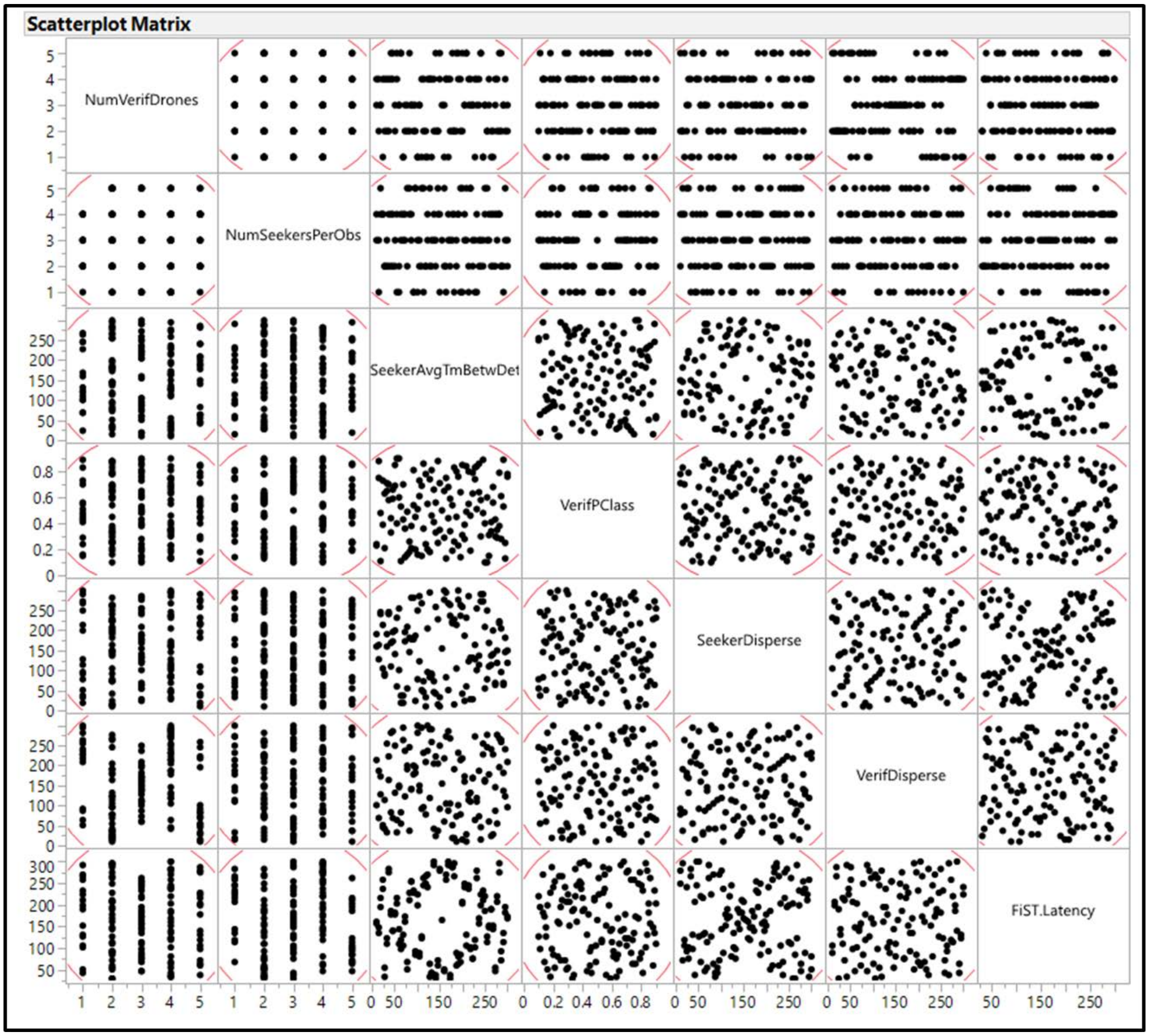

Figure 16. Scatterplot Matrix for the NOLH DOE Consisting of 129 DPs.

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V. DATA ANALYSIS AND EXPERIMENT RESULTS

This chapter contains the author's analysis of the thesis simulation experiments. Section 5.A gives a brief description of JMP Pro 13, the statistical software package used. Furthermore, the section explains how the author uses stepwise regression and partition trees to answer the thesis research questions. Sections 5.B – 5.D discuss the results for each thesis experiment set. Ultimately, Chapter V is the culmination of this study and presents quantitative information intended to enhance swarm employment in future operating environments.

A. JMP PRO 13 AND ANALYTIC METHODS

JMP Pro 13 is an advanced statistical package developed by SAS Analytics to upload, clean, organize, and analyze massive amounts of data. The Pro Series provides an analyst with an easy to use desktop interface and powerful predictive modeling tools to explore simulation design spaces efficiently. Additionally, JMP Pro 13 uses advanced algorithms, dynamically linked data, and graphic interfaces to produce professional visual products that help an analyst convey their story to stakeholders ("JMP Pro," 2018). Taking advantage of JMP's versatility, the author used the software package for initial data preparation, exploration of summary statistics, regression analysis, partition analysis, and data visualization.

1. Stepwise AIC Regression

Stepwise regression is an automated selection process designed to identify the best subset of predictor variables for a regression model (SAS Analytics, 2016). This form of regression works well under the following circumstances (SAS Analytics, 2018):

- There is limited information to guide factor selection during model development.
- An analyst wants to explore various models to identify which factors are most influential in predicting the response.

- The user seeks to remove unnecessary terms to better fit a model to the data and reduce model variability.

As the astute reader can see, all three situations apply to this study. The author recognized early in the study that the complex nature of the ISR swarm and his limited experience with swarm technology could lead to bias when analyzing results. Thus, for all three experiment outputs, the author uses stepwise regression to identify statistically significant predictor variables to a significance level of 0.05.

2. Partition Tree Analysis

A partition tree is a nonparametric technique "that splits output data to form homogeneous subsets, resulting in a hierarchical tree of decision rules. This process is useful for prediction or classification" (Zappa, 2009, p. 39). In JMP, the partition "algorithm searches all possible splits of predictors to best predict the response. These splits (or partitions) of the data are done recursively. The splits continue until the desired fit is reached" (SAS Analytics, 2016). For this thesis, the author uses partition trees to identify influential factors, performance thresholds, and create powerful visuals to explain factor interactions. In most cases, the partition tree and stepwise regression results are reinforcing mechanisms and powerful data discovery tools.

As an important aside, while conducting partition tree analysis, the author discovered that certain factors dominate tree splits and appear in multiple levels of the tree. This occurrence shows the powerful influence of such factors but typically offers less in terms of identifying useful operational thresholds for a decision maker. To gain greater insight into factor interactions and important performance thresholds, the author comments on dominant factors but only allows a factor to appear once within a partition tree.

B. STOCHASTIC VARIABILITY WITHIN A DESIGN POINT

Combat is a complex process often defined by surprise, aggression, and uncertainty. In an effort to capture the "Fog" or uncertainty of combat, MANA-V implements stochastic principles. This means that a user can run hundreds of battles with the same factor values and get a different MOE outcome each time due to random model variability.

To demonstrate this phenomenon, Figure 17 presents the factor values and summary statistics for DP 0, Experiment Set 1. The histograms and summary statistics are derived from the raw output collected by running 100 simulated battles with the factor levels in the table below. More simply, the histograms and summary statistics show the variability "within" the unique DP. All thesis experiments apply the same DOE approach and each unique DP is run for 100 replications.

Factors for Drone Employment	
Factor List	**Value**
1. Drone Sensor Range (m):	472
2. Drone Sensor Mean Time Between Detections (sec)	180
Factors for Ground Combat Element	
Factors	**Value**
1. Movement Speed of Infantry Agents (m/sec)	0.4
2. Blue Force Combat Proficiency (Phit)	.44
Factors for Supporting Arms	
Factors	**Value**
1. M777 Combat Proficiency (Phit)	.63
2. M777 Reload Time (sec)	428
3. 81mm Mortars Combat Proficiency (Phit)	.74
4. SUAS Operator's Proficiency (sec)	114

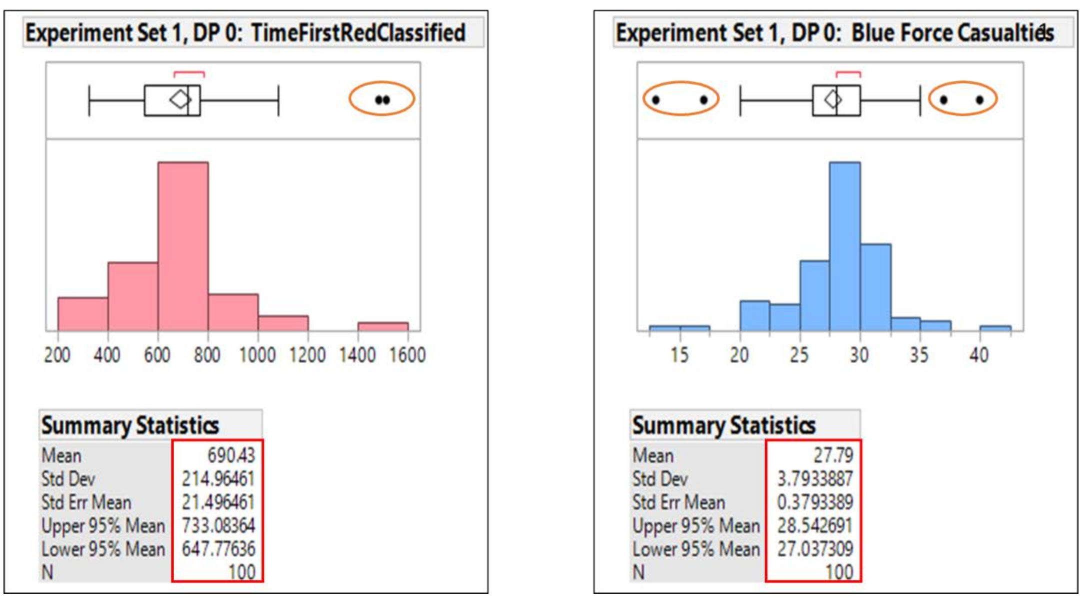


Figure 17. DP 0: Factor Values and Summary Statistics

The histogram for MOE 1:1 (time to classify the first Red fighter) shows that even with a sample size of 100 observations, there is still a fair amount of variability within the DP. While the mean time it takes to detect the first enemy fighter is 690 seconds (11.5 mins), the standard deviation is 215 seconds (3.6 mins). Additionally, we see that the outlier battles, circled in dark orange, slightly skew the distribution to the right. Although unlikely, it is possible that the first enemy fighter is not classified until around 1,400 seconds (23 mins) into the battle. In short, the stochastic elements of the model account for system complexities and environmental uncertainty, a desirable modeling trait often missing in deterministic models.

Additionally, stochastic models provide a decision maker with a distribution or performance profile for a given MOE rather a single closed form solution common to deterministic models. For example, the histogram for Blue force casualties shows a relatively normal distribution (as we might expect due to the Central Limit Theorem); however, the four outlier battles offer additional insight into possible best and worst-case scenarios. While a battlefield commander may plan to receive 27 to 28 casualties on average, they must also be prepared to assume the risk or reward associated with the extremes, meaning there is a minimal chance of receiving as few as 15 casualties or as high as 40 casualties. In chaotic and uncertain environments like combat, these performance profiles can be helpful during mission planning.

C. EXPERIMENT SET 1: BASE CASE ANALYSIS AND RESULTS

Experiment Set 1 is the baseline model consisting of 65 design points. In the design of experiment (DOE), the author varies four Blue force variables and three drone variables which results in simulation data for 6,500 missions. During analysis, the author uses "the mean outcomes for each design point (DP)" over 100 replications to enable regression and partition analysis (Zappa, 2009). This approach reduces variability within each DP and allows us to study the variability "between" design points rather than focusing on the variability "within" design points. Furthermore, this approach allows the author to reduce clutter when presenting visual products and helps identify DPs that exhibit interesting behaviors. It is important to note that a regression model created using the raw experiment data is the same as the model derived using this analysis approach on design point means. The author organizes the data in a similar manner for Experiment Sets 2 and 3.

1. Measure of Effectiveness (MOE) 1:1—ISR Integration: How Long Does it Take the Blue Force to Classify the First Hostile Agent?

During combat operations, the unit that strikes first can change the dynamic of the battle. MOE 1:1, the time it takes to identify the first hostile agent, focuses on the how quickly the company, supported by a Raven ISR drone, can locate the first enemy combatant during mission execution. Furthermore, this MOE provides insight into how well the Raven supports the infantry company under scenario conditions.

