3-2022

Simulating Autonomous Cruise Missile Swarm Behaviors in an Anti-Access Area Denial (A2AD) Environment

Kyle W. Goggins

SIMULATING AUTONOMOUS CRUISE MISSILE SWARM BEHAVIORS IN AN ANTI-ACCESS AREA DENIAL (A2AD) ENVIRONMENT

THESIS

Kyle W. Goggins, Captain, USAF

AFIT-ENS-MS-22-M-132

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENS-MS-22-M-132

SIMULATING AUTONOMOUS CRUISE MISSILE SWARM BEHAVIORS IN AN ANTI-ACCESS AREA DENIAL (A2AD) ENVIRONMENT

THESIS

Presented to the Faculty
Department of Operational Sciences
Graduate School of Engineering and Management
Air Force Institute of Technology
Air University
Air Education and Training Command
in Partial Fulfillment of the Requirements for the
Degree of Master of Science in Operations Research

Kyle W. Goggins, BS
Captain, USAF

March 24, 2022

AFIT-ENS-MS-22-M-132

SIMULATING AUTONOMOUS CRUISE MISSILE SWARM BEHAVIORS IN AN ANTI-ACCESS AREA DENIAL (A2AD) ENVIRONMENT

THESIS

Kyle W. Goggins, BS
Captain, USAF

Committee Membership:

Lance E. Champagne, PhD
Chair

Major Michael J. Garee, PhD
Member

AFIT-ENS-MS-22-M-132

Abstract

The increasingly sophisticated anti-access area denial (A2AD) threat imposed by the modern integrated air defense system (IADS), coupled with the decreasingly potent advantage provided by high-end stealth platforms, has prompted Air Force senior leaders to invest in radically changing the nature of air power for the year 2030 and beyond. A prominent element of this new vision is weapon swarming, which aims to address this challenge by overwhelming the IADS with huge numbers of low-cost, attritable aerial assets emboldened by autonomous capabilities. This research proposes a framework for classifying the different levels of autonomous capability along three independent dimensions—namely ability to act alone, ability to cooperate, and ability to adapt. A virtual combat model is constructed using the Advanced Framework for Simulation, Integration, and Modeling (AFSIM) in order to simulate the engagement between a friendly air strike package, featuring a manned penetrating bomber and an autonomous cruise missile swarm, and an enemy IADS acting in an A2AD role. The influence of varying levels of autonomy on the strike package's performance is evaluated by using the autonomy framework as the basis for a designed experiment. Analyzing the experimental results reveals which dimensions and levels of autonomy are most impactful in promoting survivability and lethality for this simulated scenario.

Table of Contents

Page

List of Figures

Figure Page

List of Tables

SIMULATING AUTONOMOUS CRUISE MISSILE SWARM BEHAVIORS IN AN ANTI-ACCESS AREA DENIAL (A2AD) ENVIRONMENT

I. Introduction

1.1 Motivation and Background

The technological nature of warfare is rapidly evolving with ever-increasing emphasis being placed on collecting, processing, and making decisions based on enormous swaths of data. As the complexity of the command and control (C2) decision space grows, the speed at which the chain of command can act upon the available information becomes more and more of a limiting factor. Autonomous systems with varying degrees of human-system interaction present an opportunity to mitigate this shortfall. The 2018 National Defense Strategy (NDS) of the United States of America [18] explicitly calls for the Department of Defense (DoD) to "invest broadly in military application of autonomy" as a key capability towards fostering an advantage in a great power competition.

A natural consequence of engaging in a great power competition is the proliferation of anti-access area denial (A2AD) environments across all aspects of joint conflict. From the perspective of the United States Air Force (USAF), modern integrated air defense systems (IADS) pose a preeminent A2AD threat, which severely inhibits the prospect of establishing air superiority by conventional means [2, 20]. This challenge prompted a shift in force structure priorities as the perceived risk of concentrating capability in a relatively small number of high-end systems grows. The USAF Science and Technology Strategy [26] envisions that overwhelming numbers of low-cost,

attritable aerial assets will soon carry out roles once fulfilled by limited numbers of high-value assets. The scale of the mission planning and air battle management (ABM) effort for such a large-scale swarm could quickly outpace human cognitive capacity, making it is an application area well-suited for autonomy-related research and development.

1.2 Problem Statement

This research seeks to evaluate the effect of several autonomous cruise missile swarm behaviors on Blue (friendly) air performance in an A2AD environment. Specifically, the A2AD scenario under study considers a Red (enemy) IADS which is engaged by a swarm of Blue networked autonomous cruise missiles in order to facilitate a follow-on strike by a penetrating bomber. Pop-up threats, which are unaccounted for at the time of mission planning, may enter the scenario to augment the Red IADS. The swarm must detect and respond to these pop-up threats as well as any other adversarial changes to mission parameters without the aid of external ABM. Modeling for the A2AD scenario is accomplished using the Advanced Framework for Simulation, Integration, and Modeling (AFSIM).

1.3 Research Questions

To address the problem statement, this research will provide answers to the following questions:

1. To what extent can a cruise missile swarm with autonomous ABM capabilities improve the survivability (i.e., ability to avoid detection and destruction by the Red IADS) of the Blue air strike package in an A2AD environment?

2. To what extent can a cruise missile swarm with autonomous ABM capabilities

improve the lethality (i.e., ability to detect and destroy elements of the Red IADS) of the Blue air strike package in an A2AD environment?

1.4 Organization of the Thesis

The remainder of this thesis contains four chapters organized as follows: Chapter II provides a review of reference material on topics including autonomy, A2AD environments, agent-based modeling and simulation (ABMS), and design of experiments (DOE). Chapter III establishes the structure for the A2AD scenario, AFSIM model implementation, and experimental design, which serves as the framework for this study. Chapter IV presents the results from the experimental simulation runs and accompanying analysis. Lastly, Chapter V discusses conclusions drawn from this research as well as suggestions for future research threads.

II. Literature Review

2.1 Chapter Overview

This chapter presents a review of pertinent sources from the literature that contributes to both the motivation for this research topic and the analytical techniques that constitute the solution methodology. The covered topics include taxonomy and combat applications of autonomous systems, anti-access area denial (A2AD), combat modeling, agent-based modeling and simulation (ABMS), and design of experiments (DOE).

2.2 Taxonomy of Autonomous Systems

Huang et al. [14] propose a common definition of autonomy as "an unmanned system's own ability of sensing, perceiving, analyzing, communicating, planning, decision-making, and acting, to achieve its goals as assigned by its human operator(s) through designed human-robot interaction." For the specific application under study in this research, autonomy refers specifically to a cruise vehicle's capacity to make sovereign command and control (C2) decisions once airborne. A prominent challenge associated with autonomy in modeling, simulation, and experimental contexts is how to define or quantify the level(s) of autonomy.

A wide variety of frameworks for levels of autonomy has been suggested in the literature. Clough devised an ordinal categorical scale to describe levels of autonomy in unmanned aerial vehicles, which is detailed in Table 1 [29]. This single-dimensional scale succeeds in covering the complete spectrum of autonomous capability but has been noted to suffer in practice due to subjectivity on where the boundary lies between levels. An alternative solution called the Autonomy Levels for Unmanned Systems (ALFUS) framework is proposed by Huang et al. [14] and is depicted in Figure

1. This three-dimensional framework offers more flexibility to specify quantifiable metrics that can be aggregated to capture a system's overall level of autonomy. In contrast to the notion that autonomy requires a quantifiable taxonomy, a task-force study by the Defense Science Board offers the recommendation that the Department of Defense (DoD) should not concern itself with defining levels of autonomy and instead consider an autonomy framework focused on "cognitive echelon, mission timelines, and human-machine system trade spaces." [9]

Table 1. Clough's Levels of Autonomy

Level	Description
0	Remotely piloted vehicle
1	Execute pre-planned mission
2	Changeable mission
3	Robust response to real-time faults/events
4	Fault/event adaptive vehicle
5	Real-time multi-vehicle coordination
6	Real-time multi-vehicle cooperation
7	Battlespace knowledge
8	Battlespace cognizance
9	Battlespace swarm cognizance
10	Fully autonomous

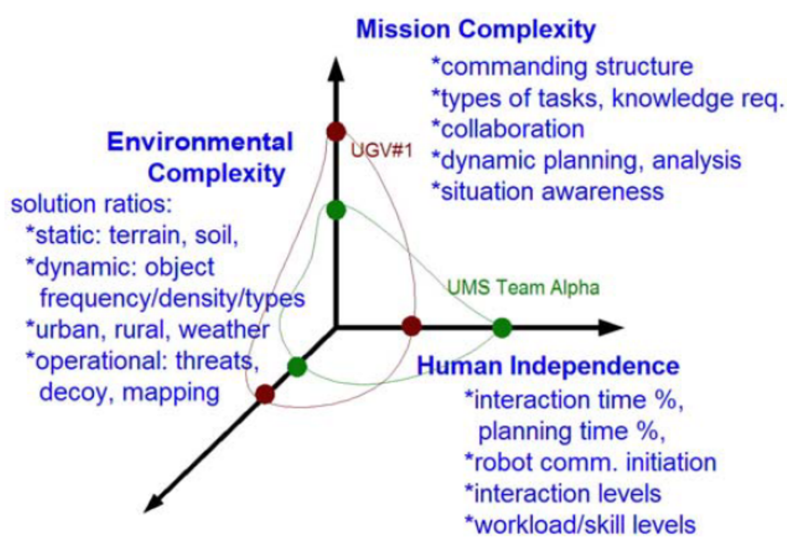


Figure 1. ALFUS Framework Concept

A recent Lockheed Martin technical report [1] develops a seven-dimensional taxonomy for defining levels of autonomy. This framework allows for a high-fidelity representation of a system's autonomy levels. One aspect of this framework that will be investigated further is whether the seven dimensions (or some subset thereof) can be interpreted as meaningfully independent, since independent or orthogonal axes would be most desirable for experimental design. Spiegel [23] and Pollack [21] both conducted thesis research on related topics and leveraged a subset of the dimensions proposed by Lockheed Martin as a framework for evaluating the effects of autonomy [1]. This research will expand upon that effort by further refining the evaluation framework for different levels of autonomous capability, specifically in application to autonomous weapon swarms in an A2AD environment.

2.3 Autonomy in Combat Applications

The DoD recognizes the potential operational utility of autonomous systems and is investing broadly in autonomy-related research and development efforts, but it has been slow to integrate autonomy with existing combat capabilities to date [8, 26]. Current DoD policy dictates that "autonomous and semi-autonomous weapon systems shall be designed to allow commanders and operators to exercise appropriate levels of human judgment over the use of force,"[6] which reflects the hesitation held by commanders to relinquish or share C2 authority with autonomous systems. A popular strategy for addressing reservations related to trust in autonomous weapon systems limits autonomous functions to established "playbooks," which place well-defined restrictions on the mission parameters that can be influenced by autonomy [4, 10, 11].

The Air Force Research Laboratory (AFRL) is currently executing two major research programs involving autonomous weapon swarms, namely Golden Horde and Gray Wolf. Golden Horde seeks to demonstrate the operational utility of integrat-

ing networked collaborative technologies in weapon formations consisting of modified Small Diameter Bomb I and Miniature Air Launched Decoy variants [10]. Gray Wolf, on the other hand, explores the potential cost-benefit advantages associated with designing a common-form-factor, modular-payload swarming weapon [10]. Both of these research efforts provide valuable insights regarding the level of autonomous weapon swarming capability that the United States Air Force (USAF) hopes to achieve in the near future as well as a realistic basis for modeling an autonomous weapon swarm.

2.4 Anti-Access Area Denial

One of the preeminent A2AD threats to airborne military assets is ground-based air defense systems. A typical modern air defense system is comprised of early warning (EW) radars, target acquisition radars (TAR), target engagement radars (TER), surface-to-air missiles (SAM), and a C2 center configured as a networked integrated air defense system (IADS) [24]. The effect of each IADS subsystem's capability combines with decision authority given by the C2 center in order to addresses every stage of the conventional "kill chain"—find, fix, track, target, engage, and assess [25].

Prior to the relatively recent paradigm shift towards strategic competition, the USAF wielded an asymmetric advantage over its adversaries for many years [18]. During those conflicts, more primitive IADSs could be reliably defeated by means of stealth, cruise missiles, conventional suppression of enemy air defenses (SEAD), or some combination thereof. However, sophisticated modern-day systems like the Russian S-400 have been deliberately designed so as to minimize the advantage offered by employing such tactics [20]. China has likewise made advancements in establishing an A2AD posture with naval-domain emphasis in the South China Sea [15]. As a result, alternative solutions such as hypersonic weapons and low-cost, attritable cruise vehicle swarms have entered the spotlight for defense research and development.

Figure 3 provides a notional illustration of how a cruise vehicle swarm versus IADS engagement might play out [10].

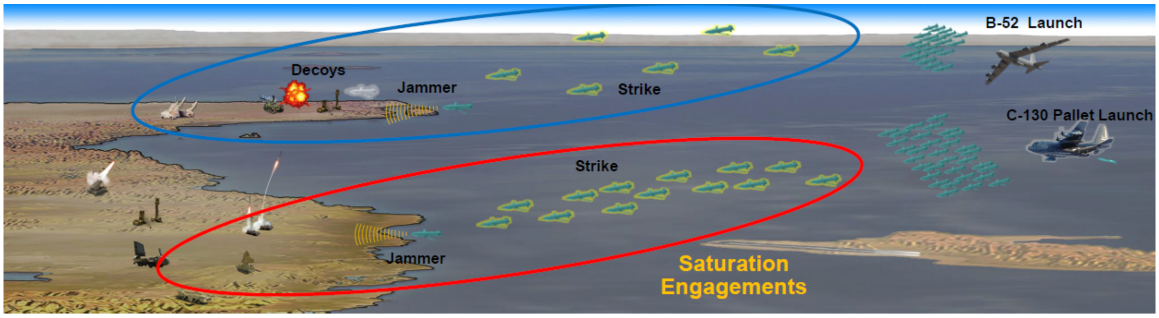


Figure 2. Notional Cruise Vehicle Swarm Versus IADS Engagement

Pelosi and Honeycutt [20] investigated the impact of cruise missile routing tactics on penetrating the S-400 air defense system. Their findings with regards to terrain masking effects may be leveraged to inspire the initial mission planned routes for the autonomous swarm in this research. Maloney's [17] research explored the utility of a hypersonic reconnaissance asset in a simulated A2AD environment. The A2AD environment consisted of a dense notional IADS laydown with randomly generated "pop-up" threats and targets to be destroyed by penetrating strike assets. This research will feature a similar A2AD environment, but seek to characterize the impact of an autonomous swarm rather than a hypersonic reconnaissance asset. Spiegel's [23] research also included an A2AD environment which was primarily characterized by navigation signal jamming and studying its impact on autonomous capabilities within a cruise missile swarm.