To begin the analysis of MOE 1:1, the author studies the summary statistics from the experiment's raw output data. The mean, the standard deviation, and the 95 percent confidence interval are derived using a sample size of 6,500 observations. Under these conditions, the summary statistics for MOE 1:1 show that on average, the infantry company identifies the first enemy combatant in 930 seconds (15.5 mins) with a standard deviation of 563 seconds (9.4 mins). The 95 percent confidence interval for the mean is [916, 943 secs]. Note that this standard deviation is quite large, which suggests that there is quite a bit of variability between DPs. In an operational sense, the data shows that on average it takes the Raven operator 15.5 minutes [15.3, 15.7 mins] to locate enemy forces in vicinity of Company Objective 1, the weapons cache.

Next, the author uses Stepwise AIC regression to explore how all seven predictor variables and their interactions, to include quadratic relationships, affect the Raven's performance. The regression results allow the author to identify which variables are statistically significant and warrant further analysis using partition trees. Figure 18 displays the regression results and highlights the statistically significant variables for MOE 1:1.

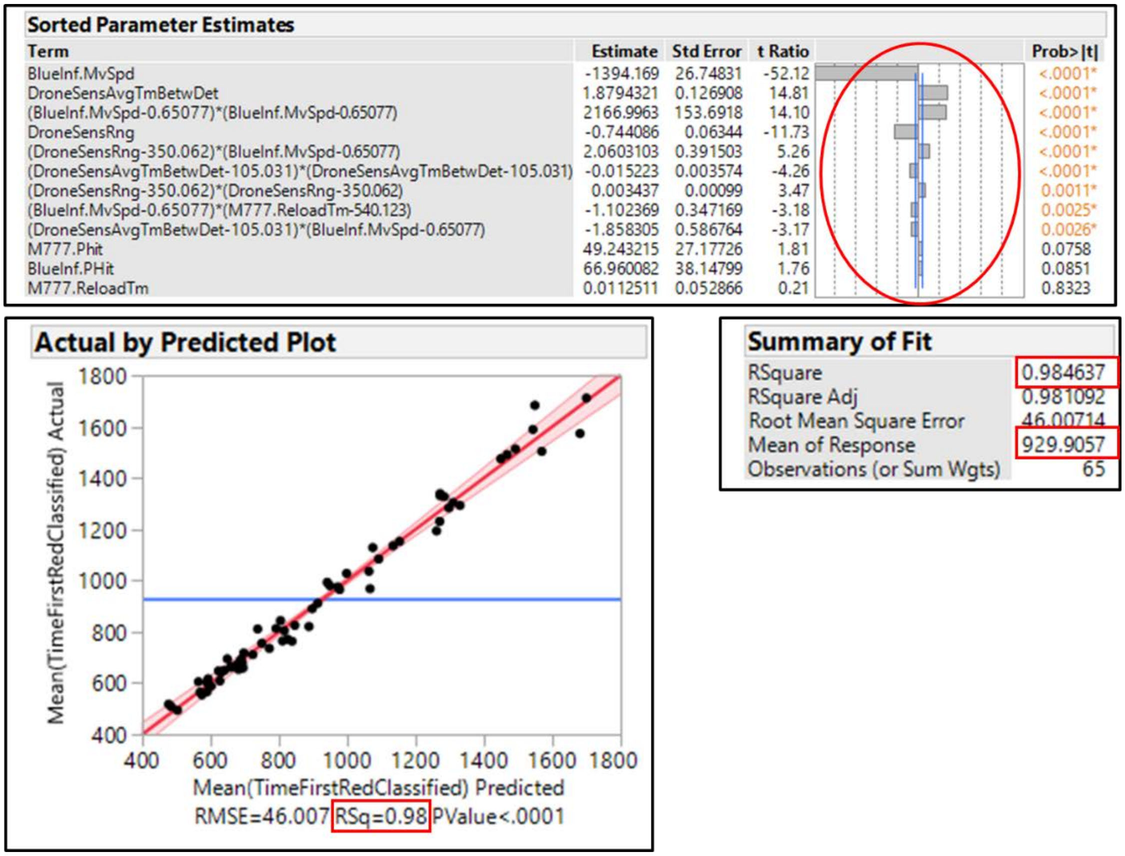


Figure 18. Stepwise Regression for the Single UAV: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 1:1)?

As discussed in the beginning of this section, by collapsing the data, the prediction plot shows the model fit for the 65 design points. The R-squared statistic informs the reader that the significant factors identified in the parameter estimate box account for over 98% of the model's variability. More simply, both the predicted plot and the high R-squared show that the model fits the data well and may be useful in gaining insight into drone employment under conditions similar to those modeled in the scenario.

The parameter estimate chart lists those factors and interactions that are statistically significant at a significance level of 0.05. We see that "Blue infantry movement speed," "drone sensor range," and "drone time to sense between detections" are the most influential primary factors. For example, as the linear term for Blue movement speed increases by one unit (a rate of one meter/sec), the average time it takes to detect the first enemy fighter decreases by 1,394 seconds (23 mins). Similarly, for each one second increase in the linear term for "drone time to sense between detections," the time to classify the first enemy fighter increases by 1.88 seconds.

At first glance this claim can appear confusing. How is it possible for movement speed to so drastically reduce detection time? First, it is important to remember that the factor range for "Blue infantry movement speed" is 0.3–1.0 m/sec. Additionally, the parameter estimate chart shows that all the significant primary factors also have quadratic terms in the regression model.

Figure 19 shows the JMP 13 Prediction Profiler tool for this regression model. The Prediction Profiler offers a visual depiction of the regression model and allows an analyst to interact with each factor graph to see how the regression coefficients affect the response. Interestingly, both drone sensor range and Blue force movement speed show positive quadratic relationships with the response. This suggests that there are minimum values for both factors and that these minimum values may represent a preferred employment strategy. The quadratic term for "drone time to sense between detections," shares a negative relationship with the response, thus there is a maximum point in the curve that represents a degraded or least preferred operational threshold. More succinctly, Figure 19 shows that all three quadratic terms have diminishing returns over the range of the design.

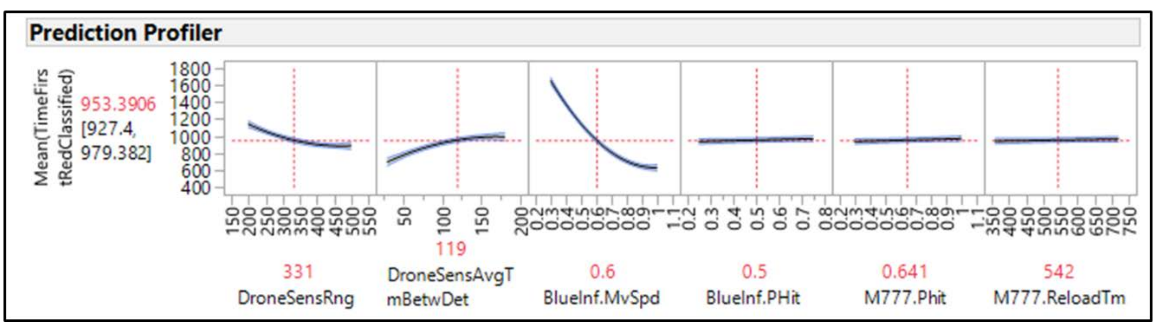


Figure 19. Visual Depiction of MOE 1:1 Regression Model

The factors highlighted by the regression make sense both logically and tactically. Of the seven variables, only those factors that pertain to observing the enemy prove to be statistically significant. For Blue force movement speed, the faster the infantry moves, the sooner the infantry reaches the enemy, increasing the likelihood of seeing an enemy combatant. Concurrently, with better sensors, the Raven operator can classify unknown agents faster and observe more area, improving the operator’s ability to find enemies in zone.

In addition to the primary factors, the parameter estimate chart shows factor interactions which positively and negatively affect the drone operator’s ability to find enemy forces. Although JMP 13 provides tools to observe these interactions and identify operational thresholds, this process becomes labor intensive. Thus, the results from stepwise regression help the author gain insight into the Raven’s performance and serve as a guide during partition tree analysis.

Figure 20 is the partition tree for MOE 1:1. The green boxes represent the preferred employment strategy and denote desirable characteristics. The red boxes highlight a degraded path through the tree and should be avoided if possible. While conducting this analysis, the factors for “Blue infantry movement speed” and “drone sensor range” dominate the splits, appearing in several levels of the model. As discussed in the partition tree section of this chapter, this occurrence shows the powerful influence of the two factors but offers less in terms of data interpretation. To gain greater insight into factor interactions and important performance thresholds, the author only allows a factor to appear once throughout the partition tree.

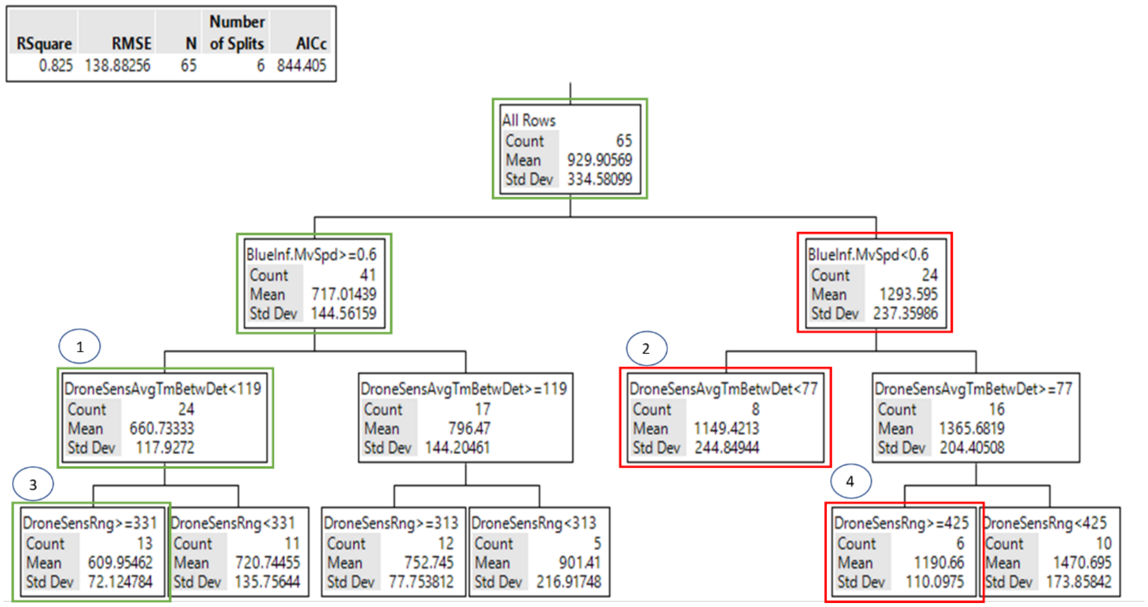


Figure 20. Partition Tree for the Single UAV: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 1:1)?

The partition tree begins with 65 observations. The first level splits the data on the most influential factor, "Blue infantry movement speed." The tree identifies the operational threshold for speed at 0.6 meters per second. The left limb of the tree represents a more aggressive patrolling style. If the Raven is unable to find enemy fighters during its first patrol loop, the infantry agents are not far behind to observe into sensor "dead zones."

Continuing to work through the partition tree, troop presence appears to have profound effects on sensor requirements. When comparing numbered "leaves" 1 and 2 in Figure 20, we see that the interaction on the left limb of the tree finds the first enemy fighter two times faster and with a reduced sensor requirement. Tactically, this finding reinforces the importance of integrating ISR coverage and ground movement.

Finally, the lowest level of the tree supports the trend that slower patrol speeds require more capable detection sensors to develop the situation and find the first enemy fighter. To prevent further performance degradation, the right path in the tree (leaf 4) requires a sensor capable of detecting targets out to 425 meters. This requirement is more than double the current capability of the Raven UAS (200 meters). While the preferred employment strategy, represented by the path leading to leaf 3, does require a sensor capable of detecting out to 331 meters, there is a significant increase in overall MOE performance when compared against the model mean.

Overall, the partition tree helps us see that integrating ISR coverage and infantry movement leads to significant reductions in sensor requirements and the average time it takes to classify the first enemy fighter. The preferred interaction path dominates the degraded path at every level of the tree. In short, the partition tree effectively captures the complexity of the company's ISR employment and adds insight into how different factors either enhance or degrade unit performance.