2.5 Combat Modeling

Combat modeling refers to the practice of designing and studying models of military operations. These models may take on a wide variety of forms, covering a broad spectrum ranging from detailed weapon effects simulations to large-scale real-world training exercises to strategic-level wargames. The diversity of simulation models has

inspired the widespread adoption of a few different classification schemes—namely dynamic versus static, continuous versus discrete, deterministic versus stochastic, high-resolution versus aggregated, and descriptive versus prescriptive [12]. A combat model's classification with regards to the high-resolution versus aggregated spectrum is often the most impactful in that it directly influences the level of decision-making that the model can support. Hill and Miller illustrate the trade-off between resolution and aggregation as it applies to DoD combat models with the hierarchy depicted in Figure 2 [13]. The combat scenario at hand in this research calls for modeling elements from both the mission and engagement levels within this hierarchy.

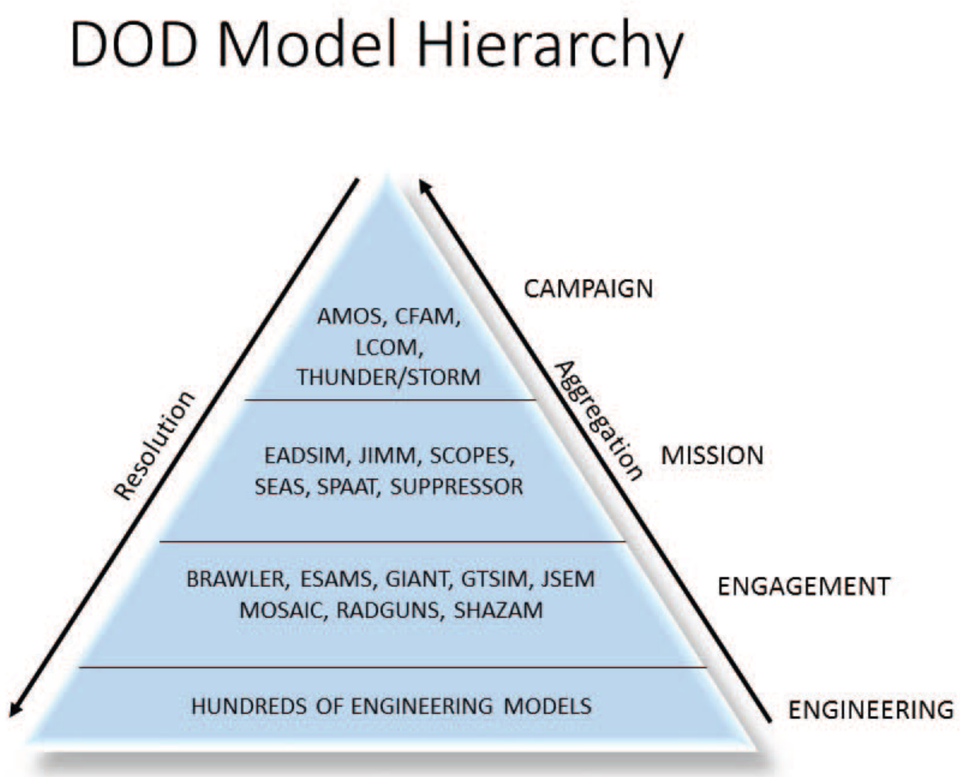


Figure 3. DoD Model Hierarchy

2.6 Agent-Based Modeling and Simulation

ABMS is among the fastest-growing application areas within the field of modeling and simulation over the last ten years. Contrary to discrete event simulation, wherein all aspects of the simulation model are driven by probability draws and event-scheduling, ABMS takes on the "agent perspective" so that agents within the model may exercise a greater degree of autonomy [3, 27]. Macal [16] further classifies ABMS into four distinct categories representing different levels of agent complexity, as summarized in Table 2. Considering the central role autonomy plays in the content of this research, ABMS is the preferred modeling paradigm for this application. In particular, an "adaptive" ABMS represents the highest, most desirable level of capability—a cruise vehicle swarm stands to benefit from being able to dynamically re-prioritize targets once it loses communication with one or more swarm members, for example [16].

Table 2. Definitions for ABMS Based on Agent Properties

ABMS definition/ agent properties	*Individuality*	*Behaviours*	*Interactions*	*Adaptability*	*Example*
Individual ABMS	Individual heterogeneous agents*	Prescribed, scripted†	Limited	None	Traffic model that has agents moving between origin–destination pairs according to a script
Autonomous ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Limited	None	Taxation model in which agents choose occupations and places to work but do not interact with others
Interactive ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Between other agents and the environment¶	None	Infectious disease model in which agents transmit and are infected through contact and respond to their disease state according to prescribed behaviours
Adaptive ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Between other agents and the environment	Agents change behaviours during the simulation‖	Healthcare model in which agents change their behaviours according to the state of their health

*Agents in the population have diverse set characteristics.
†Agent behaviour is exogenously provided and not based on endogenous events during the simulation.
‡Agent behaviour is endogenous based on the current agent state.
¶Agent behaviours are based on the observed states and behaviours of other agents and the state of the environment.
‖Agents change behaviours during the simulation, agents learn, and/or populations adjust their composition.

Advanced Framework for Simulation, Integration, and Modeling (AFSIM) serves as a suitable implementation platform for ABMS. AFSIM offers a high degree of flexibility with respect to its agent architecture, as depicted in Figure 4 [28]. Ad-

ditionally, the intended defense-oriented application of the software package means that there are many built-in templates or programmatic structures in place which facilitate modeling a scenario like the one featured in this research. Since Maloney [17], Pollack [21], and Spiegel [23] all used AFSIM as the platform for their ABMS methodology, many of the agents and environmental elements can be leveraged or modified to suit the purposes of this research.

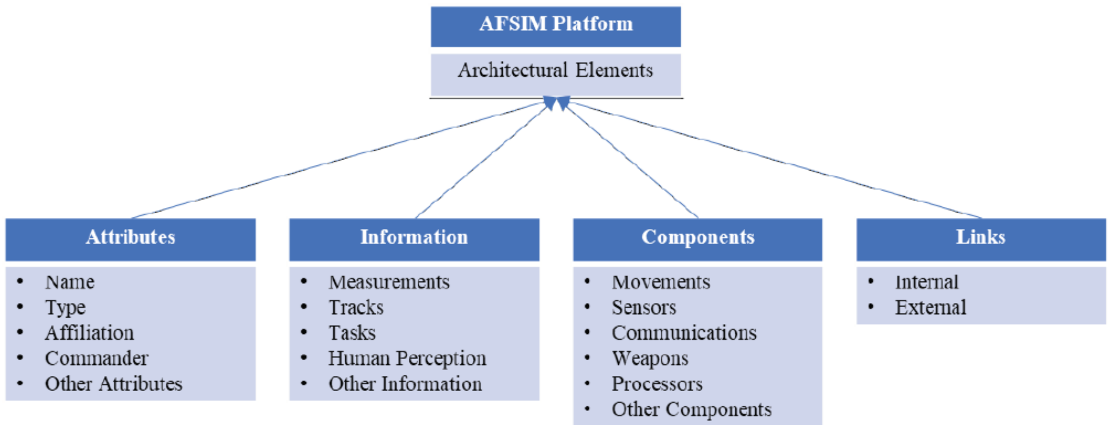


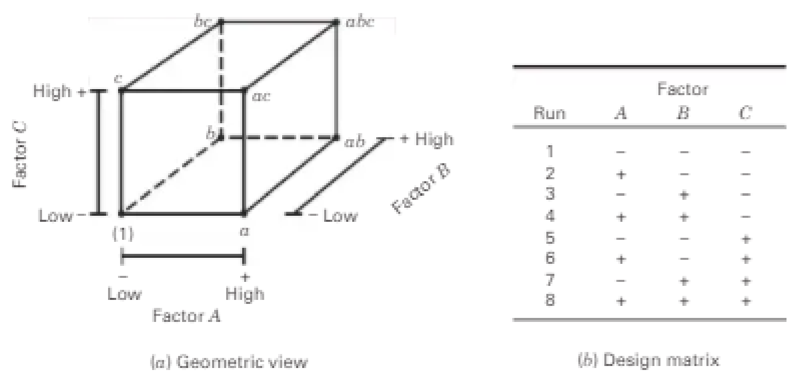
Figure 4. AFSIM Architectural Elements

2.7 Design of Experiments

At its core, DOE as a discipline acts as the statistical framework which supports the scientific method. DOE encompasses a cradle-to-grave procedure in which the experimenter identifies the factor(s) and response(s) pertinent to the system under study, develops an efficient data collection scheme based on desired outcomes, conducts the experiment, and finally draws conclusions based on statistical analysis of the observed data [19]. A thoughtfully designed and executed experiment yields a data structure which empowers the experimenter to infer causal relationships between the factor(s) and response(s).

Any system or process with stochastic elements is suitable for study via DOE,

notably including computer-based simulations featuring randomly generated numeric elements. A wide variety of experimental design types are available for use in simulation experiments, to include 2^k factorial designs, m^k factorial designs, 2^{k-p} fractional factorial designs, central composite designs, and space-filling designs (e.g., latin hypercubes) [22]. A basic visual depiction of a 2^k factorial design, a common but robust design variant, is shown in Figure 5 [19]. Several recent thesis efforts [23, 17, 7, 5, 21] made successful use of either full factorial or fractional factorial designed experiments for structurally similar research efforts. This suggests that a factorial-based design may likewise be applicable for this research, with the possibility of opting for a fractional factorial depending on the number of factors and complexity of the final scenario.



Run	Factor A	Factor B	Factor C
1	−	−	−
2	+	−	−
3	−	+	−
4	+	+	−
5	−	−	+
6	+	−	+
7	−	+	+
8	+	+	+

(b) Design matrix

Figure 5. The 2^k Factorial Design

III. Methodology

3.1 Chapter Overview

This chapter addresses the solution methodology employed in pursuit of providing statistically defensible answers to the research questions at hand. First, defining the dimensions and levels of autonomy establishes a structural baseline for discussing and assessing different capabilities within the context of autonomous weapon swarming. An overview of the A2AD scenario follows, to include key assumptions specific to the AFSIM implementation of both the IADS and the blue strike package. Next, a designed experiment approach provides the statistical basis for collecting data and analyzing results. Lastly, defining the measures of effectiveness (MOEs) provides the evaluation framework that will be used to measure and compare the effects of each dimension and level of autonomy.

3.2 Dimensions and Levels of Autonomy

We define three dimensions of autonomy as they relate to self-governing and cooperative behavior available to the cruise missile swarm. In particular, we denote these dimensions as ability to act alone, ability to cooperate, and ability to adapt. Each of these dimensions is further decomposed into low, middle, and high levels of capability specific to the context of an autonomous weapon swarm engaging an IADS.

Ability to act alone refers to an agent's capacity to navigate the action space of its mission context. In the case of an autonomous cruise missile operating as part of a swarm, this specifically refers to navigating the three-dimensional airspace in the vicinity of the IADS along a route that connects the launch point to the target. At the lowest level along this dimension, the agent calculates and follows the shortest straight-line path between its current position and its target position. The middle

level for ability to act alone adds the provision for avoiding known threat zones where feasible and minimizing the distance traveled through these zones if they cannot be avoided en route to the target. The high level augments the threat-avoidance behavior with a terrain-following capability which allows for lower-altitude ingress than either the low or middle levels can accommodate.

Ability to cooperate refers to an agent's capacity to communicate and negotiate mission execution parameters in support of a team-level prioritized object set. At the lowest level along this dimension, the communications devices are disabled so that the agents are unable to communicate with other members of the team. The middle level along the cooperation axis allows each agent to report its current objective, active track list, and self-status to the other team members. By employing sensor fusion techniques, each of the communicating agents may construct a filtered truth model of the mission environment and reallocate target assignments accordingly. The highest level along this axis sustains the capabilities introduced at the middle level and allows the team to organize in clusters based on each agent's target locations. Contrary to the middle level where asset-objective reallocations are unrestricted within the full team (and, by extension, the full geographic range of the IADS laydown), reallocations at the high level are limited to the the immediate cluster to which each swarm member's original target is assigned. In particular, these clusters are constructed using an agglomerative hierarchical clustering method built in to AFSIM, which offers the advantage of not requiring a predetermined number of clusters to create. Figure 6 illustrates an example case where targets are assigned to clusters, which are distinguished by the magenta-colored convex hulls.

Ability to adapt refers to an agent's capacity to detect and respond to changes in the mission environment. For this scenario, this dimension dictates the capability of the on-board sensor suite for each swarm member as well as what action(s) to take

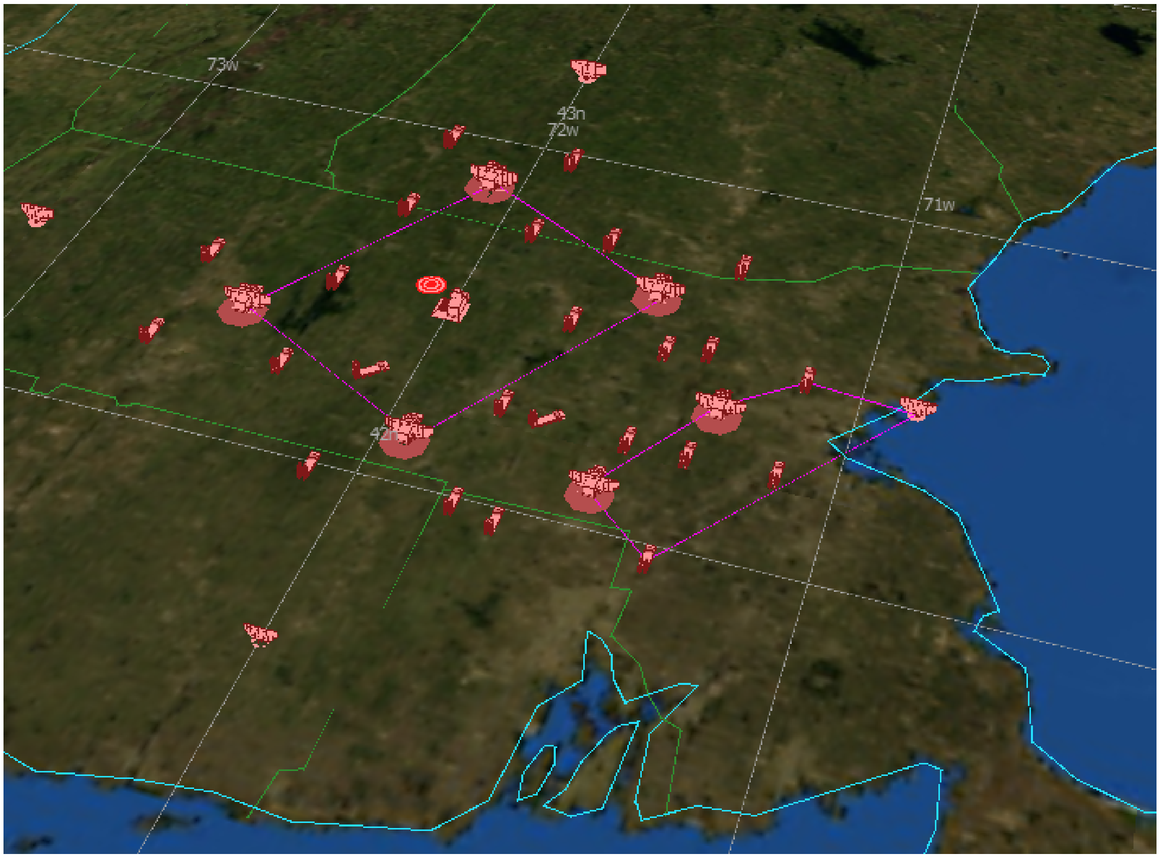


Figure 6. Sample Target Clustering Solution for High Level of Ability to Cooperate

in response to changing environmental factors. The low level for ability to adapt disables the on-board sensors so that each swarm member's situational awareness is limited to pre-briefed target data. At the middle level, each swarm member employs a radar warning receiver (RWR) that provides tracking and location information for any actively-emitting IADS assets. The high level expands upon the RWR capability by allowing each swarm member to detect incoming SAMs and execute evasive maneuvers in response to that threat. Figure 7 depicts an example case of a SAM volley approaching swarm members, which will each execute an evasive maneuver defined by the acceleration vectors shown in bright green. Table 3 provides a consolidated summary of the dimensions and levels of autonomy that serve as the autonomy framework for this study.