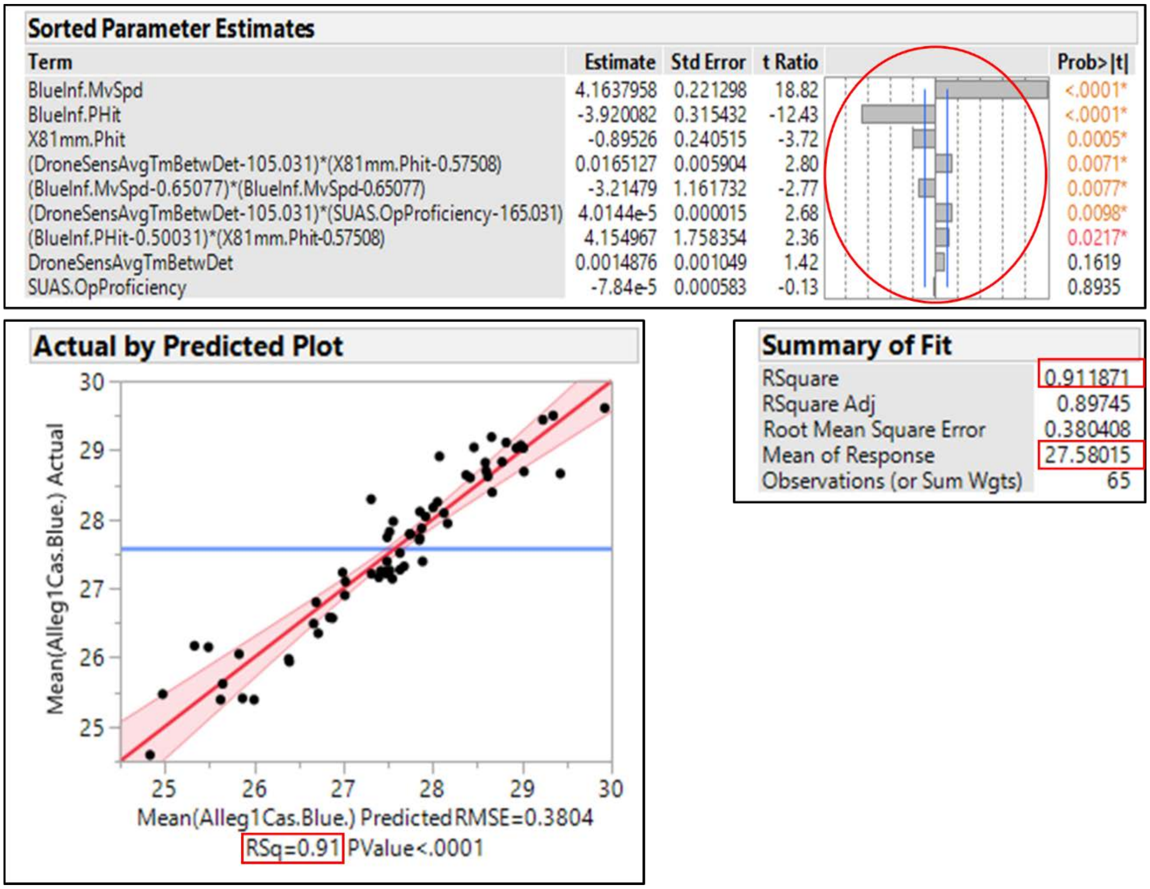
It is important to note that speed does affect mission execution. Although the left limb path offers the greatest potential reduction in time, moving at a patrol pace of 0.6 meters or greater will affect troop endurance and how much equipment the Marine squads can carry. Additionally, the faster a unit patrols in a combat zone, the less time is available to develop the situation and use ISR assets to locate enemy combatants. The next MOE looks at Blue casualty rates.

2. Measure of Effectiveness 1:2—Force Protection: How Many Blue Casualties are Sustained during Mission Execution?

Protecting the force is critical to sustained operations. An increase in casualties reduces combat power and forces a commander to commit resources to retrieve wounded personnel. Additionally, high casualty rates devastate morale both within the unit and on the home front. To maintain tempo and esprit de corps, it is essential that units integrate ISR and maneuver assets to reduce unit casualties. MOE 1:2 examines how unit performance parameters affect the number of Blue force casualties received during mission execution. Although the author investigates Blue force lethality and ISR employment, the primary focus remains on Raven integration.

Like the analysis for MOE 1:1, the summary statistics for MOE 1:2 are calculated from the experiment raw output with a sample size of 6,500. On average, the Blue force takes 28.5 casualties during the 2.5-hour (9,000 second) battle with a standard deviation of 4.3 casualties. The 95 percent confidence interval for the mean is [27.5, 27.7 casualties]. Operationally, this casualty rate is unacceptable. Assuming the Marine infantry company consists of 174 Marines (standard task organization), on average, the Red force destroys or neutralizes 15.8 percent [15.7, 16.0%] of the Marine unit's combat power.

Figure 21 displays the stepwise regression results for MOE 1:2 (Blue casualties). The significant factors in the model account for over 91% of the model's variability. The most influential factors and interactions relate to patrol speed, Blue lethality, and Raven employment. For patrol speed, each one unit (one-meter/sec) increase in speed results in 4.2 additional casualties, while increasing the lethality variables decreases Blue losses as denoted by the negative relationship with the response. For example, each one percent increase in Blue infantry probability of hit reduces friendly casualties by 0.4 personnel. In a tactical sense, this finding suggests that higher patrol rates prevent reconnaissance assets from locating enemy forces prior to close combat engagements. To the contrary, when the Blue force reduces patrol speed, the Raven operator and FiST have more time to locate and destroy enemy fighters with indirect fires.



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
BlueInf.MvSpd	4.1637958	0.221298	18.82	<.0001*
BlueInf.PHit	-3.920082	0.315432	-12.43	<.0001*
X81mm.Phit	-0.89526	0.240515	-3.72	0.0005*
(DroneSensAvgTmBetwDet-105.031)*(X81mm.Phit-0.57508)	0.0165127	0.005904	2.80	0.0071*
(BlueInf.MvSpd-0.65077)*(BlueInf.MvSpd-0.65077)	-3.21479	1.161732	-2.77	0.0077*
(DroneSensAvgTmBetwDet-105.031)*(SUAS.OpProficiency-165.031)	4.0144e-5	0.000015	2.68	0.0098*
(BlueInf.PHit-0.50031)*(X81mm.Phit-0.57508)	4.154967	1.758354	2.36	0.0217*
DroneSensAvgTmBetwDet	0.0014876	0.001049	1.42	0.1619
SUAS.OpProficiency	-7.84e-5	0.000583	-0.13	0.8935

Summary of Fit

RSquare	0.911871
RSquare Adj	0.89745
Root Mean Square Error	0.380408
Mean of Response	27.58015
Observations (or Sum Wgts)	65

Figure 21. Stepwise Regression for the Single UAV: How Many Blue Casualties Are Sustained during Mission Execution (MOE 1:2)?

Using indirect fires to destroy the enemy prior to small arms battle is commonly referred to as "shaping" or applying "shaping fires." The regression results reinforce the idea that a commander can reduce unit casualties by using ISR assets to properly develop battlefield awareness. Once locating the enemy, the commander can use strike assets to reduce enemy presence near the objective. Ultimately, "shaping" the objective does require time, but it gives the Blue force infantry troops a numerical advantage when engaging the enemy with squad weapons.

The next most significant factors, “Blue infantry probability of hit” and “81mm probability of hit,” focus on unit lethality. Both factors are negatively correlated to the average number of Blue force casualties. As an agent’s probability of hit increases, the average number of Blue force casualties decreases. This finding implies that locating the enemy is not enough. Marines must be well equipped and proficient. Weapons lethality saves lives.

Note that the regression model does not identify individual drone factors as statistically significant. Instead, several interactions involving the factors “drone time to sense between detections” and “SUAS Operator Proficiency” offer insight into how drone capabilities effect the average number of Blue force casualties. The parameter estimate chart shows that the interaction is positively correlated to the average number of Blue force casualties. The author uses partition tree analysis to further explore this interaction.

Figure 22, the partition tree for MOE 1:2, shows the relationship of “Blue infantry movement speed,” “drone time to sense between detections,” and “SUAS proficiency” on Blue force casualties. The author intentionally left out the lethality variables during tree construction. Lethality metrics are difficult to quantify, especially under combat conditions. Additionally, during a combat situation, lethality thresholds do not provide a commander with any actionable information. To the contrary, a commander can adjust patrol speeds or enhance drone performance to meet the thresholds shown below.

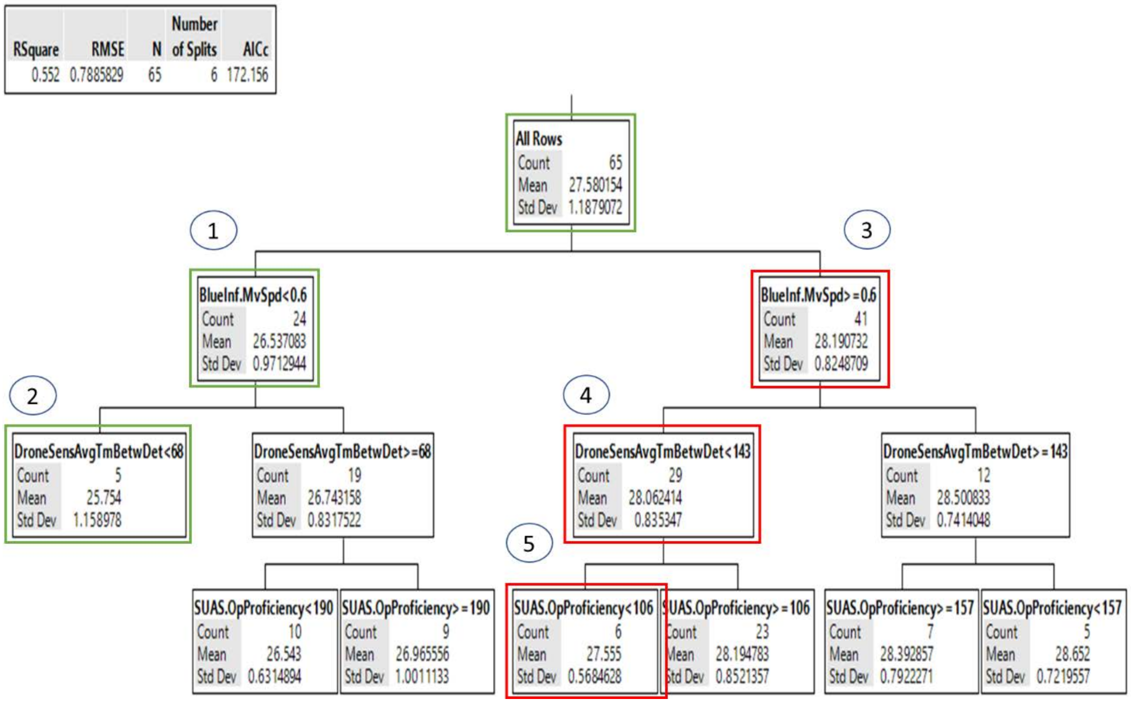


Figure 22. Partition Tree for the Single UAV: How Many Blue Casualties Are Sustained during Mission Execution (MOE 1:2)?

The left limb of the tree represents the best opportunity to reduce Blue force casualties. Similar to the partition tree for MOE 1:1 (average time it takes to classify the first enemy fighter), the first threshold splits on the movement speed 0.6 m/sec. When comparing the mean number of Blue casualties across the split, there is only a six percent difference between numbered “leaves” 1 and 3. While the preferred interaction path does show improved performance, movement speed does not drastically reduce overall unit casualties to an acceptable level.

The next split occurs on the factor “drone time to sense between detections.” This split reinforces the findings discovered in the partition tree for MOE 1:1, showing that slower patrol speeds require a sensor that can detect enemy fighters two times faster to gain any reduction in Blue force casualties. When comparing the mean number of casualties across the split (“leaves” 3 and 4), we see that the differential between the preferred and degraded paths is only two casualties. Unfortunately, it appears that sensor enhancement does little to improve unit performance as it applies to casualty reduction and begins to suggest that the Raven platform may be reaching its operational limitations for this MOE.

The right limb of the tree represents a more aggressive patrol style or a situation in which time takes priority over mission safety. Interestingly, the third level of the tree splits on “SUAS operator proficiency;” however, the factor does not appear to have much impact on overall casualty reduction. Regardless of interaction approach, the combinations on the right limb of the tree fail to outperform the preferred path.

Overall, the partition tree enables the reader to see that a slower patrol pace and better Raven sensor can reduce casualties and gives the drone operator more time to disseminate targeting data to the FiST. Unfortunately, the tree also highlights that the Raven ISR drone is limited in its ability to further affect force protection. Without drastic improvements to the system or significant improvements to unit performance, the average number of Blue force casualties remains around 25.5, or 15 percent of the company’s combat power. In a modern context, this casualty level is unacceptable.

D. EXPERIMENT SET TWO: THE EMERGENT SWARM ANALYSIS AND RESULTS

Experiment Set 2 studies the emergent swarm. The experiment DOE consists of 129 DPs developed from seven factors. For each DP, 100 independent replications are made. The experiment set ran for three days and harvested data for 12,900 simulated battles. Similar to Experiment Set 1, the author uses the mean of each DP to conduct data analysis.