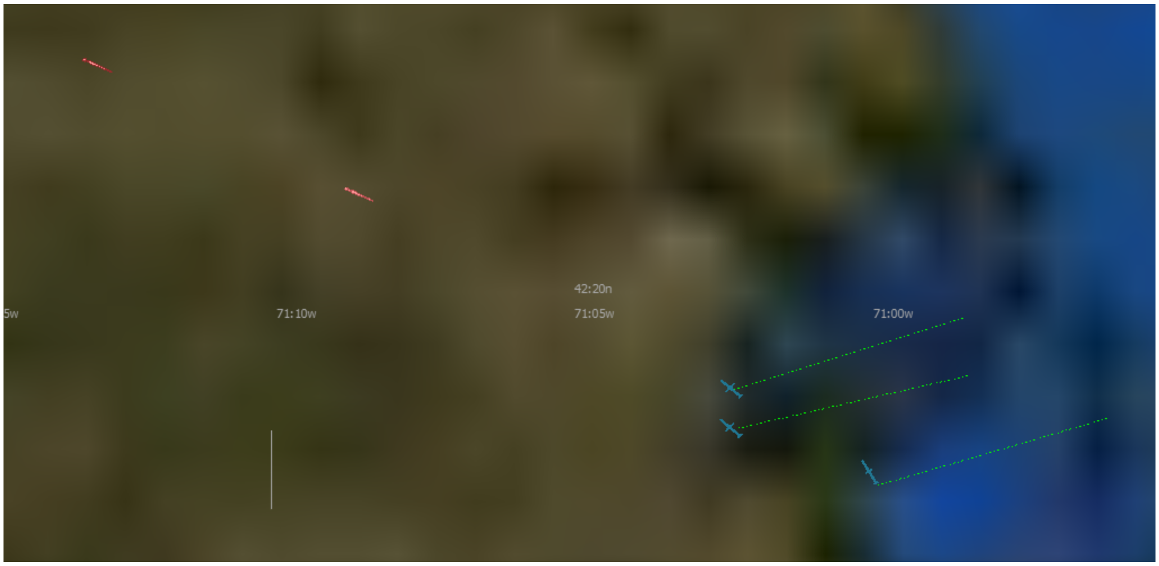


Figure 7. Sample Evasive Maneuver for High Level of Ability to Adapt

Table 3. Summary of Dimensions and Levels of Autonomy

Dimension	Low Level	Middle Level	High Level
Ability to Act Alone	Fly direct straight-line route to target	Avoid known threat zones en route to target	Avoid known threat zones plus terrain following
Ability to Cooperate	Comms turned off	Comms enable dynamic target reassignment within whole swarm	Comms enable dynamic target reassignment within same target cluster
Ability to Adapt	RWR turned off	RWR enables geolocation of transmitting radar sites	Radar enables geolocation plus incoming threat detection and evasive maneuvering

3.3 A2AD Scenario

The simulated combat scenario under study for this research consists of two primary, opposing force elements. The first is a red IADS acting in a defensive A2AD role. A blue air strike package, which includes an autonomous cruise missile swarm and a manned penetrating bomber, engages the red IADS in an offensive capacity.

The following sections elucidate the specific capabilities, limitations, and assumptions associated with each of these force elements as implemented in the AFSIM combat model at hand.

3.3.1 Red IADS

The Red IADS implementation features several distinct entity types—air operations center (AOC), tactical operations center (TOC), EW fusion center, EW radar, TAR, TER, SAM launcher, and air defense artillery (ADA). Each of these entity types leverages the generic representative combat tactics and C2 capabilities established within the AFSIM IADS demonstration scenario [28]. In regards to the IADS command chain, the AOC serves as the top-level command authority, which assigns engagement tasks based on tracking information received from subordinates. The EW fusion center and TOCs report directly to the AOC. The EW fusion center serves as the commander for 11 individual EW radar sites. Each of six TOC entities commands its own SAM battalion. Each SAM battalion consists of one TOC, one TAR site, one TER site, one ADA site, and four SAM launcher sites. Figure 8 depicts the IADS laydown as implemented in AFSIM for this scenario.

The EW radars operate constantly so as to provide the AOC with advanced warning of inbound threats. The TAR and TER sites, on the other hand, employ basic emissions control tactics. These radars only operate once the SAM battalion to which they belong receives an engagement task from the AOC. Additionally, a pop-up red entity enters the scenario with a stochastically-determined arrival time and location relative to the rest of the IADS. This pop-up entity is never considered among the swarm's pre-briefed target set, which allows it to serve the purpose of testing the swarm's ability to adapt to its arrival.

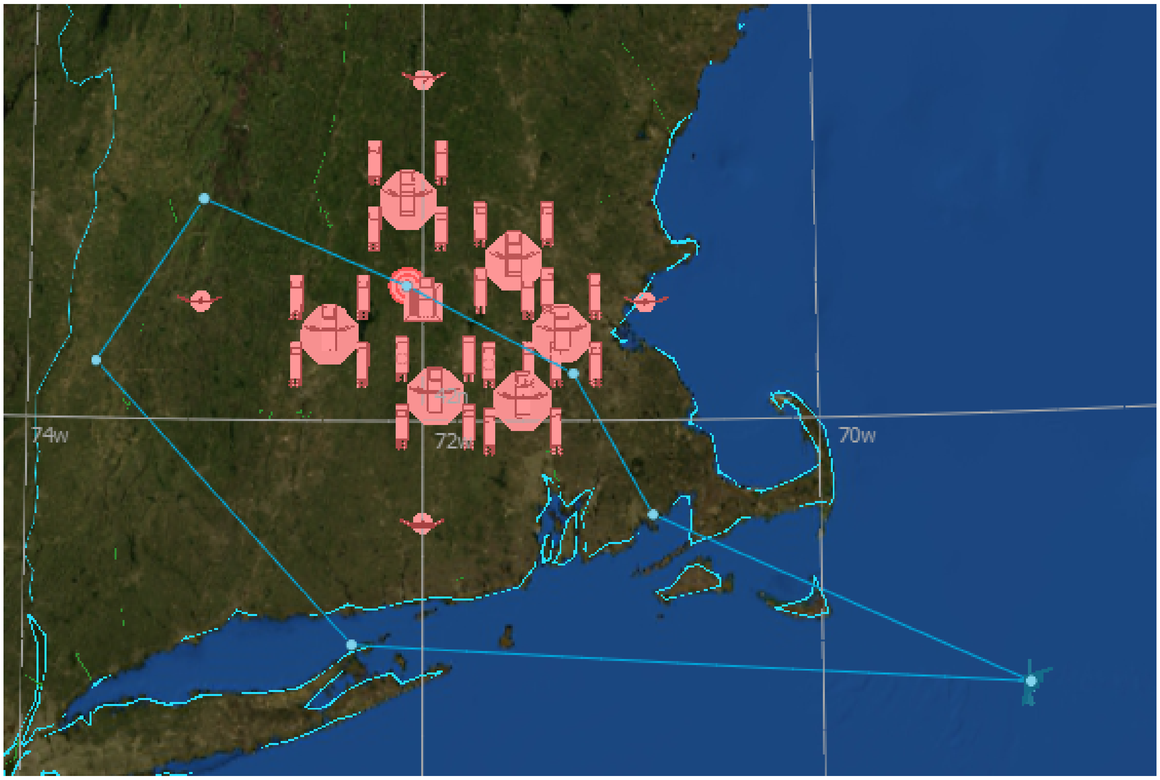


Figure 8. Red IADS Laydown

3.3.2 Cruise Missile Swarm

The cruise missile swarm includes 24 individual cruise missile entities, which draw inspiration from the cruise vehicle platform developed for the Gray Wolf technology demonstration program in terms of technical specifications [10]. Upon initialization in the scenario, each cruise missile faces a five percent probability of failing to successfully deploy in order to simulate a reliability process based on Gray Wolf's targeted reliability figures. Each cruise missile carries enough fuel to support a maximum range of 250 nautical miles. Aerodynamically, the deployable wings can endure a maximum load of 2 g when performing maneuvers that depart from straight-and-level flight. The kinetic payload assumes a simplified binary response for probability of kill such that probability of kill equals 1.0 within a 40 meter radius and zero beyond that radius for all IADS target types, which is notionally based on a proposed Gray Wolf

explosive payload.

The sensor suite on the missiles includes provisions for navigation via global positioning system (GPS), threat detection and geolocation via a RWR, and communication to other blue players via a datalink transceiver. Unlike the autonomous swarm utilized in Spiegel's [23] research scenario, this cruise missile swarm operates without the need for any dedicated external air battle management (ABM). By removing the central ABM authority, each swarm member's agency in the scenario reflects its own perception and situational awareness based on its dimensions and levels of autonomy.

Since the number of IADS assets exceeds the number of swarm members, the swarm must implement a target prioritization scheme that matches individual cruise missiles with targets. Each IADS asset is assigned to a priority category based on its platform type as shown in Table 4. The final priority score used in assigning targets is then computed as the product of the priority category and the distance between the cruise missile launch point and the target platform location, where the lowest priority score corresponds to the highest targeting priority. Each swarm member receives a single pre-briefed target track for its respective target platform based on the initial target prioritization outcome, as well as location data for known SAM threat rings. Any other elements of situational awareness must be sensed or shared based on the ability to adapt and ability to cooperate levels, respectively. Note that the pop-up entity always receives a priority score of zero, which artificially forces it into the targeting solution if its presence is known to the swarm regardless of how many cruise missiles remain active in the scenario.

3.3.3 Penetrating Bomber

The penetrating bomber entity is representative of a generic low-observable strategic bomber aircraft. This bomber flies a fixed, high-altitude ingress route in order

Table 4. Target Priority Categories By Platform Type

Priority Category	Platform Type
0	Pop-Up
1	AOC
2	TOC, EW Fusion Center
3	EW Radar
4	SAM Launcher, TER, TAR, ADA

to engage a Red airbase-type target, which constitutes the top-level objective for the Blue air strike package. Notably, the bomber entity's definition in this combat simulation renders it invulnerable to damage from SAM engagements. While this modeling method introduces a deliberate departure from operational realism, it enables a more robust evaluation of threats against the bomber's survivability. In particular, it accommodates an end-to-end assessment of the number of SAM shot opportunities incurred along the bomber's route, which would not be possible in the case of a destructible bomber.

3.4 Designed Experiment for the A2AD Scenario

A carefully designed and conducted simulation experiment allows us to make statistically defensible inferences about causal relationships that drive correlations between the control factors and responses. The dimensions and levels of autonomy within the swarm serve as the control factors for the designed experiment used in this study—all other simulation parameters will remain constant across experimental samples. Since the dimensions and levels of autonomy are all independent (i.e., no disallowed combinations), there are no restrictions on constructing a balanced design matrix featuring all possible combinations. This structure constitutes a 3^3 full factorial design with 27 unique treatment combinations, as shown in Table 5. Note that all three control factors are represented by categorical variable types with no meaningful notion of in-between values. Each treatment combination is replicated 20 times (i.e.,

20 independent repeated trials with distinct random number seeds), which results in a total of 540 experimental trials.

Table 5. A2AD Scenario Design Matrix

Treatment	Alone	Coop	Adapt
1	Low	Low	Low
2	Mid	Low	Low
3	High	Low	Low
4	Low	Mid	Low
5	Mid	Mid	Low
6	High	Mid	Low
7	Low	High	Low
8	Mid	High	Low
9	High	High	Low
10	Low	Low	Mid
11	Mid	Low	Mid
12	High	Low	Mid
13	Low	Mid	Mid
14	Mid	Mid	Mid
15	High	Mid	Mid
16	Low	High	Mid
17	Mid	High	Mid
18	High	High	Mid
19	Low	Low	High
20	Mid	Low	High
21	High	Low	High
22	Low	Mid	High
23	Mid	Mid	High
24	High	Mid	High
25	Low	High	High
26	Mid	High	High
27	High	High	High

3.5 Measures of Effectiveness

MOEs act as the analytical bridge between the raw numerical data obtained from executing the design matrix in AFSIM and germane answers to the research questions underpinning this study. Since the research questions address the impact of

autonomy on survivability and lethality, respectively, the four MOEs follow a parallel structure—the first two MOEs quantify survivability performance while the remaining two quantify lethality performance. Table 6 provides a summary of the measure of effectiveness (MOE) framework implemented for this research effort.

Table 6. Measures of Effectiveness

MOE	Category	Metric
MOE 1.1	Survivability	# of SAM hits on penetrating bomber
MOE 1.2	Survivability	# of swarm members shot down
MOE 2.1	Lethality	# of IADS members destroyed by swarm members
MOE 2.2	Lethality	Pop-up entity destroyed (boolean)

The first survivability MOE is a count of the number of times the penetrating bomber gets hit by SAMs over the course of each individual simulation run. The second survivability MOE is a count of the number of swarm members that are defeated by SAMs over the course of the scenario. Both of these measures are intended to reflect the degree to which the swarm's tactics disrupt the IADS kill chain.

The first lethality MOE is a count of the number of IADS members that are defeated by swarm members. Finally, the second lethality MOE is a boolean indicator of whether or not the swarm was able to successfully target and defeat the pop-up entity. Since the pop-up entity overrides all other target priorities by design, we consider only a single pop-up entity in order to evaluate the swarm's ability to detect and destroy the pop-up threat with minimal diversion from the other IADS targets. These measures both address the swarm's capacity to execute its own kill chain in support of the overall strike package objectives.

3.6 Analysis Plan

Since the designed experiment features a balanced number of samples across all treatment combinations, experimental data for the first three MOEs may be analyzed

using analysis of variance (ANOVA). First, an ANOVA for each of these MOEs tests the null hypothesis that none of the dimensions of autonomy (or their interaction effects) has a significant effect on the MOE against the alternative hypothesis that at least one significant effect is present. If we reject the null hypothesis in this initial test, then we proceed to test all of the main and interaction effects in order to determine which specific effects are in fact significant. Analysis for the fourth MOE leverages an analogous sequential testing procedure in which ANOVA methods are substituted with log-likelihood methods due to the boolean nature of the measure.

IV. Results and Analysis

4.1 Chapter Overview

This chapter presents the results obtained from conducting the designed experiment as well as the accompanying analytical process. In order to glean insights about the experimental outcomes, we apply techniques including analysis of variance (ANOVA) and log-likelihood methods, which allow us to make statistical inferences regarding relationships between the control factors and response variables. All statistical tests are conducted at the $\alpha = 0.05$ level of significance.

4.2 Survivability Performance

4.2.1 Measure of Effectiveness (MOE) 1.1: Number of Surface-to-Air Missile (SAM) Hits On Penetrating Bomber

Figure 9 shows the MOE 1.1 treatment means and 95% confidence intervals for all treatment combinations. A smaller number of SAM hits on the penetrating bomber corresponds to more favorable performance by the cruise missile swarm in promoting the penetrating bomber's survivability. The full-model ANOVA test returns an F-statistic of 4.809 with a p-value less than 0.0001. Since this p-value is less than the significance level of 0.05, we reject the null hypothesis that all treatment means are equal (i.e., no autonomy effects are significant) and conclude that at least one of the autonomy effects offers statistically significant explanatory value for the bomber's survivability. Figure 9 reflects this result as well since there are treatment pairs whose 95 percent confidence intervals do not overlap, such as Treatment 1 and Treatment 20. As such, we proceed to the individual effect tests in order to identify which specific effects are significant.

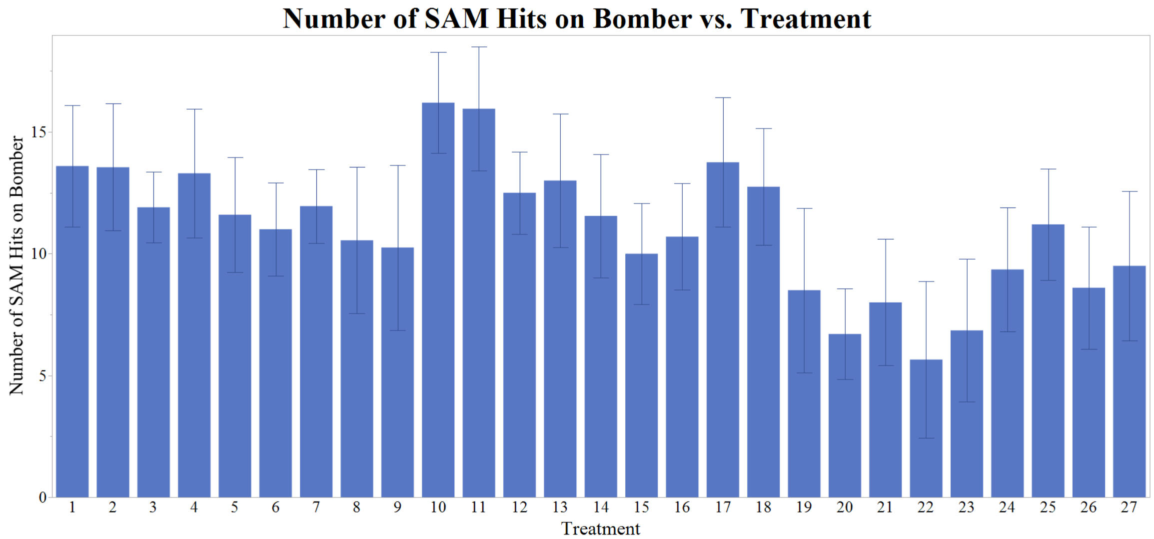


Figure 9. Number of SAM Hits on Bomber vs Treatment

Table 7 details the individual effect tests for the MOE 1.1 data. By examining the p-values relative to the significance level of 0.05, we conclude that both the ability to cooperate and ability to adapt main effects and their interaction effect contribute significantly to the penetrating bomber's survivability. This result implies that, for this scenario, dynamic communication and situational awareness within the swarm influence the bomber's survivability more than any individual swarm member's routing to its target.

Table 7. Number of SAM Hits on Bomber Individual Effect Tests

Source	DF	Sum of Squares	F Ratio	Prob > F
Alone	2	97.51	1.507	0.2225
Co-op	2	237.0	5.083	**0.0174**
Alone*Co-op	4	52.55	0.4526	0.7705
Adapt	2	2190	37.72	**< 0.0001**
Alone*Adapt	4	230.1	1.982	0.0960
Co-op*Adapt	4	471.0	4.056	**0.0030**
Alone*Co-op*Adapt	8	361.7	1.558	0.1350

Figure 10 shows the mean response for MOE 1.1 aggregated by levels for the two statistically significant factors, ability to cooperate and ability to adapt. This plot

indicates that the bomber's survivability benefits the most with ability to adapt at the high level, where the cruise missiles leverage their radar warning receiver (RWR) and execute evasive maneuvers. With ability to adapt at the high level, the low and middle levels of ability to cooperate yield the lowest point estimates, which represent a 40 percent reduction in SAM hits on the bomber relative to the no-autonomy case.

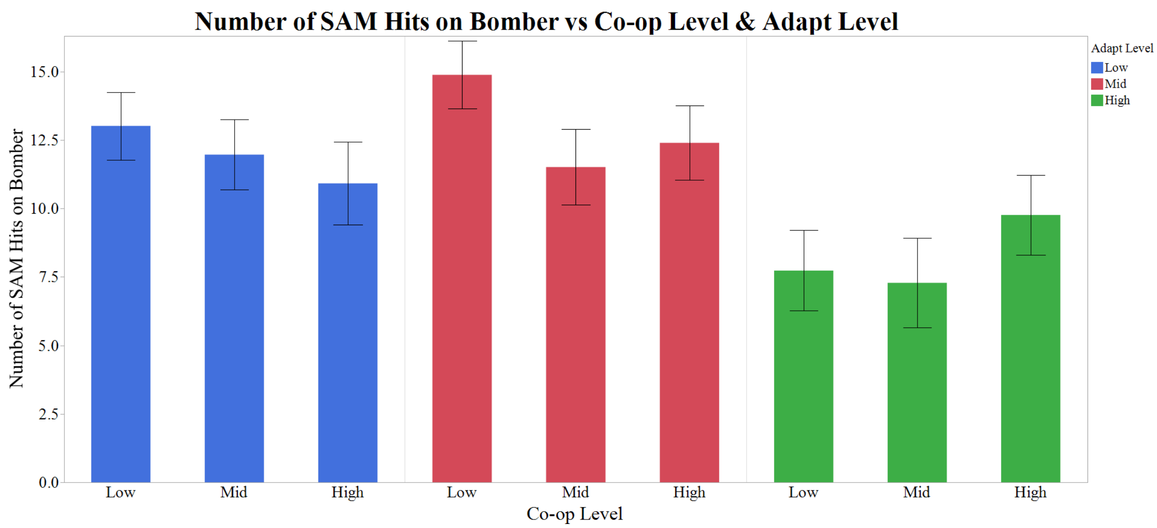


Figure 10. Number of SAM Hits on Bomber vs Co-op Level and Adapt Level

4.2.2 MOE 1.2: Number of Swarm Members Shot Down

Figure 11 shows the MOE 1.2 treatment means and 95% confidence intervals for all treatment combinations. In similar fashion to MOE 1.1, a smaller number of swarm members shot down corresponds to more favorable performance by the cruise missile swarm in promoting its own survivability. The full-model ANOVA test returns an F-statistic of 2.753 with a p-value less than 0.0001. Since this p-value is less than the significance level of 0.05, we reject the null hypothesis that all treatment means are equal (i.e., no autonomy effects are significant) and conclude that at least one of the autonomy effects offers statistically significant explanatory value for the swarm's survivability. This result can likewise be observed in Figure 11 since there

are treatment pairs whose 95 percent confidence intervals do not overlap, such as Treatment 1 and Treatment 23. As such, we proceed again to the individual effect tests in order to determine the specific effects that are significant.

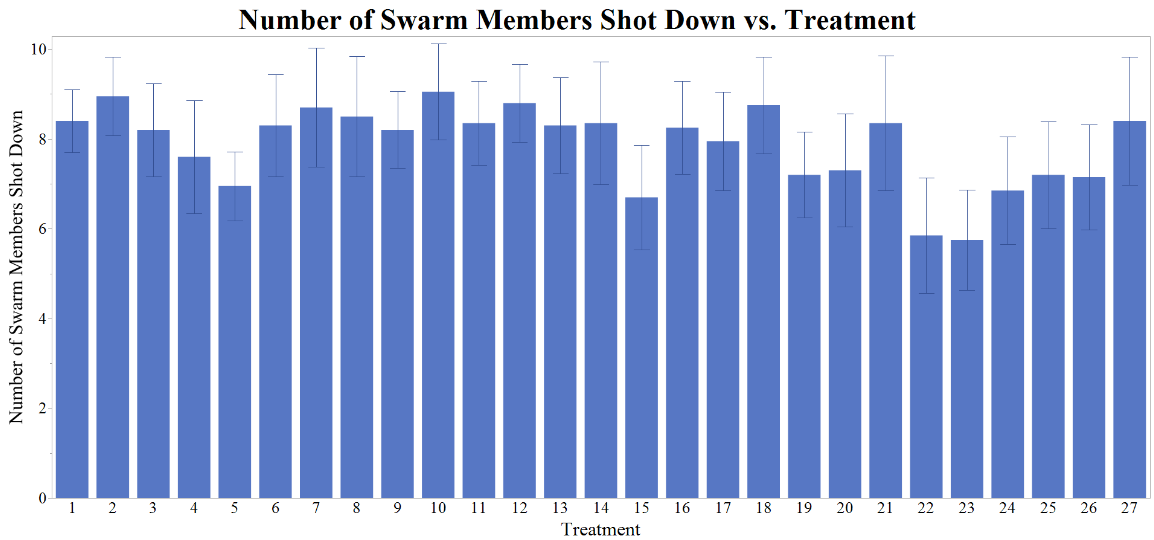


Figure 11. Number of Swarm Members Shot Down vs Treatment

Table 8 details the individual effect tests for the MOE 1.2 data. By examining the p-values and comparing to the significance level of 0.05, we observe that only the main effects for ability to cooperate and ability to adapt contribute significantly to the swarm's survivability. This result tells us that, for this scenario, dynamic communication and situational awareness within the swarm influence the swarm's survivability more than individual swarm member's routing parameters.

Table 8. Number of Swarm Members Shot Down Individual Effect Tests

Source	**DF**	**Sum of Squares**	**F Ratio**	**Prob > F**
Alone	2	12.28	1.505	0.3505
Co-op	2	127.9	10.93	**< 0.0001**
Alone*Co-op	4	3.274	0.1400	0.9673
Adapt	2	151.7	12.97	**< 0.0001**
Alone*Adapt	4	45.17	1.931	0.1039
Co-op*Adapt	4	14.15	0.6052	0.6590
Alone*Co-op*Adapt	8	63.95	1.368	0.2081

Figure 12 shows the mean response for MOE 1.2 aggregated by levels for the two statistically significant factors, ability to cooperate and ability to adapt. This plot indicates that the cruise missile swarm's survivability benefits the most with ability to adapt at the high level, where the cruise missiles leverage their RWR and execute evasive maneuvers, and ability to cooperate at the middle level, where the swarm communicates target tracking information and dynamically reassigns targets without clustering restrictions. This treatment combination leads to a 28 percent reduction in the number of cruise missiles shot down relative to the no-autonomy case. Interestingly, the cluster-based target reassignment behavior associated with the high level of ability to cooperate performs more comparably to the low level of ability to cooperate, where the swarm's datalink is disabled, in terms of swarm survivability.

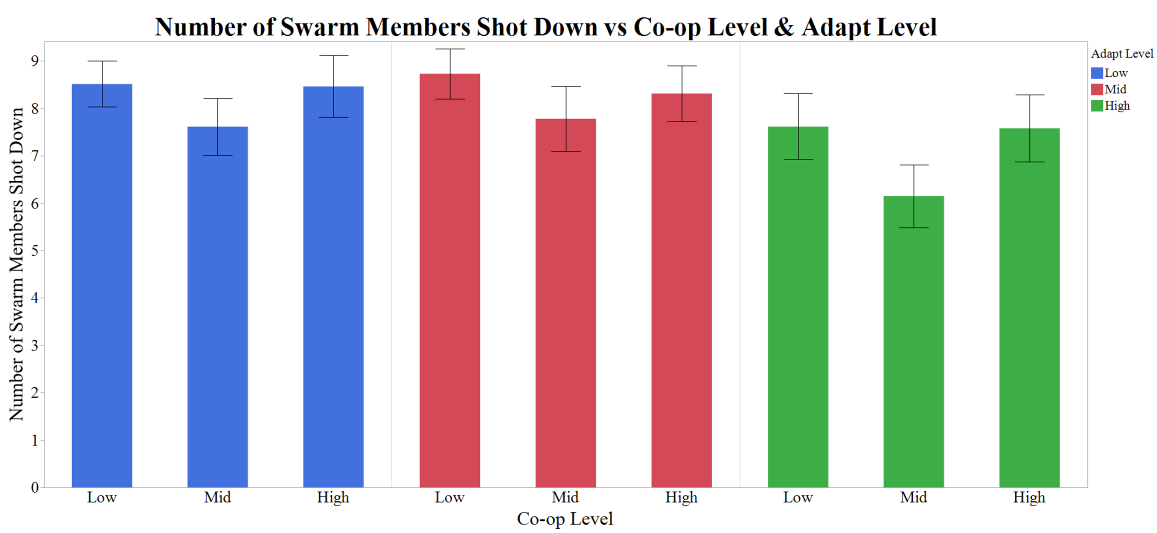


Figure 12. Number of Swarm Members Shot Down vs Co-op Level and Adapt Level

4.3 Lethality Performance

4.3.1 MOE 2.1: Number of Integrated Air Defense System (IADS) Targets Destroyed By Swarm Members

Figure 13 shows the MOE 2.1 treatment means and 95% confidence intervals for each treatment combination. A larger number of IADS targets destroyed by the swarm corresponds to more favorable performance by the cruise missile swarm in enhancing the overall strike mission's lethality. The full-model ANOVA test returns an F-statistic of 8.915 with a p-value less than 0.0001. Since this p-value is less than the significance level of 0.05, we reject the null hypothesis that all treatment means are equal (i.e., no autonomy effects are significant) and conclude that at least one of the autonomy effects offers statistically significant explanatory value for the swarm's lethality against integrated air defense system (IADS) targets. Figure 13 depicts this result visually in that there are treatment pairs whose 95 percent confidence intervals do not overlap, such as Treatment 1 and Treatment 19. As such, we proceed once again to the individual effect tests in order to identify which specific effects are significant.