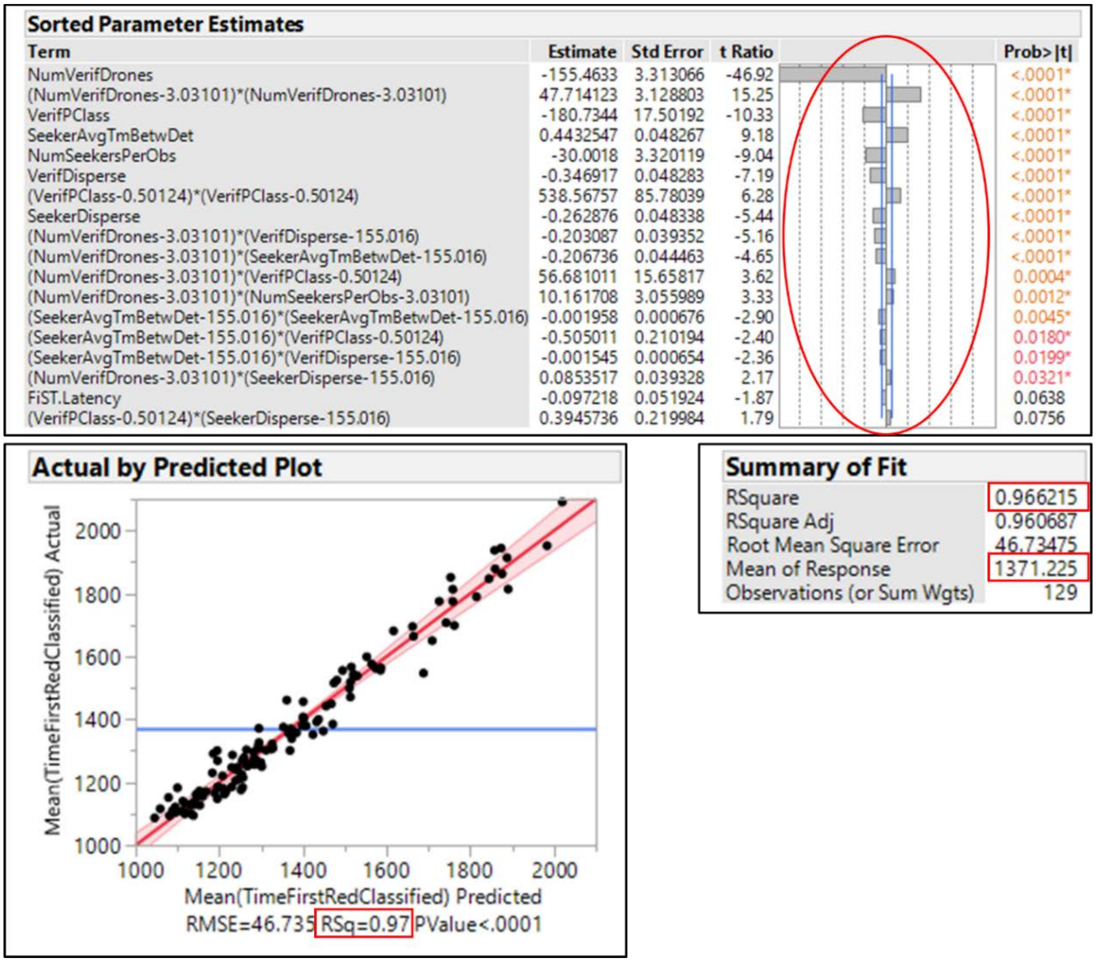
The results from Experiment Set 1 identify performance thresholds and TTPs for integrating the Raven UAV into ground combat operations. Experiment Sets 2 and 3 investigate the Marine infantry company’s performance when deploying different swarm control strategies. Concurrently, the analysis from this section seeks to identify operational thresholds intended to answer primary thesis questions.

1. Measure of Effectiveness (MOE) 2:1—Swarm Integration: How Long Does it Take the Blue Force to Classify the First Hostile Agent?

The summary statistics from the raw experiment output show that, on average, the emergent swarm identifies the first enemy combatant in 1,371 seconds (22.85 mins) with a standard deviation of 400 seconds (7 mins). The 95 percent confidence interval for the mean is [1,364, 1,378 secs]. On average, the swarm central planner locates the first enemy combatant within 22.8 minutes [22.7, 23.0 mins]. When comparing the emergent swarm mean to the company's performance using the Raven, the emergent swarm takes 6.5 minutes longer, on average, to locate an enemy fighter on the battlefield.

Figure 23 displays the stepwise regression results for MOE 2:1. The significant factors and interactions in the model account for over 97% of the model's variability. When applying a significance level of 0.05, six of the seven primary factors are statistically significant. The regression shows that the "number of verification drones" dominates the model. With each verification drone added to the swarm, the associated linear term in the regression decreases the response (MOE 2:1) by 155 seconds (2.5 mins). Furthermore, the verification drone's "probability to classify" factor reduces the average time to detect the first Red fighter by two seconds per percentage point.

In addition to highlighting the most influential primary factors, the regression model identifies statistically significant interactions between the number of drones in the swarm, drone dispersion, and sensor thresholds. Note that the number of statistically significant factors highlights the complexity of the swarm system. This reinforces the author's decision to use simulation to study swarm technologies. A single stochastic process simply cannot account for the swarm's complexity. To further explore these relationships, the author uses partition analysis.



Sorted Parameter Estimates

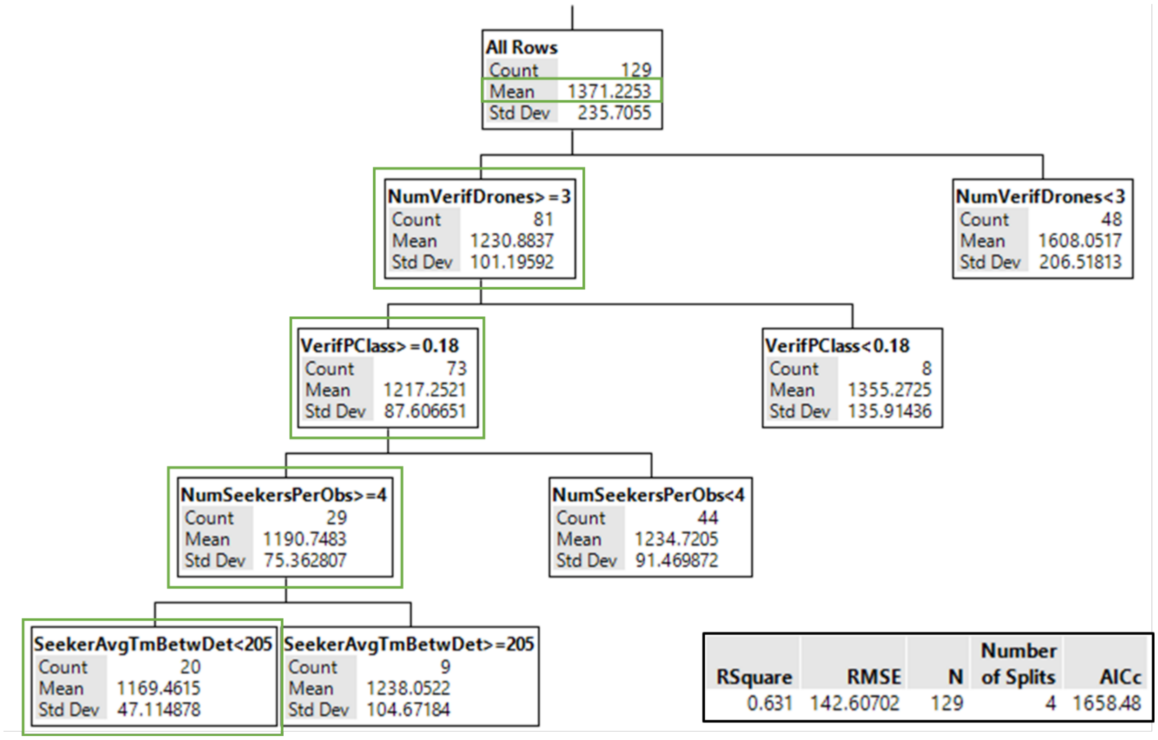
Term	Estimate	Std Error	t Ratio	Prob>|t|
NumVerifDrones	-155.4633	3.313066	-46.92	<.0001*
(NumVerifDrones-3.03101)*(NumVerifDrones-3.03101)	47.714123	3.128803	15.25	<.0001*
VerifPClass	-180.7344	17.50192	-10.33	<.0001*
SeekerAvgTmBetwDet	0.4432547	0.048267	9.18	<.0001*
NumSeekersPerObs	-30.0018	3.320119	-9.04	<.0001*
VerifDisperse	-0.346917	0.048283	-7.19	<.0001*
(VerifPClass-0.50124)*(VerifPClass-0.50124)	538.56757	85.78039	6.28	<.0001*
SeekerDisperse	-0.262876	0.048338	-5.44	<.0001*
(NumVerifDrones-3.03101)*(VerifDisperse-155.016)	-0.203087	0.039352	-5.16	<.0001*
(NumVerifDrones-3.03101)*(SeekerAvgTmBetwDet-155.016)	-0.206736	0.044463	-4.65	<.0001*
(NumVerifDrones-3.03101)*(VerifPClass-0.50124)	56.681011	15.65817	3.62	0.0004*
(NumVerifDrones-3.03101)*(NumSeekersPerObs-3.03101)	10.161708	3.055989	3.33	0.0012*
(SeekerAvgTmBetwDet-155.016)*(SeekerAvgTmBetwDet-155.016)	-0.001958	0.000676	-2.90	0.0045*
(SeekerAvgTmBetwDet-155.016)*(VerifPClass-0.50124)	-0.505011	0.210194	-2.40	0.0180*
(SeekerAvgTmBetwDet-155.016)*(VerifDisperse-155.016)	-0.001545	0.000654	-2.36	0.0199*
(NumVerifDrones-3.03101)*(SeekerDisperse-155.016)	0.0853517	0.039328	2.17	0.0321*
FiST.Latency	-0.097218	0.051924	-1.87	0.0638
(VerifPClass-0.50124)*(SeekerDisperse-155.016)	0.3945736	0.219984	1.79	0.0756

Summary of Fit

RSquare	0.966215
RSquare Adj	0.960687
Root Mean Square Error	46.73475
Mean of Response	1371.225
Observations (or Sum Wgts)	129

Figure 23. Stepwise Regression for the Emergent Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 2:1)?

Figure 24 is the left limb of the partition tree and identifies the swarm characteristics with the greatest potential to reduce the average time to locate the first enemy fighter. Additionally, each characteristic displays an operational threshold which represents a change in the system's performance continuum. Identifying these thresholds can offer great insight into system interactions and help an analyst identify parameter values that either enhance or degrade overall system performance. This concept is often referred to as identifying "the knee in the curve."



RSquare	RMSE	N	Number of Splits	AICc
0.631	142.60702	129	4	1658.48

Preferred Performance Path (Left Limb)

Partition Tree for the Emergent Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 2:1)?

The partition tree begins with 129 observations and an overall mean time to detect the first enemy fighter of 1371 seconds. The first split occurs on the most significant factor, which is the "number of verification drones." Note that the partition tree highlights the limitations of the emergent swarm with respect to MOE 2:1. Regardless of swarm enhancement, the emergent swarm fails to outperform the Raven. In fact, when compared against the Raven scenario's most efficient employment strategy, on average, it takes the central planner twice as long to locate the first enemy fighter.

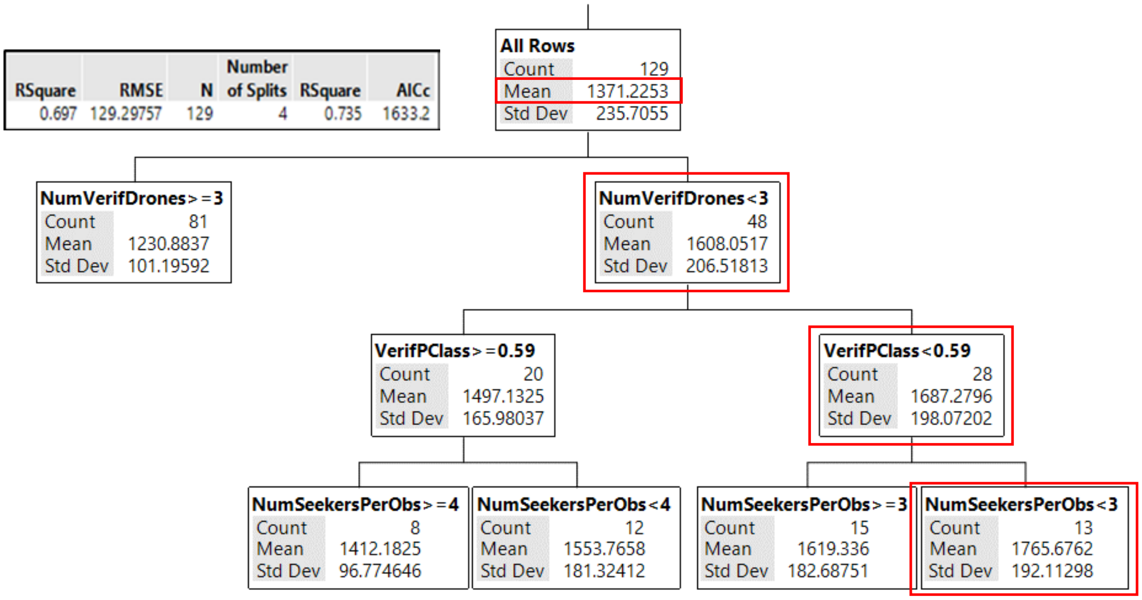
This finding is consistent with the seminal research included in the thesis literature review. In most cases, piloted UAVs do not require complex feedback loops or interactions between multiple systems. If the UAV pilot locates a target, he or she can pass targeting information directly to the FiST in accordance with the company's standard operating procedures. The limitation to this process is the proficiency of the drone operator or the complexity of the unit's targeting procedures.