Table 9 details the individual effect tests for the MOE 2.1 data. By comparing the p-values to the significance level of 0.05, we conclude that only the ability to act alone and ability to adapt main effects contribute significantly to the swarm's lethality against IADS targets. This result tells us that, for this scenario, the routing parameters available to individual swarm members and situational awareness within the swarm influence the swarm's lethality more prominently than communication and dynamic target reallocation.

Figure 14 shows the mean response for MOE 2.1 aggregated by levels for the two statistically significant factors, ability to act alone and ability to adapt. This plot indicates that the cruise missile swarm's lethality benefits the most with ability to

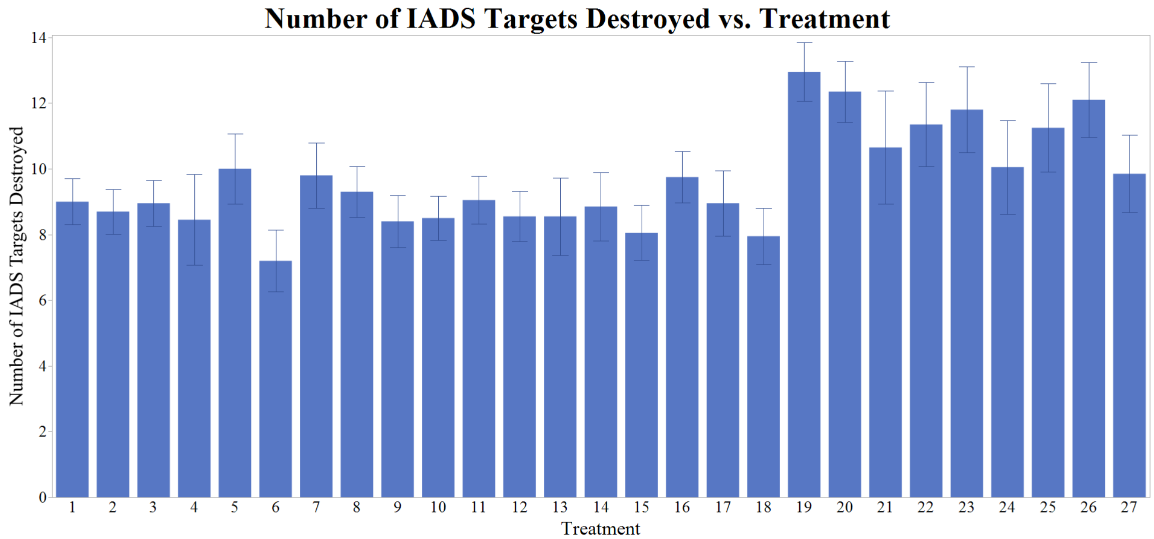


Figure 13. Number of IADS Targets Destroyed vs Treatment

Table 9. MOE 2.1 Effect Tests

Source	**DF**	**Sum of Squares**	**F Ratio**	**Prob > F**
Alone	2	172.1	17.43	**< 0.0001**
Co-op	2	22.58	2.286	0.1027
Alone*Co-op	4	30.14	1.526	0.1933
Adapt	2	810.6	82.07	**< 0.0001**
Alone*Adapt	4	23.64	1.197	0.3113
Co-op*Adapt	4	27.27	1.381	0.2394
Alone*Co-op*Adapt	8	58.34	1.477	0.1628

adapt at the high level, where the cruise missiles leverage their RWR and execute evasive maneuvers, and ability to act alone at the low or middle levels. These levels of autonomy lead to a 30 percent increase in the number of IADS targets destroyed by the swarm compared to the no-autonomy case. The fact that the lethality performance suffers at the high level of ability to act alone, where the cruise missiles leverage terrain-following for low-altitude ingress while avoiding known threat zones, challenges the conventional intuition that low-level approaches are favorable for IADS strike engagements.

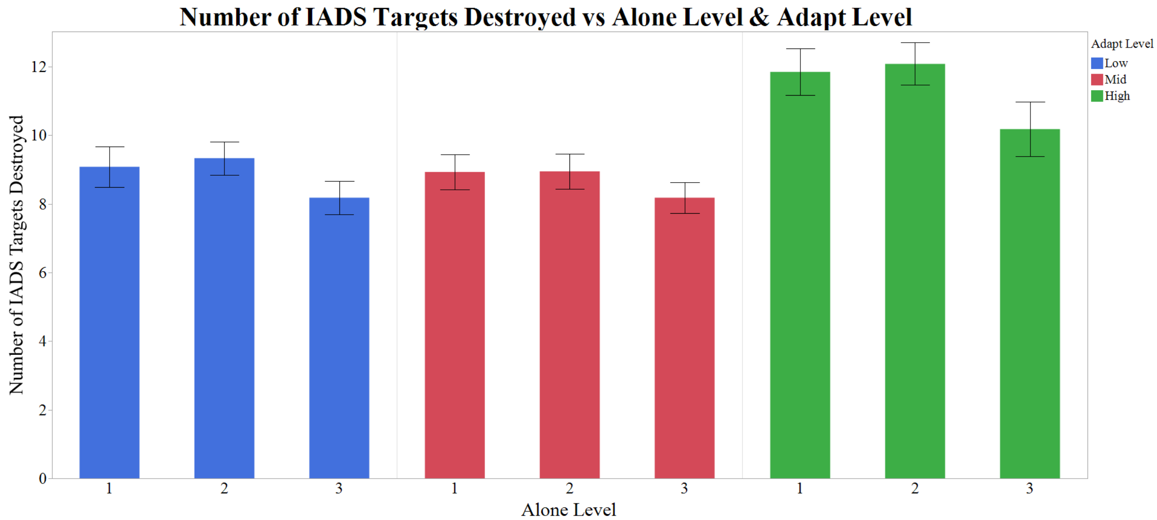


Figure 14. Number of IADS Targets Destroyed vs Alone Level and Adapt Level

4.3.2 MOE 2.2: Pop-Up Threat Destroyed

Figure 15 shows the MOE 2.2 treatment means and 95 percent confidence intervals for the proportion of runs where the pop-up threat is destroyed across each treatment combination. A larger proportion of trials where the swarm successfully defeated the pop-up threat corresponds to more favorable lethality performance. We note that treatment combinations where the ability to cooperate is at the low level (i.e., Treatments 1-3, 10-12, and 19-21) never succeed in destroying the pop-up threat. Since the swarm has no means to communicate dynamic target reassignments at this level and the pop-up threat enters the scenario after initial target matching, th result aligns with expectations.

Unlike the preceding MOEs, ANOVA testing methods are not appropriate for MOE 2.2. An underlying assumption for ANOVA is that the data is normally distributed, and that assumption would be violated by the MOE 2.2 data due to the Boolean nature of the response. Instead, we leverage statistical tests based on log-likelihood methods that more general data distributions. The full-model log-likelihood test returns a χ^2-statistic of 348.4 with a p-value less than 0.0001. Since this p-value

is less than the significance level of 0.05, we reject the null hypothesis that all treatment means are equal (i.e., no autonomy effects are significant) and conclude that at least one of the autonomy effects offers statistically significant explanatory value for the swarm's lethality against the pop-up threat. Figure 15 reflects this result as well since there are treatment pairs whose 95 percent confidence intervals do not overlap, such as Treatment 5 and Treatment 13. As such, we proceed to the individual effect tests in order to determine the specific effects that are significant.

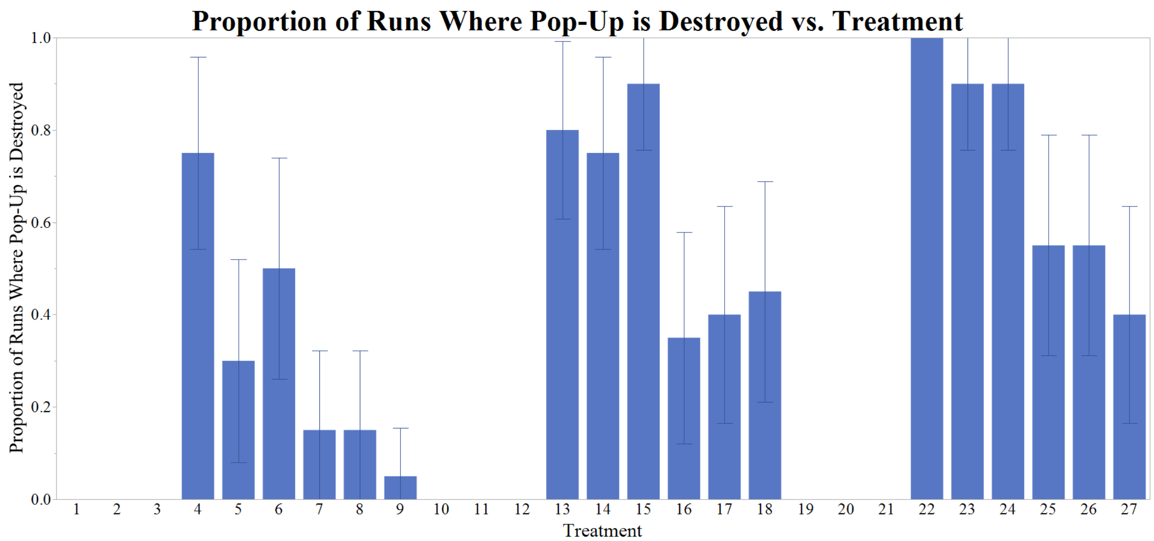


Figure 15. Proportion of Runs Where Pop-Up is Destroyed vs Treatment

Table 10 details the individual effect likelihood ratio tests for the MOE 2.2 data. By examining the p-values relative to the significance level of 0.05, we observe that only the ability to cooperate main effect contributes significantly to the swarm's lethality against the pop-up threat. This result tells us that, for this scenario, dynamic communication influences the swarm's ability to engage pop-up threats more than pre-briefed data on terrain and enemy locations or sensor-based situational awareness within the swarm.

Figure 16 shows the mean response for MOE 2.2 aggregated by levels for the lone statistically significant factor, ability to cooperate. This plot indicates that

Table 10. MOE 2.2 Effect Likelihood Ratio Tests

Source	DF	Likelihood Ratio χ^2	Prob $> \chi^2$
Alone	2	9.936×10^{-6}	1.000
Co-op	2	271.7	**< 0.0001**
Alone*Co-op	4	5.715	0.2215
Adapt	2	1.453×10^{-5}	1.000
Alone*Adapt	4	1.344×10^{-5}	1.000
Co-op*Adapt	4	2.355	0.6707
Alone*Co-op*Adapt	8	2.670	0.9534

the cruise missile swarm's lethality benefits the most with ability to cooperate at the middle level, where the swarm communicates target tracking information and dynamically reassigns targets without clustering restrictions. In particular, ability to cooperate at the middle level leads to a 76 percent probability of destroying the pop-up threat, compared to a 34 percent probability at the high level. Again we see that the cluster-based target reassignment behavior associated with the high level of ability to cooperate does not offer improved performance over the middle level.

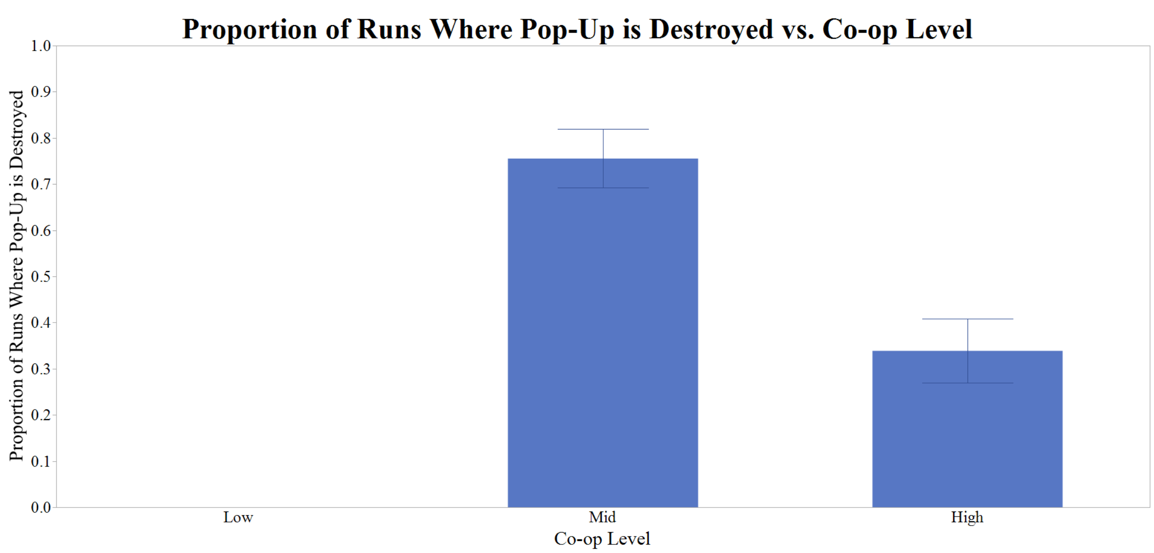


Figure 16. Proportion of Runs Where Pop-Up is Destroyed vs Co-op Level

V. Conclusions and Recommendations

5.1 Chapter Overview

This closing chapter presents the conclusions drawn from this research effort. The results from the simulation experiments are connected back to the problem statement so as to provide answers to the research questions. Lastly, we offer recommendations for future research threads based on these results and conclusions.

5.2 Conclusions

As the demand for autonomous capabilities in United States Air Force (USAF) weapon system grows, the demand for versatile and consistent frameworks for evaluating such systems will likewise grow. The three-dimensional framework proposed in this study aims to characterize autonomous systems based on their ability to act alone, ability to cooperate, and ability to adapt. While each of these dimensions was limited to three specific levels of capability for the purposes of this anti-access area denial (A2AD) scenario, the underlying framework could feasibly be adapted to suit the purposes of a broad variety of future autonomy studies.

This research specifically explored the utility of autonomy in a cruise missile swarm engaging an IADS acting in an A2AD role in order to preempt a manned strike mission by a penetrating bomber. The two research questions that serve to frame the objectives of this study are revisited and discussed below.

1. To what extent can a cruise missile swarm with autonomous air battle management (ABM) capabilities improve the survivability (i.e., ability to avoid detection and destruction by the Red IADS) of the Blue air strike package in an A2AD environment?

The ability to cooperate and ability to adapt dimensions of autonomy both significantly influenced the survivability of the manned penetrating bomber and autonomous cruise missile swarm alike relative to the no-autonomy case. Further, the constructive interaction effect between these two dimensions was significant in affecting the penetrating bomber's survivability. In particular, the treatment combinations featuring the middle level of ability to cooperate, where the swarm communicates target tracking information and dynamically reassigns targets without clustering restrictions, and the high level of ability to adapt, where the cruise missiles leverage their RWR and execute evasive maneuvers, yielded the best overall survivability performance. This combination of levels yields a 40 percent reduction in surface-to-air missiles (SAM) hits on the bomber and a 28 percent reduction in the number of cruise missiles shot down compared to the no-autonomy case. The ability to act alone dimension, which addresses navigation-related capabilities in the context of this study, was found to be insignificant in affecting the survivability metrics. This result challenges the conventional wisdom which would suggest that cruise missile routing is indeed an impactful consideration and may warrant additional investigation in future research efforts.

2. To what extent can a cruise missile swarm with autonomous ABM capabilities improve the lethality (i.e., ability to detect and destroy elements of the Red IADS) of the Blue air strike package in an A2AD environment?

The ability to act alone and ability to adapt dimensions of autonomy both significantly influenced the lethality of the swarm against IADS target types, while only the ability to cooperate dimension significantly impacted the lethality against the pop-up threat. In terms of overall lethality, the best performance was observed with ability to act alone at either the low or middle levels, where the missiles either fly straight line routes to target locations or attempt to avoid known threat zones en route, respec-

tively, ability to cooperate at the middle level, and ability to adapt at the high level. This combination of levels yields a 30 percent increase in the number of IADS targets destroyed by the swarm and a 76 percent increase in the probability that the swarm destroys the pop-up threat. It is interesting to note that the high level for ability to act alone, where the missiles leverage terrain-following while avoiding known threat zones, as well as the high level for ability to cooperate, where the swarm performs dynamic cluster-based target reassignments, both offer reduced lethality performance relative to the middle levels in these dimensions.

5.3 Recommendations for Future Research

A number of potential avenues exist for expanding on this research in terms of both depth and breadth. One possibility would be to introduce non-kinetic payload types, such as jammers and radar decoys, into the autonomous swarm to investigate the operational considerations of a mixed strike package in the A2AD scenario. Another interesting extension would be to use the evaluation framework from this study to compare the performance of operationally realistic "playbook" tactics such as those being developed under Golden Horde. Many of those playbooks pay special attention to flight formations and engagement geometry, both of which fall outside the scope of this study. The flight formation and engagement geometry elements would also lend themselves well to a study involving "loyal wingman"-style autonomous agents operating in more direct cooperation with manned systems.

Rather than explicitly dictating the tactical parameters underlying the various dimensions and levels of autonomy as was the case for this research, an alternative approach would be to consider those parameters as tunable hyperparameters for a machine learning or approximate dynamic programming technique. Such a technique might lead to context-sensitive policies for various autonomous behaviors that result

in superior swarm performance. Reframing the problem in this manner could also open the door for studying a broader range of autonomous capability and promoting the development of emergent behaviors.

Appendix A. JMP Statistical Output

Table 11. MOE 1.1 Full-Model Analysis of Variance (ANOVA) Test

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	26	3629	139.6	4.809
Error	513	14891	29.02	**Prob > F**
Total	539	18521		< 0.0001

Table 12. MOE 1.2 Full-Model ANOVA Test

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	26	418.4	16.09	2.753
Error	513	2999	5.846	**Prob > F**
Total	539	3417		< 0.0001

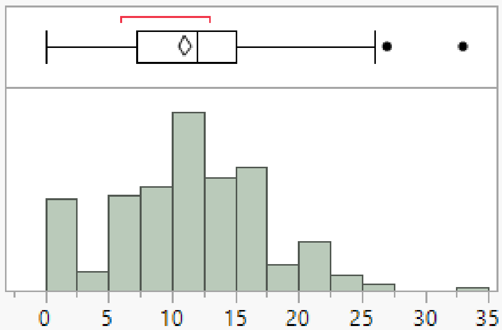
Table 13. MOE 2.1 Full-Model ANOVA Test

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	26	1145	44.03	8.915
Error	513	2533	4.938	**Prob > F**
Total	539	3678		< 0.0001

Table 14. MOE 2.2 Log-Likelihood Full Model Test

Model	**-LogLikelihood**	**DF**	χ^2
Difference	174.2	26	348.4
Full	180.1		**Prob >** χ^2
Reduced	354.3		< 0.0001

BomberHit



Quantiles

100.0%	maximum	33
99.5%		26.295
97.5%		23
90.0%		18
75.0%	quartile	15
50.0%	median	12
25.0%	quartile	7.25
10.0%		2
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	11.053704
Std Dev	5.8619623
Std Err Mean	0.2522587
Upper 95% Mean	11.549234
Lower 95% Mean	10.558173
N	540

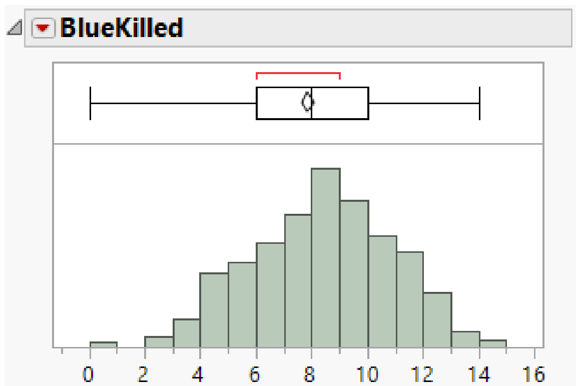
Figure 17. MOE 1.1 Distribution

Expanded Estimates

Nominal factors expanded to all levels

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	11.053704	0.231856	47.67	<.0001*
AloneLevel[1]	0.512963	0.327894	1.56	0.1183
AloneLevel[2]	-0.042593	0.327894	-0.13	0.8967
AloneLevel[3]	-0.47037	0.327894	-1.43	0.1520
CoopLevel[1]	0.8240741	0.327894	2.51	0.0123*
CoopLevel[2]	-0.798148	0.327894	-2.43	0.0153*
CoopLevel[3]	-0.025926	0.327894	-0.08	0.9370
AloneLevel[1]*CoopLevel[1]	0.3759259	0.463712	0.81	0.4179
AloneLevel[1]*CoopLevel[2]	-0.118519	0.463712	-0.26	0.7984
AloneLevel[1]*CoopLevel[3]	-0.257407	0.463712	-0.56	0.5791
AloneLevel[2]*CoopLevel[1]	0.2314815	0.463712	0.50	0.6179
AloneLevel[2]*CoopLevel[2]	-0.212963	0.463712	-0.46	0.6462
AloneLevel[2]*CoopLevel[3]	-0.018519	0.463712	-0.04	0.9682
AloneLevel[3]*CoopLevel[1]	-0.607407	0.463712	-1.31	0.1908
AloneLevel[3]*CoopLevel[2]	0.3314815	0.463712	0.71	0.4750
AloneLevel[3]*CoopLevel[3]	0.2759259	0.463712	0.60	0.5521
AdaptLevel[1]	0.912963	0.327894	2.78	0.0056*
AdaptLevel[2]	1.8796296	0.327894	5.73	<.0001*
AdaptLevel[3]	-2.792593	0.327894	-8.52	<.0001*
AloneLevel[1]*AdaptLevel[1]	0.4703704	0.463712	1.01	0.3109
AloneLevel[1]*AdaptLevel[2]	-0.146296	0.463712	-0.32	0.7525
AloneLevel[1]*AdaptLevel[3]	-0.324074	0.463712	-0.70	0.4850
AloneLevel[2]*AdaptLevel[1]	-0.024074	0.463712	-0.05	0.9586
AloneLevel[2]*AdaptLevel[2]	0.8592593	0.463712	1.85	0.0645
AloneLevel[2]*AdaptLevel[3]	-0.835185	0.463712	-1.80	0.0723
AloneLevel[3]*AdaptLevel[1]	-0.446296	0.463712	-0.96	0.3363
AloneLevel[3]*AdaptLevel[2]	-0.712963	0.463712	-1.54	0.1248
AloneLevel[3]*AdaptLevel[3]	1.1592593	0.463712	2.50	0.0127*
CoopLevel[1]*AdaptLevel[1]	0.2259259	0.463712	0.49	0.6263
CoopLevel[1]*AdaptLevel[2]	1.1259259	0.463712	2.43	0.0155*
CoopLevel[1]*AdaptLevel[3]	-1.351852	0.463712	-2.92	0.0037*
CoopLevel[2]*AdaptLevel[1]	0.7981481	0.463712	1.72	0.0858
CoopLevel[2]*AdaptLevel[2]	-0.618519	0.463712	-1.33	0.1828
CoopLevel[2]*AdaptLevel[3]	-0.17963	0.463712	-0.39	0.6986
CoopLevel[3]*AdaptLevel[1]	-1.024074	0.463712	-2.21	0.0277*
CoopLevel[3]*AdaptLevel[2]	-0.507407	0.463712	-1.09	0.2744
CoopLevel[3]*AdaptLevel[3]	1.5314815	0.463712	3.30	0.0010*
AloneLevel[1]*CoopLevel[1]*AdaptLevel[1]	-0.775926	0.655788	-1.18	0.2373
AloneLevel[1]*CoopLevel[1]*AdaptLevel[2]	0.5740741	0.655788	0.88	0.3818
AloneLevel[1]*CoopLevel[1]*AdaptLevel[3]	0.2018519	0.655788	0.31	0.7584
AloneLevel[1]*CoopLevel[2]*AdaptLevel[1]	0.4685185	0.655788	0.71	0.4753
AloneLevel[1]*CoopLevel[2]*AdaptLevel[2]	1.2351852	0.655788	1.88	0.0602
AloneLevel[1]*CoopLevel[2]*AdaptLevel[3]	-1.703704	0.655788	-2.60	0.0096*
AloneLevel[1]*CoopLevel[3]*AdaptLevel[1]	0.3074074	0.655788	0.47	0.6394
AloneLevel[1]*CoopLevel[3]*AdaptLevel[2]	-1.809259	0.655788	-2.76	0.0060*
AloneLevel[1]*CoopLevel[3]*AdaptLevel[3]	1.5018519	0.655788	2.29	0.0224*
AloneLevel[2]*CoopLevel[1]*AdaptLevel[1]	0.3685185	0.655788	0.56	0.5744
AloneLevel[2]*CoopLevel[1]*AdaptLevel[2]	0.0185185	0.655788	0.03	0.9775
AloneLevel[2]*CoopLevel[1]*AdaptLevel[3]	-0.387037	0.655788	-0.59	0.5553
AloneLevel[2]*CoopLevel[2]*AdaptLevel[1]	-0.087037	0.655788	-0.13	0.8945
AloneLevel[2]*CoopLevel[2]*AdaptLevel[2]	-0.57037	0.655788	-0.87	0.3848
AloneLevel[2]*CoopLevel[2]*AdaptLevel[3]	0.6574074	0.655788	1.00	0.3166
AloneLevel[2]*CoopLevel[3]*AdaptLevel[1]	-0.281481	0.655788	-0.43	0.6679
AloneLevel[2]*CoopLevel[3]*AdaptLevel[2]	0.5518519	0.655788	0.84	0.4005
AloneLevel[2]*CoopLevel[3]*AdaptLevel[3]	-0.27037	0.655788	-0.41	0.6803
AloneLevel[3]*CoopLevel[1]*AdaptLevel[1]	0.4074074	0.655788	0.62	0.5347
AloneLevel[3]*CoopLevel[1]*AdaptLevel[2]	-0.592593	0.655788	-0.90	0.3666
AloneLevel[3]*CoopLevel[1]*AdaptLevel[3]	0.1851852	0.655788	0.28	0.7778
AloneLevel[3]*CoopLevel[2]*AdaptLevel[1]	-0.381481	0.655788	-0.58	0.5610
AloneLevel[3]*CoopLevel[2]*AdaptLevel[2]	-0.664815	0.655788	-1.01	0.3112
AloneLevel[3]*CoopLevel[2]*AdaptLevel[3]	1.0462963	0.655788	1.60	0.1112
AloneLevel[3]*CoopLevel[3]*AdaptLevel[1]	-0.025926	0.655788	-0.04	0.9685
AloneLevel[3]*CoopLevel[3]*AdaptLevel[2]	1.2574074	0.655788	1.92	0.0557
AloneLevel[3]*CoopLevel[3]*AdaptLevel[3]	-1.231481	0.655788	-1.88	0.0610

Figure 18. MOE 1.1 Parameter Estimates



Quantiles

100.0%	maximum	14
99.5%		14
97.5%		12
90.0%		11
75.0%	quartile	10
50.0%	median	8
25.0%	quartile	6
10.0%		4
2.5%		3
0.5%		1.41
0.0%	minimum	0

Summary Statistics

Mean	7.8648148
Std Dev	2.5178883
Std Err Mean	0.1083527
Upper 95% Mean	8.0776601
Lower 95% Mean	7.6519696
N	540