To the contrary, the swarm targeting process requires an additional step. The seeker drones must contact the nearest verification UAV before the central planner can classify the unknown contact. Thus, the autonomous interactions within the swarm account for the additional time required to detect an enemy fighter. Further research should be conducted to determine if this observation is a system limitation, vulnerability, or both.

Next, the tree shows that that the preferred employment strategy requires three verification drones and four seeker drones per verification drone. This results in a total of 15 drones per swarm. Recall, that the assumed operational flight time for each drone is 45 minutes. Under this assumption, the UAV support section must deploy four emergent swarms or 60 individual drones to provide ISR coverage for the 2.5-hour battle.

As a final observation, an increase in drones does reduce sensor requirements. To enhance swarm performance, seeker drones must maintain an average time between detection of less than 205 seconds and the verification drone must meet a classification threshold of 18 percent. When compared to the Raven, a seeker drone's "average time between detections" can be three times as long. This means that the Raven requires a sensor capable of detecting an enemy fighter three times faster than the seeker drone. Typically, as drone capability requirements increase, so does platform cost and maintenance. Further research must be conducted to determine if the reduction in sensor requirements produces enough cost savings to make the emergent employment strategy viable.

For completeness, Figure 25 presents the right limb of the tree. The right limb represents a degraded employment strategy. Under no conditions can this approach outperform the left limb of the tree. Note that as the number of verification drones decreases, the sensor requirements increase threefold. This observation supports the claim that a greater number of less capable drones can reduce overall sensor requirements.



Degraded Performance Path (Right Limb)

Figure 24. Partition Tree for the Emergent Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 2:1)?

2. Measure of Effectiveness 2:2—Force Protection: How Many Blue Casualties Are Sustained during Mission Execution?

For MOE 2:2, the presented summary statistics come from the raw data with a sample size of 12,900 observations. On average, the Blue force takes 31.1 casualties during the 2.5-hour battle with a standard deviation of 10.1 casualties. The 95 percent confidence interval for the mean is [30.9, 31.3 casualties]. Assuming a standard Marine infantry company, on average, the Red force destroys or neutralizes 17.9 percent [17.8, 18.0%] of the Marine unit's combat power. When compared to the results from Experiment Set 1, the Marine infantry company receives approximately four more casualties.

Figure 26 displays the stepwise regression results for MOE 2:2. The significant factors and interactions in the model account for over 88% of the model's variability. The stepwise regression identifies that five of the seven primary factors are statistically significant at a significance level of 0.05. The most influential factor in the regression is "FiST latency." For each 20 second increase in "FiST latency," the number of Blue casualties increases by one Marine.

Recall that FiST latency represents the proficiency of the UAV support section and its ability to relay targeting data to the FiST. This relationship is not surprising. The regression results support common knowledge that poor or inefficient targeting practices result in delayed indirect fires. Without timely fire support, the Blue force receives more casualties.

Additionally, the regression model shows that the size of the swarm can dramatically effect casualty levels. The negative signs associated with the regression coefficients for "number of verification drones" and "number of seeker drones per verification drone" signify that the addition of one drone results in a reduction in casualties. The partition tree in Figure 27 shows how properly aligning the most influential factors can result in significant casualty reduction.

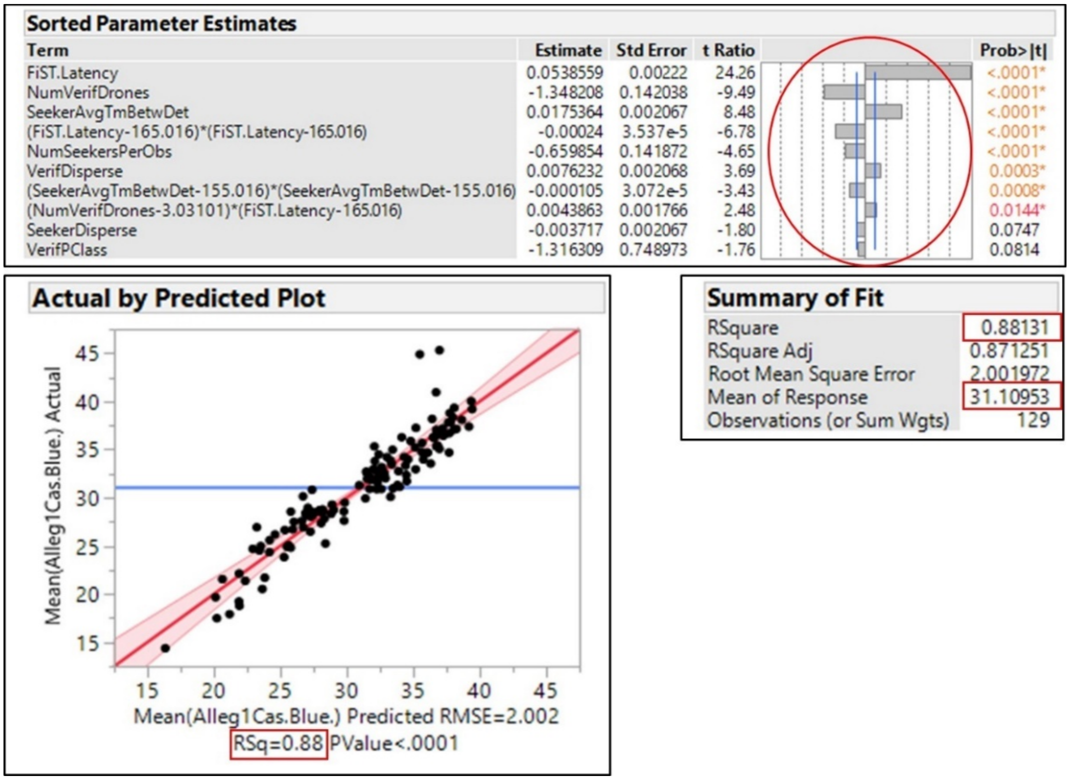
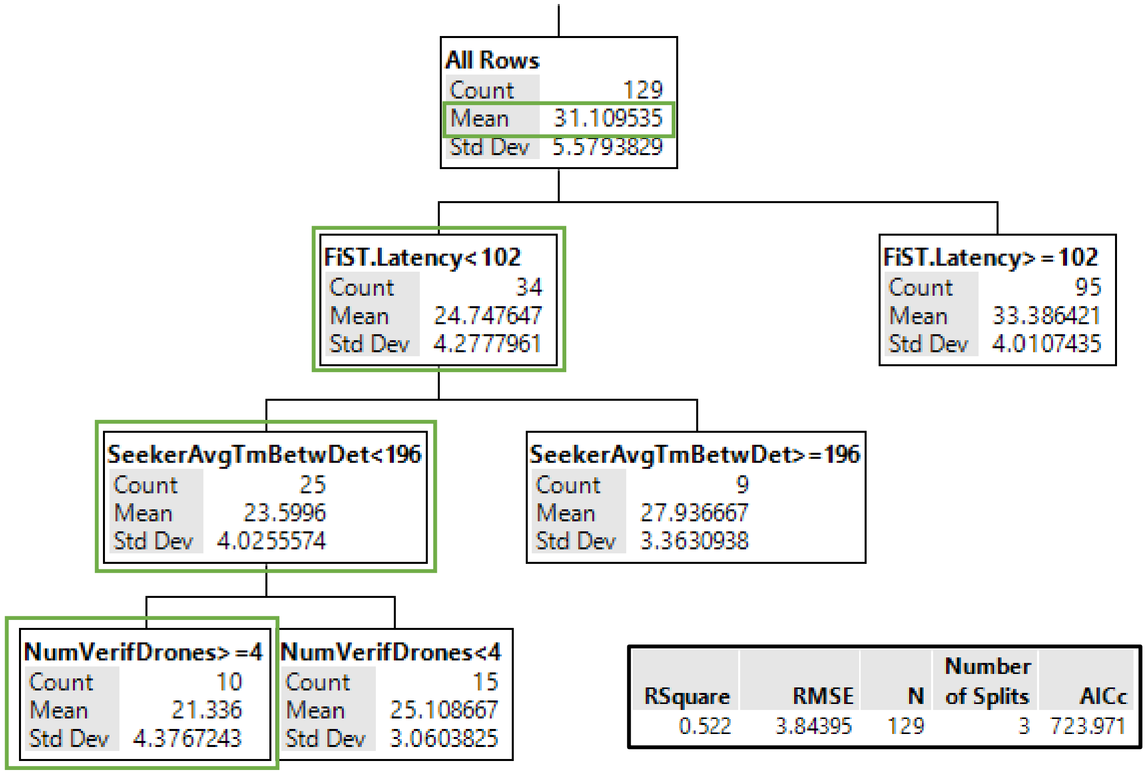


Figure 25. Stepwise Regression for the Emergent Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 2:2)?

Figure 27 is the left limb of the partition tree and identifies the swarm characteristics with the greatest potential to reduce the average number of Blue force casualties. Similar to Experiment Set 1, the author only splits on a factor once to gain more insight into factor interactions. Interestingly, drone sensor requirements play a limited role in minimizing casualties. Instead, "FiST latency" and the "number of verification drones" dominate the splits. The presented partition tree is a combination of the most influential factors identified in the stepwise regression with the addition of sensor factors. This approach attempts to provide insight into drone employment strategy as well as answer the questions introduced in the thesis problem statement.



Preferred Performance Path (Left Limb)

Figure 26. Partition Tree for the Emergent Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 2:2)?

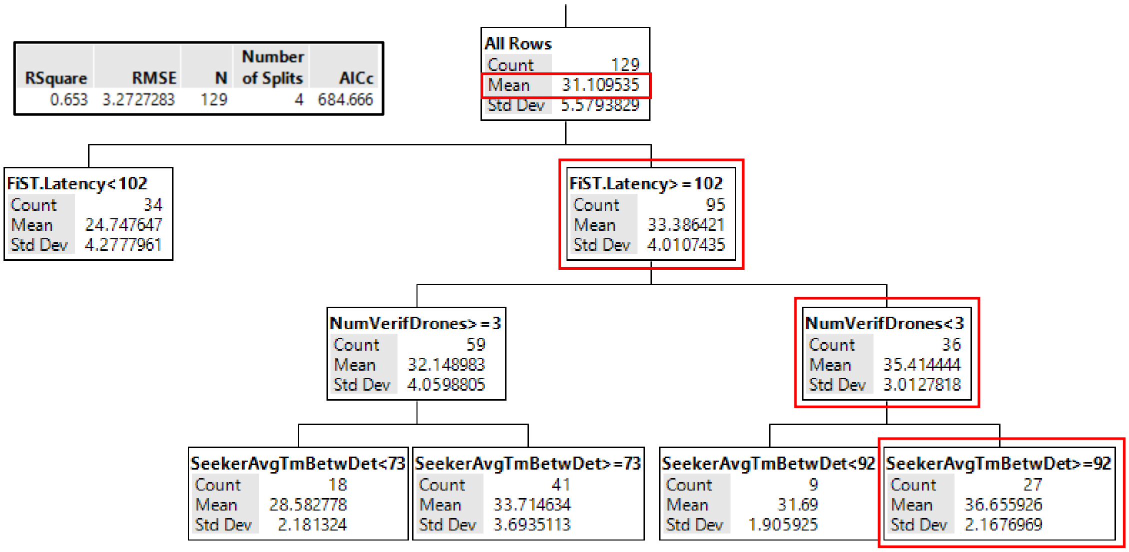
The first split occurs on the most significant factor, which is “FiST latency.” In order to reduce Blue force casualties, the UAV support section must be able to confirm and transmit targeting data to the FiST in less than 102 seconds, or just under two minutes. Note that failing to achieve this performance measure can have dire consequences. The casualty difference between the higher and lower latency times is 8.6 Marines. In an operational context, 8.6 Marines represents just over half an infantry squad. Furthermore, the casualty differential widens even more to 12.1 Marines when comparing the preferred employment strategy (the left limb, green boxes) against the higher FiST latencies. In short, it is important that the UAV support section is well trained and properly organized to efficiently and effectively pass targeting data to the FiST.

Since there is no current targeting standard for ISR swarms, it is difficult to determine if this time requirement is achievable; however, this latency level provides an initial requirement goal. Additionally, further investigation is required to determine if the time threshold applies to other scenarios. Identifying operational thresholds will assist fire support personnel in developing practical reporting procedures that enhance unit performance and reduce casualties.

The next significant factor is “seeker average time between detections.” The partition tree identifies the sensor threshold as less than 196 seconds. This requirement fits well with the seeker sensor threshold discovered in MOE 2:1. Recall that the preferred employment strategy for MOE 2:1 recommends the “seeker average time between detections” meet an operational threshold of 205 seconds or less. Thus, reducing that requirement further to 196 seconds meets the needs of both MOEs.

The final factor important to this interaction is the “number of verification drones.” The partition tree suggests that at least four verification drones are required in the preferred employment strategy. Since the partition model did not split on the factor “number of seeker drones per verification drone,” the author applies the finding from MOE 2:1 to nest the two findings and remain consistent. Recall that the preferred employment strategy for MOE 2:1 recommends deploying four seeker drones for every one verification drone. Combining the two findings suggests that an individual swarm consists of four verification drones and 16 seeker drones, for a total of 20 drones per swarm. Under the scenario assumptions, the UAV support section must prepare and deploy 80 individual drones to meet the infantry company’s needs during the 2.5-hour battle.

Figure 28 is the right limb of the tree for MOE 2:2 (Blue casualties). Consistent with the other partition tree models, the right limb represents the degraded employment strategy. The regression shows that failing to reduce “FiST Latency” below 102 seconds has dire consequences. The first order effect is the need for a seeker sensor that is twice as capable as the need in the preferred employment strategy. In addition to the need for a better sensor, on average, the degraded path results in 12 more casualties when compared against the mean for the lower latencies.



Degraded Performance Path (Right Limb)

Figure 27. Partition Tree for the Emergent Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 2:2)?

E. EXPERIMENT SET THREE: THE HIERARCHICAL SWARM ANALYSIS AND RESULTS

Experiment Set 3 examines the hierarchal swarm, which distributes drone teams to search along two parallel axes. More specifically, the swarm is decomposed into two distinct squads, one that patrols the agricultural area and the other the urban sprawl. The experiment DOE is identical to Experiment Set 2 and consists of 129 DPs developed from seven factors. The experiment set ran for three days and harvested data for 12,900 simulated battles. The author continues to use the mean across DPs in the conduct of his data analysis.

1. Measure of Effectiveness (MOE) 3:1—Swarm Integration: How Long Does it Take the Blue Force to Classify the First Hostile Agent?

For MOE 3:1, the presented summary statistics come from the raw data with a sample size of 12,900 observations. On average, the hierarchical swarm identifies the first enemy combatant in 1,834 seconds with a standard deviation of 385 seconds (6 mins). The 95 percent confidence interval for the mean is [1,827, 1,841 secs]. On average, the swarm central planner locates the first enemy combatant within 30.6 minutes [30.5, 30.7 min].

When comparing the model mean of the three different ISR approaches, the hierarchical swarm takes significantly longer to locate the first enemy combatant.

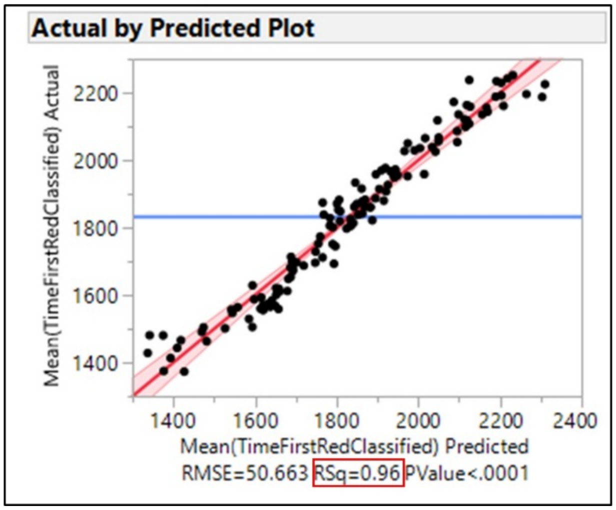
Figure 29 displays the stepwise regression results for MOE 3:1. The significant factors and interactions in the model account for over 96% of the model's variability. The regression model shows that six of the seven primary factors are statistically significant at a significance level of 0.05. The only factor not included in the model is FiST latency, which should have no impact on the time to first detection.

The most influential primary factors are the "number of verification drones per zone," "the dispersion between verification drones," and the "seeker's average time between detections." Adding two verification drones, one in each zone, decreases the average time it takes to locate the first enemy fighter by 237 seconds or roughly four minutes. The significant factors seem to suggest that the power of the hierarchical control strategy is related to sensor distribution across the battlefield. To further explore the complex interactions of the swarm, the author uses partition trees.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
NumVerifDronesPerZone	-237.3597	6.258945	-37.92	<.0001*
VerifDisperse	-0.988836	0.052353	-18.89	<.0001*
SeekerAvgTmBetwDet	0.8915056	0.052344	17.03	<.0001*
(NumVerifDronesPerZone-2.0155)*(VerifDisperse-155.016)	-0.883589	0.066615	-13.26	<.0001*
NumSeekersPerVerif	-60.98061	6.252825	-9.75	<.0001*
(NumVerifDronesPerZone-2.0155)*(NumVerifDronesPerZone-2.0155)	85.651957	9.570475	8.95	<.0001*
(SeekerAvgTmBetwDet-155.016)*(VerifDisperse-155.016)	-0.004112	0.000687	-5.99	<.0001*
(SeekerAvgTmBetwDet-155.016)*(SeekerAvgTmBetwDet-155.016)	-0.004247	0.000737	-5.76	<.0001*
VerifPClass	-97.412	18.97998	-5.13	<.0001*
(NumSeekersPerVerif-2.0155)*(VerifDisperse-155.016)	0.27482	0.082802	3.32	0.0012*
(NumSeekersPerVerif-2.0155)*(SeekerAvgTmBetwDet-155.016)	0.2519487	0.085741	2.94	0.0040*
(NumVerifDronesPerZone-2.0155)*(SeekerAvgTmBetwDet-155.016)	-0.225295	0.07732	-2.91	0.0043*
SeekerDisperse	-0.114522	0.052376	-2.19	0.0308*
(SeekerAvgTmBetwDet-155.016)*(VerifPClass-0.50124)	-0.425275	0.228453	-1.86	0.0653
(VerifDisperse-155.016)*(VerifDisperse-155.016)	-0.001387	0.000746	-1.86	0.0654

Actual by Predicted Plot

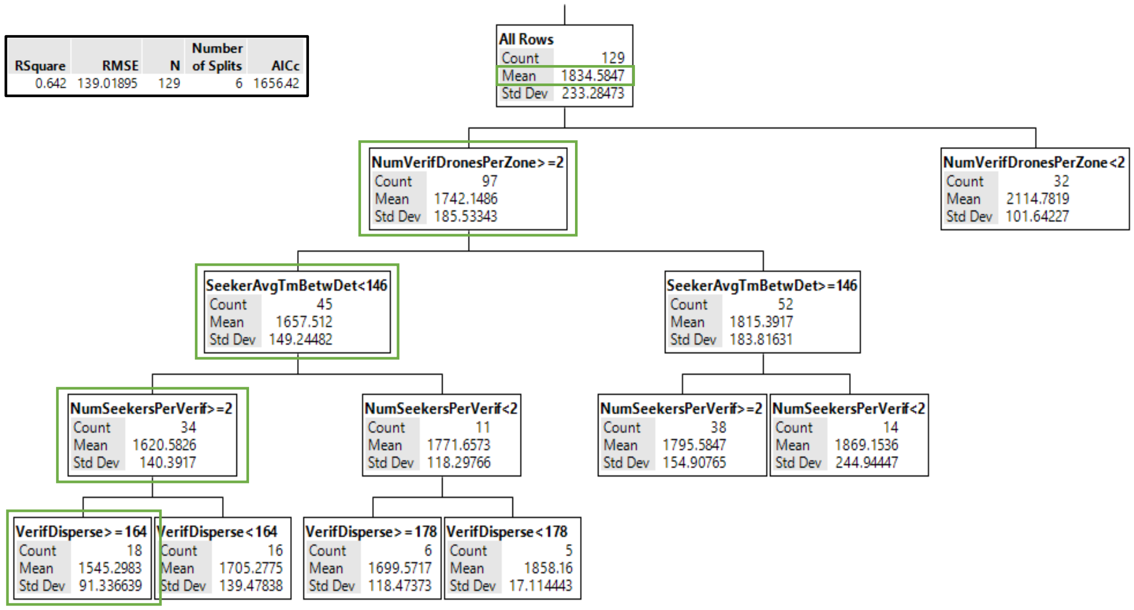


Summary of Fit

RSquare	0.958364
RSquare Adj	0.952837
Root Mean Square Error	50.66254
Mean of Response	1834.585
Observations (or Sum Wgts)	129

Figure 28. Stepwise Regression for the Hierarchical Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 3:1)

Figure 30 is the left limb of the partition tree and identifies the swarm characteristics with the greatest potential to reduce the average time to locate the first enemy fighter. Similar to the emergent swarm, the regression tree begins with 129 observations. The first split occurs on the most significant factor, which is "number of verification drones per zone." Regardless of swarm enhancement, the hierarchical swarm fails to outperform the Raven or the emergent control strategy. In fact, when compared against the Raven scenario's most efficient employment strategy, on average, it takes the central planner two and a half times as long to locate the first enemy fighter. When compared to the emergent swarm, the hierarchical control strategy takes 5.9 minutes longer to locate the first hostile agent.



Preferred Performance Path (Left Limb)

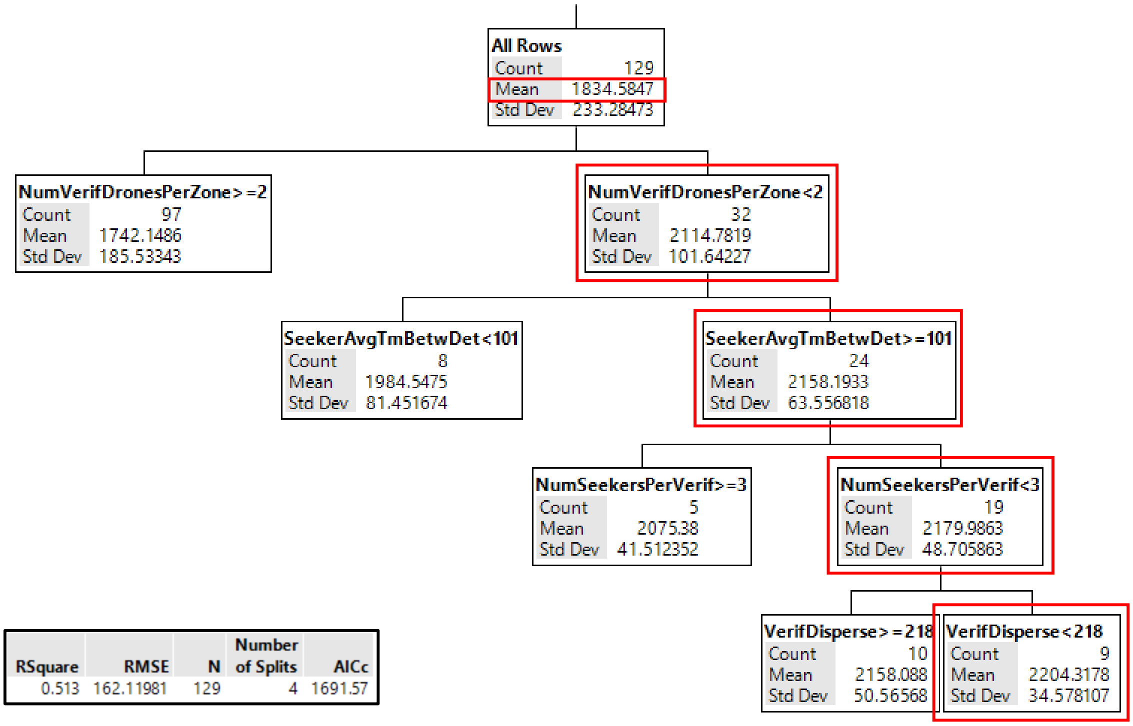
Figure 29. Partition Tree for the Hierarchical Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 3:1)?

Two of the most influential factors in the partition tree pertain to swarm size. The results show that that the preferred employment strategy requires two verification drones per zone and two seeker drones per verification drone. More simply, each subswarm contains six drones for a swarm total of 12 drones. Applying scenario assumptions, the UAV support section must deploy four hierarchal swarms or 48 individual drones to provide ISR coverage for the 2.5-hour battle. This is a significant reduction when compared to the emergent control strategy.