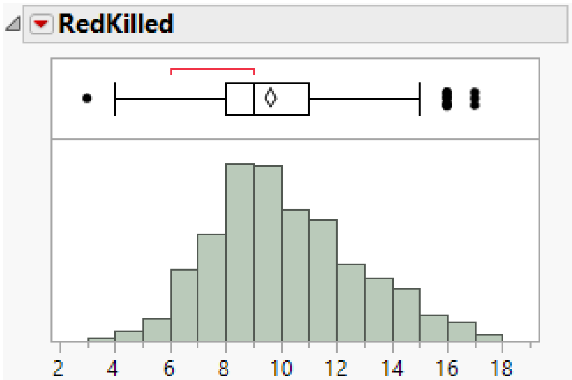
Figure 19. MOE 1.2 Distribution

Expanded Estimates

Nominal factors expanded to all levels

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	7.8648148	0.104043	75.59	<.0001*
AloneLevel[1]	-0.025926	0.14714	-0.18	0.8602
AloneLevel[2]	-0.17037	0.14714	-1.16	0.2475
AloneLevel[3]	0.1962963	0.14714	1.33	0.1828
CoopLevel[1]	0.4240741	0.14714	2.88	0.0041*
CoopLevel[2]	-0.681481	0.14714	-4.63	<.0001*
CoopLevel[3]	0.2574074	0.14714	1.75	0.0808
AloneLevel[1]*CoopLevel[1]	-0.046296	0.208087	-0.22	0.8240
AloneLevel[1]*CoopLevel[2]	0.0925926	0.208087	0.44	0.6565
AloneLevel[1]*CoopLevel[3]	-0.046296	0.208087	-0.22	0.8240
AloneLevel[2]*CoopLevel[1]	0.0814815	0.208087	0.39	0.6955
AloneLevel[2]*CoopLevel[2]	0.0037037	0.208087	0.02	0.9858
AloneLevel[2]*CoopLevel[3]	-0.085185	0.208087	-0.41	0.6824
AloneLevel[3]*CoopLevel[1]	-0.035185	0.208087	-0.17	0.8658
AloneLevel[3]*CoopLevel[2]	-0.096296	0.208087	-0.46	0.6437
AloneLevel[3]*CoopLevel[3]	0.1314815	0.208087	0.63	0.5278
AdaptLevel[1]	0.3351852	0.14714	2.28	0.0231*
AdaptLevel[2]	0.412963	0.14714	2.81	0.0052*
AdaptLevel[3]	-0.748148	0.14714	-5.08	<.0001*
AloneLevel[1]*AdaptLevel[1]	0.0592593	0.208087	0.28	0.7759
AloneLevel[1]*AdaptLevel[2]	0.2814815	0.208087	1.35	0.1767
AloneLevel[1]*AdaptLevel[3]	-0.340741	0.208087	-1.64	0.1021
AloneLevel[2]*AdaptLevel[1]	0.1037037	0.208087	0.50	0.6184
AloneLevel[2]*AdaptLevel[2]	0.1092593	0.208087	0.53	0.5998
AloneLevel[2]*AdaptLevel[3]	-0.212963	0.208087	-1.02	0.3066
AloneLevel[3]*AdaptLevel[1]	-0.162963	0.208087	-0.78	0.4339
AloneLevel[3]*AdaptLevel[2]	-0.390741	0.208087	-1.88	0.0610
AloneLevel[3]*AdaptLevel[3]	0.5537037	0.208087	2.66	0.0080*
CoopLevel[1]*AdaptLevel[1]	-0.107407	0.208087	-0.52	0.6060
CoopLevel[1]*AdaptLevel[2]	0.0314815	0.208087	0.15	0.8798
CoopLevel[1]*AdaptLevel[3]	0.0759259	0.208087	0.36	0.7154
CoopLevel[2]*AdaptLevel[1]	0.0981481	0.208087	0.47	0.6374
CoopLevel[2]*AdaptLevel[2]	0.187037	0.208087	0.90	0.3692
CoopLevel[2]*AdaptLevel[3]	-0.285185	0.208087	-1.37	0.1711
CoopLevel[3]*AdaptLevel[1]	0.0092593	0.208087	0.04	0.9645
CoopLevel[3]*AdaptLevel[2]	-0.218519	0.208087	-1.05	0.2942
CoopLevel[3]*AdaptLevel[3]	0.2092593	0.208087	1.01	0.3151
AloneLevel[1]*CoopLevel[1]*AdaptLevel[1]	-0.103704	0.294279	-0.35	0.7247
AloneLevel[1]*CoopLevel[1]*AdaptLevel[2]	0.1074074	0.294279	0.36	0.7153
AloneLevel[1]*CoopLevel[1]*AdaptLevel[3]	-0.003704	0.294279	-0.01	0.9900
AloneLevel[1]*CoopLevel[2]*AdaptLevel[1]	-0.142593	0.294279	-0.48	0.6282
AloneLevel[1]*CoopLevel[2]*AdaptLevel[2]	0.1685185	0.294279	0.57	0.5671
AloneLevel[1]*CoopLevel[2]*AdaptLevel[3]	-0.025926	0.294279	-0.09	0.9298
AloneLevel[1]*CoopLevel[3]*AdaptLevel[1]	0.2462963	0.294279	0.84	0.4030
AloneLevel[1]*CoopLevel[3]*AdaptLevel[2]	-0.275926	0.294279	-0.94	0.3489
AloneLevel[1]*CoopLevel[3]*AdaptLevel[3]	0.0296296	0.294279	0.10	0.9198
AloneLevel[2]*CoopLevel[1]*AdaptLevel[1]	0.4185185	0.294279	1.42	0.1556
AloneLevel[2]*CoopLevel[1]*AdaptLevel[2]	-0.403704	0.294279	-1.37	0.1707
AloneLevel[2]*CoopLevel[1]*AdaptLevel[3]	-0.014815	0.294279	-0.05	0.9599
AloneLevel[2]*CoopLevel[2]*AdaptLevel[1]	-0.603704	0.294279	-2.05	0.0407*
AloneLevel[2]*CoopLevel[2]*AdaptLevel[2]	0.6240741	0.294279	2.12	0.0344*
AloneLevel[2]*CoopLevel[2]*AdaptLevel[3]	-0.02037	0.294279	-0.07	0.9448
AloneLevel[2]*CoopLevel[3]*AdaptLevel[1]	0.1851852	0.294279	0.63	0.5294
AloneLevel[2]*CoopLevel[3]*AdaptLevel[2]	-0.22037	0.294279	-0.75	0.4543
AloneLevel[2]*CoopLevel[3]*AdaptLevel[3]	0.0351852	0.294279	0.12	0.9049
AloneLevel[3]*CoopLevel[1]*AdaptLevel[1]	-0.314815	0.294279	-1.07	0.2852
AloneLevel[3]*CoopLevel[1]*AdaptLevel[2]	0.2962963	0.294279	1.01	0.3145
AloneLevel[3]*CoopLevel[1]*AdaptLevel[3]	0.0185185	0.294279	0.06	0.9498
AloneLevel[3]*CoopLevel[2]*AdaptLevel[1]	0.7462963	0.294279	2.54	0.0115*
AloneLevel[3]*CoopLevel[2]*AdaptLevel[2]	-0.792593	0.294279	-2.69	0.0073*
AloneLevel[3]*CoopLevel[2]*AdaptLevel[3]	0.0462963	0.294279	0.16	0.8751
AloneLevel[3]*CoopLevel[3]*AdaptLevel[1]	-0.431481	0.294279	-1.47	0.1432
AloneLevel[3]*CoopLevel[3]*AdaptLevel[2]	0.4962963	0.294279	1.69	0.0923
AloneLevel[3]*CoopLevel[3]*AdaptLevel[3]	-0.064815	0.294279	-0.22	0.8258

Figure 20. MOE 1.2 Parameter Estimates



Quantiles

100.0%	maximum	17
99.5%		17
97.5%		15
90.0%		13
75.0%	quartile	11
50.0%	median	9
25.0%	quartile	8
10.0%		7
2.5%		5
0.5%		4
0.0%	minimum	3

Summary Statistics

Mean	9.6425926
Std Dev	2.6122376
Std Err Mean	0.1124128
Upper 95% Mean	9.8634135
Lower 95% Mean	9.4217717
N	540

Figure 21. MOE 2.1 Distribution

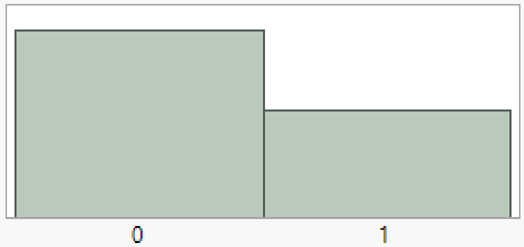
Expanded Estimates

Nominal factors expanded to all levels

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	9.6425926	0.09563	100.83	<.0001*
AloneLevel[1]	0.312963	0.135241	2.31	0.0211*
AloneLevel[2]	0.4796296	0.135241	3.55	0.0004*
AloneLevel[3]	-0.792593	0.135241	-5.86	<.0001*
CoopLevel[1]	0.212963	0.135241	1.57	0.1159
CoopLevel[2]	-0.275926	0.135241	-2.04	0.0418*
CoopLevel[3]	0.062963	0.135241	0.47	0.6417
AloneLevel[1]*CoopLevel[1]	-0.018519	0.191259	-0.10	0.9229
AloneLevel[1]*CoopLevel[2]	-0.22963	0.191259	-1.20	0.2305
AloneLevel[1]*CoopLevel[3]	0.2481481	0.191259	1.30	0.1951
AloneLevel[2]*CoopLevel[1]	-0.301852	0.191259	-1.58	0.1151
AloneLevel[2]*CoopLevel[2]	0.3703704	0.191259	1.94	0.0534
AloneLevel[2]*CoopLevel[3]	-0.068519	0.191259	-0.36	0.7203
AloneLevel[3]*CoopLevel[1]	0.3203704	0.191259	1.68	0.0945
AloneLevel[3]*CoopLevel[2]	-0.140741	0.191259	-0.74	0.4621
AloneLevel[3]*CoopLevel[3]	-0.17963	0.191259	-0.94	0.3481
AdaptLevel[1]	-0.775926	0.135241	-5.74	<.0001*
AdaptLevel[2]	-0.953704	0.135241	-7.05	<.0001*
AdaptLevel[3]	1.7296296	0.135241	12.79	<.0001*
AloneLevel[1]*AdaptLevel[1]	-0.096296	0.191259	-0.50	0.6148
AloneLevel[1]*AdaptLevel[2]	-0.068519	0.191259	-0.36	0.7203
AloneLevel[1]*AdaptLevel[3]	0.1648148	0.191259	0.86	0.3892
AloneLevel[2]*AdaptLevel[1]	-0.012963	0.191259	-0.07	0.9460
AloneLevel[2]*AdaptLevel[2]	-0.218519	0.191259	-1.14	0.2538
AloneLevel[2]*AdaptLevel[3]	0.2314815	0.191259	1.21	0.2267
AloneLevel[3]*AdaptLevel[1]	0.1092593	0.191259	0.57	0.5681
AloneLevel[3]*AdaptLevel[2]	0.287037	0.191259	1.50	0.1340
AloneLevel[3]*AdaptLevel[3]	-0.396296	0.191259	-2.07	0.0388*
CoopLevel[1]*AdaptLevel[1]	-0.196296	0.191259	-1.03	0.3052
CoopLevel[1]*AdaptLevel[2]	-0.201852	0.191259	-1.06	0.2917
CoopLevel[1]*AdaptLevel[3]	0.3981481	0.191259	2.08	0.0379*
CoopLevel[2]*AdaptLevel[1]	-0.040741	0.191259	-0.21	0.8314
CoopLevel[2]*AdaptLevel[2]	0.0703704	0.191259	0.37	0.7131
CoopLevel[2]*AdaptLevel[3]	-0.02963	0.191259	-0.15	0.8769
CoopLevel[3]*AdaptLevel[1]	0.237037	0.191259	1.24	0.2158
CoopLevel[3]*AdaptLevel[2]	0.1314815	0.191259	0.69	0.4921
CoopLevel[3]*AdaptLevel[3]	-0.368519	0.191259	-1.93	0.0546
AloneLevel[1]*CoopLevel[1]*AdaptLevel[1]	-0.081481	0.270481	-0.30	0.7633
AloneLevel[1]*CoopLevel[1]*AdaptLevel[2]	-0.425926	0.270481	-1.57	0.1159
AloneLevel[1]*CoopLevel[1]*AdaptLevel[3]	0.5074074	0.270481	1.88	0.0612
AloneLevel[1]*CoopLevel[2]*AdaptLevel[1]	-0.087037	0.270481	-0.32	0.7477
AloneLevel[1]*CoopLevel[2]*AdaptLevel[2]	0.0518519	0.270481	0.19	0.8481
AloneLevel[1]*CoopLevel[2]*AdaptLevel[3]	0.0351852	0.270481	0.13	0.8966
AloneLevel[1]*CoopLevel[3]*AdaptLevel[1]	0.1685185	0.270481	0.62	0.5335
AloneLevel[1]*CoopLevel[3]*AdaptLevel[2]	0.3740741	0.270481	1.38	0.1673
AloneLevel[1]*CoopLevel[3]*AdaptLevel[3]	-0.542593	0.270481	-2.01	0.0454*
AloneLevel[2]*CoopLevel[1]*AdaptLevel[1]	-0.348148	0.270481	-1.29	0.1986
AloneLevel[2]*CoopLevel[1]*AdaptLevel[2]	0.3907407	0.270481	1.44	0.1492
AloneLevel[2]*CoopLevel[1]*AdaptLevel[3]	-0.042593	0.270481	-0.16	0.8749
AloneLevel[2]*CoopLevel[2]*AdaptLevel[1]	0.612963	0.270481	2.27	0.0239*
AloneLevel[2]*CoopLevel[2]*AdaptLevel[2]	-0.264815	0.270481	-0.98	0.3280
AloneLevel[2]*CoopLevel[2]*AdaptLevel[3]	-0.348148	0.270481	-1.29	0.1986
AloneLevel[2]*CoopLevel[3]*AdaptLevel[1]	-0.264815	0.270481	-0.98	0.3280
AloneLevel[2]*CoopLevel[3]*AdaptLevel[2]	-0.125926	0.270481	-0.47	0.6417
AloneLevel[2]*CoopLevel[3]*AdaptLevel[3]	0.3907407	0.270481	1.44	0.1492
AloneLevel[3]*CoopLevel[1]*AdaptLevel[1]	0.4296296	0.270481	1.59	0.1128
AloneLevel[3]*CoopLevel[1]*AdaptLevel[2]	0.0351852	0.270481	0.13	0.8966
AloneLevel[3]*CoopLevel[1]*AdaptLevel[3]	-0.464815	0.270481	-1.72	0.0863
AloneLevel[3]*CoopLevel[2]*AdaptLevel[1]	-0.525926	0.270481	-1.94	0.0524
AloneLevel[3]*CoopLevel[2]*AdaptLevel[2]	0.212963	0.270481	0.79	0.4314
AloneLevel[3]*CoopLevel[2]*AdaptLevel[3]	0.312963	0.270481	1.16	0.2478
AloneLevel[3]*CoopLevel[3]*AdaptLevel[1]	0.0962963	0.270481	0.36	0.7220
AloneLevel[3]*CoopLevel[3]*AdaptLevel[2]	-0.248148	0.270481	-0.92	0.3593
AloneLevel[3]*CoopLevel[3]*AdaptLevel[3]	0.1518519	0.270481	0.56	0.5748