As a final observation, the hierarchical swarm requires more capable sensors than the emergent control strategy. To enhance swarm performance, seeker drones must maintain an average time between detection of less than 146 seconds and the verification drone must meet a classification threshold of 69 percent. Surprisingly, the sensor requirements are closer to the Raven characteristics than the emergent swarm, particularly with respect to "verification drone probability of classification." Further research must be conducted to determine if the hierarchical swarm configuration produces enough cost savings to make the swarm employment strategy viable.

At first glance, the hierarchical swarm's inability to reach performance parity with the emergent swarm and the increase in sensor requirements did not make sense. The author believed that minor adjustments to the hierarchical swarm, particularly increasing the number of drones per zone, would result in the hierarchical swarm locating fighters on the battlefield much more efficiently. Perplexed by this finding, the author conducted a more thorough investigation and entered several scenario "seeds" with characteristics close to the partition thresholds. By visually studying each "seeded scenario," the author discovered that distributing sensors across the battlefield comes at a price. While the central planner is able to investigate more locations, that does not translate into more area. Rather, splitting the swarm into two equal subswarms reduces ISR volume at each location, affecting the swarm's ability to locate the first enemy combatant. Further research should be conducted to examine how other subswarm distributions (e.g., increasing the number of subswarms) affect locating enemy forces.

For completeness, Figure 31 is provided to show the right limb of the tree. Under no conditions can this approach outperform the left limb of the tree. Note that as the number of verification drones decreases, both the number of seeker drones and the sensor requirements increase. The degraded path results in a significant increase in the average time to locate the first enemy fighter and implies an increased cost when employing the swarm.



Degraded Performance Path (Right Limb)

Figure 30. Partition Tree for the Hierarchical Swarm: How Long Does it Take the Blue Force to Identify the First Enemy Fighter (MOE 3:1)?

2. Measure of Effectiveness 3:2—Force Protection: How Many Blue Casualties are Sustained during Mission Execution?

Using the raw output data, with a sample size of 12,900 observations, on average, the Blue force takes 25.6 casualties with a standard deviation of 12.5 casualties. The 95 percent confidence interval for the mean is [25.4, 25.8 casualties]. Assuming a standard Marine infantry company, on average, the Red force destroys or neutralizes 14.7 percent [14.6, 14.8%] of the Marine unit's combat power. When compared to the mean results from Experiment Sets 1 and 2, on average, the Marine infantry company receives less casualties. Overall results show that the hierarchical control strategy offers the best potential options for casualty reduction even though it takes the longest to locate the enemy.

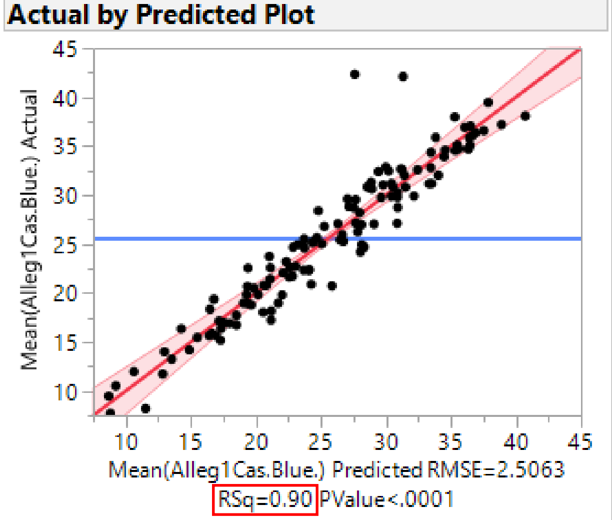
Figure 32 displays the stepwise regression results for MOE 3:2. The significant factors and interactions in the model account for over 90% of the model's variability. The stepwise regression identifies that six of the seven primary factors are statistically significant at a significance level of 0.05. The only factor not included in the model is "dispersion between seeker drones."

While the regression identifies "FiST latency" as the most influential factor, the factor "number of verification drones per zone" emerges as a close second. Similar to the emergent swarm, the regression model shows that both swarm size and sensor capabilities have a profound effect on Blue force casualties. Almost all of the regression coefficients for factors related to the number of drones or drone sensor capabilities have a negative correlation to the response. Thus, as the size of each subswarm grows and the probabilities of detection and classification increase, the number of Marine casualties decreases.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
FiST.Latency	0.0477093	0.002782	17.15	<.0001*
NumVerifDronesPerZone	-5.283729	0.309431	-17.08	<.0001*
SeekerAvgTmBetwDet	0.041324	0.002591	15.95	<.0001*
NumSeekersPerVerif	-3.14176	0.309771	-10.14	<.0001*
(SeekerAvgTmBetwDet-155.016)*(SeekerAvgTmBetwDet-155.016)	-0.000236	4.088e-5	-5.76	<.0001*
VerifPClass	-3.923054	0.939001	-4.18	<.0001*
VerifDisperse	-0.009399	0.00259	-3.63	0.0004*
(NumVerifDronesPerZone-2.0155)*(VerifDisperse-155.016)	-0.010674	0.003352	-3.18	0.0019*
(NumVerifDronesPerZone-2.0155)*(NumVerifDronesPerZone-2.0155)	1.4185562	0.457319	3.10	0.0024*
(NumSeekersPerVerif-2.0155)*(FiST.Latency-165.016)	0.0122527	0.004037	3.03	0.0030*
(NumVerifDronesPerZone-2.0155)*(FiST.Latency-165.016)	0.0105932	0.003972	2.67	0.0088*
(NumSeekersPerVerif-2.0155)*(NumSeekersPerVerif-2.0155)	0.9278933	0.462037	2.01	0.0470*
(FiST.Latency-165.016)*(FiST.Latency-165.016)	-7.335e-5	4.58e-5	-1.60	0.1120
(VerifDisperse-155.016)*(FiST.Latency-165.016)	5.1427e-5	0.000033	1.56	0.1218

Actual by Predicted Plot

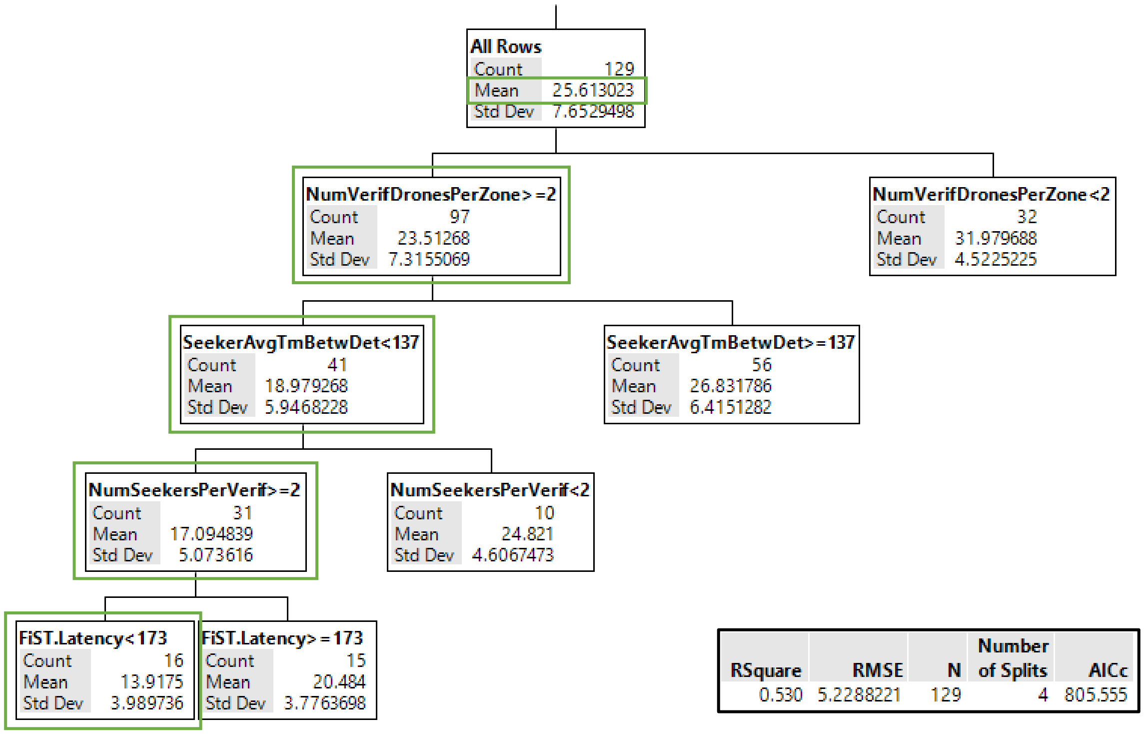


Summary of Fit

RSquare	0.904481
RSquare Adj	0.892751
Root Mean Square Error	2.506259
Mean of Response	25.61302
Observations (or Sum Wgts)	129

Figure 31. Stepwise Regression for the Hierarchical Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 3:2)?

Figure 33 is the left limb of the partition tree and identifies the swarm characteristics with the greatest potential to reduce the average number of Blue force casualties. Like the emergent swarm, the number of drones dominates the splits; however, the effect of the FiST is reduced. The presented partition tree represents the best splits according to the JMP 13 algorithm.



Preferred Performance Path (Left Limb)

Figure 32. Partition Tree for the Hierarchical Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 3:2)?

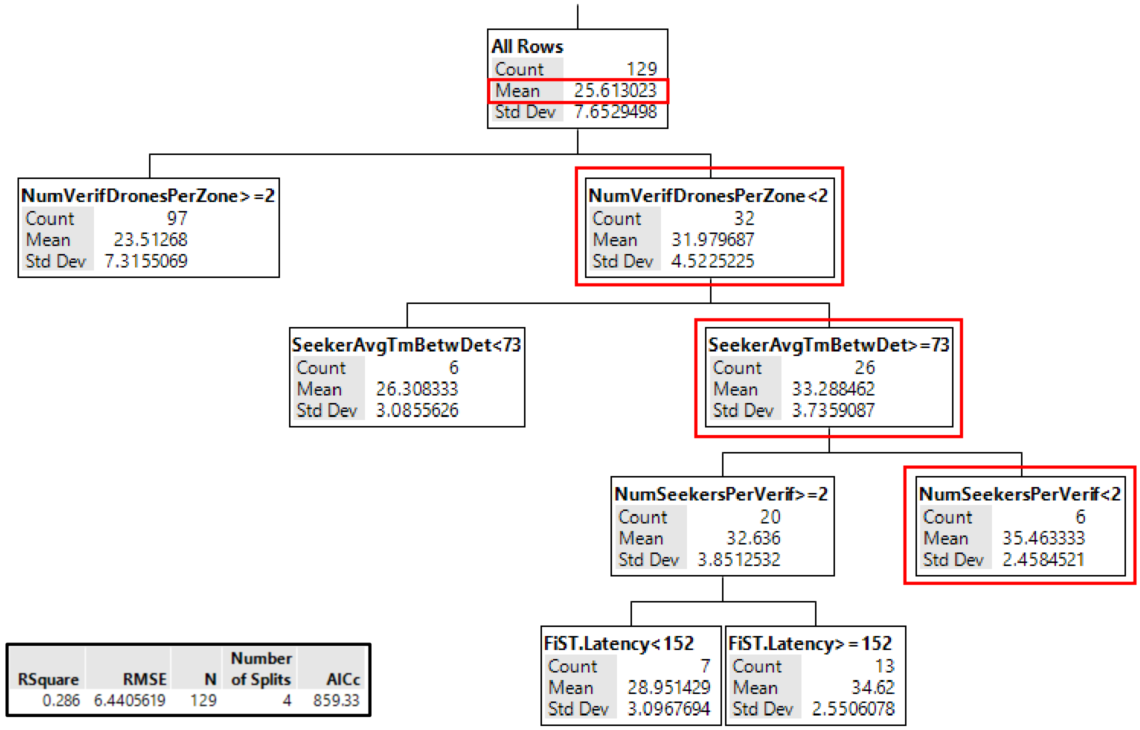
The first split occurs on the factor “number of verification drones per zone.” Swarm size continues to have an important influence on unit performance and the tree results reinforce the need for two verification drones per zone and two seeker drones per verification drone. Interestingly, the preferred swarm size for MOEs 3:1 and 3:2 are the same. It appears that two subswarms of six drones offers the most potential for decreasing the time it takes to locate the first enemy combatant and reduce Blue force casualties.

The next significant factor is “seeker average time between detections.” The regression identifies the sensor threshold as less than 137 seconds, only nine seconds less than the operational threshold discovered during analysis of MOE 3:1. This could represent another cost savings advantage of the hierarchical swarm. Investing in a slightly more capable sensor both increases the central planner’s ability to quickly locate enemy forces and can potentially decrease the mean number of Blue force casualties from 26.8 to 18.9.

The final factor important to this interaction is “FiST Latency.” In order to further reduce Blue force casualties, the UAV support section must be able to confirm and transmit targeting data to the FiST in less than 173 seconds, or just under three minutes. Achieving the operational threshold can potentially reduce casualties by an additional three to four personnel.

Overall, the hierarchical swarm significantly outperforms the other ISR employment strategies with respect to casualty reduction. It appears that distributing the swarm allows the central planner to locate more of the enemy for FiST prosecution. The effective use of “shaping fires” provides the infantry company with a potent advantage. As the preferred path shows, employing the hierarchical swarm with the proper characteristics can potentially reduce the mean number of Blue force casualties by 50 percent. Moreover, the hierarchical approach requires less UAVs, reducing the UAV support section’s workload. It is recommended that follow-on studies explore larger battlefields and study how subswarm management affects the central planner.

Figure 34, is the right limb of the tree for MOE 3:2. Consistent with the other partition tree models, the right limb represents the degraded employment strategy. Failing to plan appropriately for swarm employment can have dire consequences. The partition tree shows that getting the swarm composition wrong results in significantly more casualties and greater requirements with respect to sensor capabilities and UAV support section proficiency.

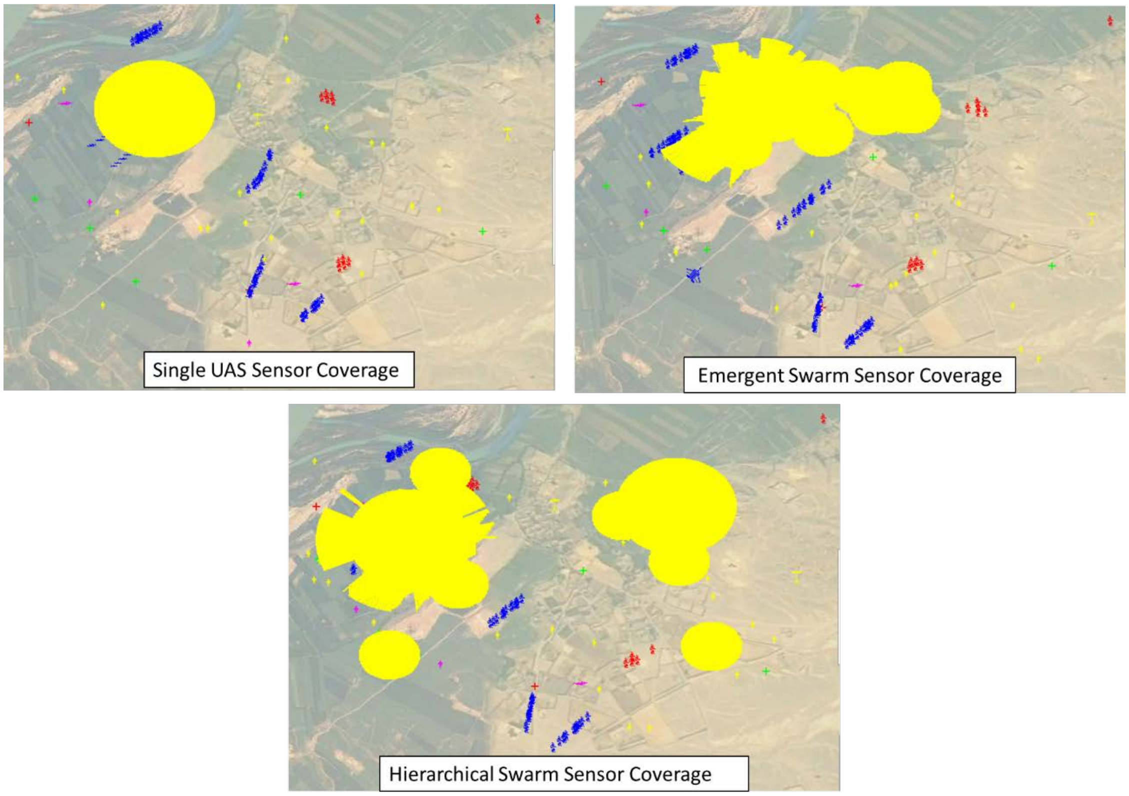


Degraded Performance Path (Right Limb)

Figure 33. Partition Tree for the Hierarchical Swarm: How Many Blue Casualties Are Sustained during Mission Execution (MOE 3:2)?

3. Explaining the Significant Difference in Casualty Reduction

In an effort to explain why the hierarchical swarm offers such a significant reduction in Blue force casualties over the other two employment strategies, the author returned to data analysis and the simulation model to see if there was a clear explanation for this phenomenon. A thorough review in both areas reveals that while distributing sensors across the battlefield takes more time and effort (when comparing the swarms against a single UAV), the overall increase in battlefield situational awareness allows the FiST and UAV support section to target a greater number of enemies. More simply, a single drone can only investigate a single event in a single area. To the contrary, a swarm increases visibility into an area and allows the UAV support section to prosecute multiple targets simultaneously. To show this concept visually, Figure 35 provides a line-of-sight (LOS) study for each of the three ISR approaches.



[Best Viewed in Color]

Figure 34. LOS Studies Extracted from MANA-V Simulation Runs.

The three LOS studies show the stark differences between the ISR employment strategies. Without question, the swarms surveil a greater amount of the battlefield. When comparing sensor distribution between swarms, the emergent swarm concentrates around the verification drones. From the visual in Figure 35, it appears that the emergent swarm effectively reconnoiters one axis of advance (the agricultural area), but fails to locate enemy fighters in the urban area before Blue infantry units enter the village. To the contrary, the hierarchical swarm effectively covers both axes of advance and begins to destroy or neutralize enemy fighters with indirect fires (IDF). To further investigate this claim, Figure 36 displays the summary statistics for Red fighters killed by IDF.

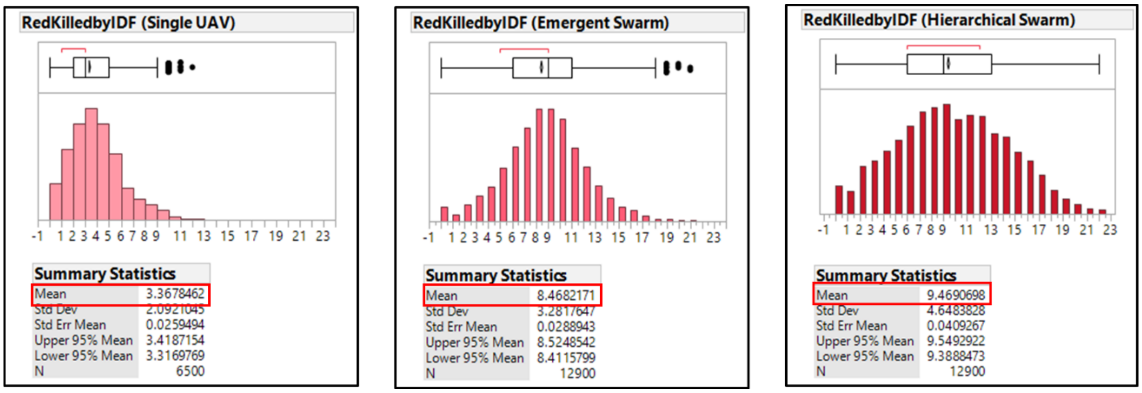


Figure 35. Summary Statistics for Number of Red Fighters Killed by IDF

Figure 36 shows that the swarms, on average, engage and destroy twice as many enemy fighters with IDF when compared to the single UAV. Interestingly, there is practically no difference in the targeting performance between swarms (i.e., one additional Red fighter killed on average). Initially the author assumed that the hierarchical swarm's superior potential for reducing Blue force casualties was linked to destroying more of the enemy through IDF; however, the summary statistics do not strongly support this hypothesis. While it seems plausible that the distributed nature of the hierarchical swarm accounts for its potential reduction in Blue casualties, more research is needed to explore how the subswarm distribution effects protecting the force.

VI. THESIS CONCLUSION AND FUTURE RESEARCH

Future operating environments promise to be complex and chaotic. Adversaries are taking advantage of technology proliferation, deploying hybrid forces, and using robust anti-access and area denial (A2/AD) capabilities to challenge U.S. military supremacy within the global commons. Although the Department of Defense (DoD) will need many technologies to combat these emerging threats, autonomous swarms are maturing at a rapid pace and offer viable solutions for gaining access to areas either unreachable or too dangerous to send military personnel (Scharre, 2014). Additionally, ISR swarms offer a unique ability to deploy multiple sensors and capabilities with a potential reduction in manpower requirements. As these complex systems integrate into manned units, simulation will be a valuable tool for studying swarm employment and optimizing performance.

A. STUDY SUMMARY

This thesis explores drone swarm employment in support of a Marine infantry company and attempts to quantify system performance under combat conditions. The thesis scenario realistically depicts a challenging hybrid threat that seeks to deny U.S. forces access to an enemy stronghold. Based on current events and DoD forecasts, it is likely that U.S. ground forces will fight similar threats for the foreseeable future. The ARSENL drone swarm architecture and the author's combat experiences serve as the basis for this study. A realistic model, efficient design of experiment, and rigorous analysis process produced interesting results based on the output from 30,000 simulated battles.

B. STUDY FINDINGS

The thesis findings show that the different UAV control strategies have a profound effect on sensor coverage, indirect fire employment, and unit casualties. Both the regressions and partition trees illustrate that integrating ISR platforms with maneuver involves complex relationships that require optimal planning and skill to manage. Insights from this study and recommended follow-on work can help shape planning tools that ground forces will need to properly leverage ISR technologies on future battlefields.

It is important to note that while some of the findings may be applicable in a general context, the remarks on swarm size and swarm configurations apply specifically to the thesis scenario.

1. Primary Findings:

- The hierarchical swarm demonstrates the greatest potential for casualty reduction and can do so with fewer UAVs than the emergent swarm. When implementing the preferred swarm configuration, Blue force casualties can potentially be reduced by 50 percent.

- Data analysis and visual study of the emergent swarm show that the volume of the swarm, coupled with inherent sensor overlap, results in the largest reduction in sensor capability requirements.

- On average, both drone swarms enabled the FiST to target and engage twice as many enemy targets when compared to the singular ISR drone, despite requiring more time to detect the first enemy fighter.

- The preferred employment strategy for the hierarchical swarm calls for two subswarms of six drones. Each subswarm consists of two verification and four seeker drones. Under scenario conditions, 48 UAVs are needed to provide ISR for the company during the 2.5-hour battle.

- The preferred employment strategy for the emergent swarm recommends deploying a 15-drone swarm consisting of three verification and 12 seeker drones. Under scenario conditions, 60 UAVs are needed to provide ISR for the company during the 2.5-hour battle.

- ISR planners must be aware of swarm scaling and its implications on combat service support. Although the preferred employment configurations for the swarms only differ by three drones, the overall mission requirement differs by 12 UAVs.

2. Secondary Findings:

- On average, the Raven UAV discovers the first enemy fighter two times faster than the emergent swarm and three times faster than the hierarchical swarm. This shows that the autonomous coordination between the seeker and verification drones adds time to the target detection process. Combining single UAV employment with the hierarchical swarm may be an effective strategy for maximizing unit performance.

- For the Raven experiment, unit movement speed is the most influential factor on company performance, followed by unit lethality factors.

- When deploying a singular UAV like the Raven, an aggressive patrolling speed allows the infantry units to close with the enemy and cover down on UAV sensor "dead zones." This integrated coverage gives the UAV operator more time to "sense between detections," and accomplish the mission with a less capable detection sensor.

- When deploying a singular UAV, it is important to balance unit patrol speed with mission execution. Although an aggressive patrol pace allows the company to locate enemy fighters faster, the Raven operator and company fire support team (FiST) have less time to reconnoiter the battlefield. This reduced reconnaissance time results in a higher average number of Blue force casualties.

- When the Blue force reduces patrol speed, the Raven operator and FiST have more time to locate and destroy enemy fighters with indirect fires. Shaping the battlefield prior to moving into direct fire range reduces the number of friendly casualties.

- Failing to plan appropriately for swarm employment can have dire consequences. Partition trees for both the emergent and hierarchical control strategies show that implementing the wrong swarm composition results in significant increases to swarm MOEs (the time it takes to locate the first enemy fighter and Blue force casualties).

C. FOLLOW-ON WORK

- Analyze drone employment and performance on a larger battlefield. The author recommends employing the swarms in support of reconnaissance or armored units.

- Analyze different delivery profiles/approaches (e.g., aerial platforms, ground vehicles, canon delivered, etc.).

- Expand factor exploration to include Blue force parameters in order to gain a better understanding of how the infantry unit's performance effects swarm employment.

- Expand factor exploration to include enemy and civilian parameters in order to gain insight into how non-decision factors effect drone performance.

- Analyze the cost/savings relationship between reduced sensor requirements and swarm size.

- Conduct further research on UAV support section task organization, C2 configurations, and single drone / swarm combinations.

- Further research using MANA-V to model and analyze aerial swarm behavior.

- Perform a human factors study on central planner interaction with the ground control station to determine appropriate scope of control.

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