Figure 22. MOE 2.1 Parameter Estimates

PopUpKilled



Frequencies

Level	Count	Prob
0	343	0.63519
1	197	0.36481
Total	540	1.00000

N Missing 0
2 Levels

Figure 23. MOE 2.2 Distribution

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq
Intercept	Unstable	5.62734085	387.23702	0.00	0.9884
AloneLevel[1]	Unstable	-1.3969128	574.36532	0.00	0.9981
AloneLevel[2]	Unstable	0.71705256	533.7694	0.00	0.9989
CoopLevel[1]	Unstable	13.5755539	744.86526	0.00	0.9855
CoopLevel[2]	Unstable	-8.7974286	441.51814	0.00	0.9841
AloneLevel[1]*CoopLevel[1]	Unstable	1.39691281	1067.5388	0.00	0.9990
AloneLevel[1]*CoopLevel[2]	Unstable	-2.6622666	714.02979	0.00	0.9970
AloneLevel[2]*CoopLevel[1]	Unstable	-0.7170526	1046.2568	0.00	0.9995
AloneLevel[2]*CoopLevel[2]	Unstable	1.6368555	574.36534	0.00	0.9977
AdaptLevel[1]	Unstable	1.45832703	533.7694	0.00	0.9978
AdaptLevel[2]	Unstable	0.38951782	533.7694	0.00	0.9994
AloneLevel[1]*AdaptLevel[1]	Unstable	0.9242061	774.47404	0.00	0.9990
AloneLevel[1]*AdaptLevel[2]	Unstable	1.52526733	774.47403	0.00	0.9984
AloneLevel[2]*AdaptLevel[1]	Unstable	-0.5411226	744.86528	0.00	0.9994
AloneLevel[2]*AdaptLevel[2]	Unstable	-0.5639954	744.86528	0.00	0.9994
CoopLevel[1]*AdaptLevel[1]	Unstable	-1.458327	1046.2568	0.00	0.9989
CoopLevel[1]*AdaptLevel[2]	Unstable	-0.3895178	1046.2568	0.00	0.9997
CoopLevel[2]*AdaptLevel[1]	Unstable	1.62798923	574.36534	0.00	0.9977
CoopLevel[2]*AdaptLevel[2]	Unstable	1.2198595	574.36534	0.00	0.9983
AloneLevel[1]*CoopLevel[1]*AdaptLevel[1]	Unstable	-0.9242061	1489.7305	0.00	0.9995
AloneLevel[1]*CoopLevel[1]*AdaptLevel[2]	Unstable	-1.5252673	1489.7305	0.00	0.9992
AloneLevel[1]*CoopLevel[2]*AdaptLevel[1]	Unstable	2.12013249	883.03628	0.00	0.9981
AloneLevel[1]*CoopLevel[2]*AdaptLevel[2]	Unstable	2.70832812	883.03628	0.00	0.9976
AloneLevel[2]*CoopLevel[1]*AdaptLevel[1]	Unstable	0.54112255	1474.5546	0.00	0.9997
AloneLevel[2]*CoopLevel[1]*AdaptLevel[2]	Unstable	0.56399538	1474.5546	0.00	0.9997
AloneLevel[2]*CoopLevel[2]*AdaptLevel[1]	Unstable	-0.8817162	774.47407	0.00	0.9991
AloneLevel[2]*CoopLevel[2]*AdaptLevel[2]	Unstable	-1.3278146	774.47407	0.00	0.9986

For log odds of 0/1

Figure 24. MOE 2.2 Parameter Estimates

Appendix B. Simulation Experiment Results

Table 15. Simulation Experiment Results, Runs 1-60

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
1	1	1	1	1	1	13	11	6	0
2	1	2	1	1	1	11	8	10	0
3	1	3	1	1	1	15	8	9	0
4	1	4	1	1	1	12	9	11	0
5	1	5	1	1	1	8	8	11	0
6	1	6	1	1	1	14	8	9	0
7	1	7	1	1	1	19	8	10	0
8	1	8	1	1	1	13	10	7	0
9	1	9	1	1	1	12	11	7	0
10	1	10	1	1	1	12	9	8	0
11	1	11	1	1	1	12	10	8	0
12	1	12	1	1	1	9	7	11	0
13	1	13	1	1	1	8	8	9	0
14	1	14	1	1	1	27	7	10	0
15	1	15	1	1	1	13	9	10	0
16	1	16	1	1	1	7	5	9	0
17	1	17	1	1	1	20	7	10	0
18	1	18	1	1	1	23	7	10	0
19	1	19	1	1	1	17	10	7	0
20	1	20	1	1	1	7	8	8	0
21	2	1	2	1	1	13	8	8	0
22	2	2	2	1	1	13	8	10	0
23	2	3	2	1	1	5	11	8	0
24	2	4	2	1	1	20	7	11	0
25	2	5	2	1	1	18	10	8	0
26	2	6	2	1	1	15	8	9	0
27	2	7	2	1	1	16	9	8	0
28	2	8	2	1	1	11	11	8	0
29	2	9	2	1	1	6	9	9	0
30	2	10	2	1	1	24	9	6	0
31	2	11	2	1	1	9	9	10	0
32	2	12	2	1	1	14	12	8	0
33	2	13	2	1	1	12	11	9	0
34	2	14	2	1	1	9	8	10	0
35	2	15	2	1	1	14	11	8	0
36	2	16	2	1	1	15	7	9	0
37	2	17	2	1	1	16	9	8	0
38	2	18	2	1	1	24	6	9	0
39	2	19	2	1	1	3	5	12	0
40	2	20	2	1	1	14	11	6	0
41	3	1	3	1	1	15	10	7	0
42	3	2	3	1	1	11	7	10	0
43	3	3	3	1	1	13	8	8	0
44	3	4	3	1	1	4	3	13	0
45	3	5	3	1	1	13	8	10	0
46	3	6	3	1	1	11	4	11	0
47	3	7	3	1	1	8	9	9	0
48	3	8	3	1	1	14	11	8	0
49	3	9	3	1	1	10	9	10	0
50	3	10	3	1	1	14	6	8	0
51	3	11	3	1	1	15	10	8	0
52	3	12	3	1	1	7	9	10	0
53	3	13	3	1	1	15	9	8	0
54	3	14	3	1	1	13	10	8	0
55	3	15	3	1	1	13	9	9	0
56	3	16	3	1	1	15	6	9	0
57	3	17	3	1	1	10	10	9	0
58	3	18	3	1	1	11	9	7	0
59	3	19	3	1	1	10	6	10	0
60	3	20	3	1	1	16	11	7	0

Table 16. Simulation Experiment Results, Runs 61-120

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
61	4	1	1	2	1	2	8	10	1
62	4	2	1	2	1	12	10	9	1
63	4	3	1	2	1	20	4	8	1
64	4	4	1	2	1	12	9	12	1
65	4	5	1	2	1	8	8	9	1
66	4	6	1	2	1	23	8	3	1
67	4	7	1	2	1	22	4	8	1
68	4	8	1	2	1	8	6	14	1
69	4	9	1	2	1	14	11	7	1
70	4	10	1	2	1	18	9	5	0
71	4	11	1	2	1	7	4	12	1
72	4	12	1	2	1	17	11	6	1
73	4	13	1	2	1	14	4	12	1
74	4	14	1	2	1	17	10	7	0
75	4	15	1	2	1	8	5	11	1
76	4	16	1	2	1	17	10	4	0
77	4	17	1	2	1	6	5	11	1
78	4	18	1	2	1	16	11	6	0
79	4	19	1	2	1	15	10	8	1
80	4	20	1	2	1	10	5	7	0
81	5	1	2	2	1	0	5	13	1
82	5	2	2	2	1	0	9	12	0
83	5	3	2	2	1	15	9	8	0
84	5	4	2	2	1	15	7	8	1
85	5	5	2	2	1	7	7	9	0
86	5	6	2	2	1	15	5	11	0
87	5	7	2	2	1	15	8	10	0
88	5	8	2	2	1	14	6	13	0
89	5	9	2	2	1	13	6	12	0
90	5	10	2	2	1	13	7	8	0
91	5	11	2	2	1	10	11	7	1
92	5	12	2	2	1	11	7	11	0
93	5	13	2	2	1	10	7	9	0
94	5	14	2	2	1	12	5	12	0
95	5	15	2	2	1	19	5	11	0
96	5	16	2	2	1	17	7	5	0
97	5	17	2	2	1	8	5	13	1
98	5	18	2	2	1	9	9	7	0
99	5	19	2	2	1	17	7	10	1
100	5	20	2	2	1	12	7	11	1
101	6	1	3	2	1	10	12	6	1
102	6	2	3	2	1	14	11	7	0
103	6	3	3	2	1	12	8	5	0
104	6	4	3	2	1	14	6	12	1
105	6	5	3	2	1	12	11	7	1
106	6	6	3	2	1	15	9	7	0
107	6	7	3	2	1	12	11	5	1
108	6	8	3	2	1	12	8	6	1
109	6	9	3	2	1	9	7	7	0
110	6	10	3	2	1	6	8	6	1
111	6	11	3	2	1	12	7	9	1
112	6	12	3	2	1	6	10	5	0
113	6	13	3	2	1	13	11	6	0
114	6	14	3	2	1	21	8	6	0
115	6	15	3	2	1	8	4	10	0
116	6	16	3	2	1	16	7	6	0
117	6	17	3	2	1	5	4	11	0
118	6	18	3	2	1	8	5	7	1
119	6	19	3	2	1	10	11	7	1
120	6	20	3	2	1	5	8	9	1

Table 17. Simulation Experiment Results, Runs 121-180

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
121	7	1	1	3	1	11	5	9	0
122	7	2	1	3	1	8	5	12	1
123	7	3	1	3	1	9	9	11	0
124	7	4	1	3	1	12	4	14	0
125	7	5	1	3	1	12	10	8	0
126	7	6	1	3	1	16	10	7	1
127	7	7	1	3	1	6	9	11	0
128	7	8	1	3	1	8	12	8	0
129	7	9	1	3	1	10	9	11	0
130	7	10	1	3	1	14	6	11	1
131	7	11	1	3	1	13	12	8	0
132	7	12	1	3	1	20	12	8	0
133	7	13	1	3	1	9	8	10	0
134	7	14	1	3	1	12	5	14	0
135	7	15	1	3	1	14	11	7	0
136	7	16	1	3	1	13	8	10	0
137	7	17	1	3	1	13	5	11	0
138	7	18	1	3	1	11	11	9	0
139	7	19	1	3	1	12	10	10	0
140	7	20	1	3	1	16	13	7	0
141	8	1	2	3	1	4	9	8	0
142	8	2	2	3	1	8	12	7	0
143	8	3	2	3	1	9	6	10	1
144	8	4	2	3	1	8	0	14	0
145	8	5	2	3	1	1	8	10	1
146	8	6	2	3	1	11	10	9	0
147	8	7	2	3	1	7	9	9	0
148	8	8	2	3	1	14	9	11	0
149	8	9	2	3	1	18	8	10	1
150	8	10	2	3	1	14	10	7	0
151	8	11	2	3	1	10	12	9	0
152	8	12	2	3	1	12	9	8	0
153	8	13	2	3	1	20	11	9	0
154	8	14	2	3	1	18	12	8	0
155	8	15	2	3	1	3	6	11	0
156	8	16	2	3	1	12	8	8	0
157	8	17	2	3	1	10	11	10	0
158	8	18	2	3	1	7	7	9	0
159	8	19	2	3	1	0	5	11	0
160	8	20	2	3	1	25	8	8	0
161	9	1	3	3	1	13	10	8	0
162	9	2	3	3	1	2	7	10	0
163	9	3	3	3	1	18	7	8	0
164	9	4	3	3	1	13	10	6	0
165	9	5	3	3	1	5	7	8	0
166	9	6	3	3	1	21	10	8	0
167	9	7	3	3	1	2	6	10	0
168	9	8	3	3	1	7	11	8	0
169	9	9	3	3	1	11	5	9	0
170	9	10	3	3	1	11	8	6	0
171	9	11	3	3	1	16	9	9	0
172	9	12	3	3	1	21	9	8	0
173	9	13	3	3	1	16	8	8	0
174	9	14	3	3	1	0	9	9	1
175	9	15	3	3	1	7	10	10	0
176	9	16	3	3	1	0	5	10	0
177	9	17	3	3	1	2	7	13	0
178	9	18	3	3	1	22	8	7	0
179	9	19	3	3	1	12	11	6	0
180	9	20	3	3	1	6	7	7	0

Table 18. Simulation Experiment Results, Runs 181-240

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
181	10	1	1	1	2	17	11	7	0
182	10	2	1	1	2	13	8	10	0
183	10	3	1	1	2	21	7	9	0
184	10	4	1	1	2	16	7	9	0
185	10	5	1	1	2	16	6	11	0
186	10	6	1	1	2	15	8	8	0
187	10	7	1	1	2	13	11	8	0
188	10	8	1	1	2	17	14	7	0
189	10	9	1	1	2	22	11	8	0
190	10	10	1	1	2	24	9	8	0
191	10	11	1	1	2	14	6	11	0
192	10	12	1	1	2	10	10	9	0
193	10	13	1	1	2	16	12	8	0
194	10	14	1	1	2	16	9	8	0
195	10	15	1	1	2	17	8	9	0
196	10	16	1	1	2	4	7	9	0
197	10	17	1	1	2	22	9	9	0
198	10	18	1	1	2	19	10	7	0
199	10	19	1	1	2	16	6	10	0
200	10	20	1	1	2	16	12	5	0
201	11	1	2	1	2	16	9	8	0
202	11	2	2	1	2	11	11	8	0
203	11	3	2	1	2	14	11	7	0
204	11	4	2	1	2	20	6	11	0
205	11	5	2	1	2	16	9	8	0
206	11	6	2	1	2	16	9	10	0
207	11	7	2	1	2	33	7	9	0
208	11	8	2	1	2	14	9	11	0
209	11	9	2	1	2	13	5	12	0
210	11	10	2	1	2	10	11	6	0
211	11	11	2	1	2	16	11	8	0
212	11	12	2	1	2	11	9	10	0
213	11	13	2	1	2	15	10	8	0
214	11	14	2	1	2	21	10	8	0
215	11	15	2	1	2	14	7	11	0
216	11	16	2	1	2	16	5	9	0
217	11	17	2	1	2	8	8	10	0
218	11	18	2	1	2	23	7	9	0
219	11	19	2	1	2	14	7	10	0
220	11	20	2	1	2	18	6	8	0
221	12	1	3	1	2	15	10	8	0
222	12	2	3	1	2	13	8	9	0
223	12	3	3	1	2	14	8	8	0
224	12	4	3	1	2	12	8	10	0
225	12	5	3	1	2	9	9	9	0
226	12	6	3	1	2	17	8	10	0
227	12	7	3	1	2	12	8	9	0
228	12	8	3	1	2	12	8	9	0
229	12	9	3	1	2	7	11	7	0
230	12	10	3	1	2	12	9	8	0
231	12	11	3	1	2	15	8	9	0
232	12	12	3	1	2	11	11	9	0
233	12	13	3	1	2	7	4	13	0
234	12	14	3	1	2	13	11	7	0
235	12	15	3	1	2	9	10	8	0
236	12	16	3	1	2	15	9	9	0
237	12	17	3	1	2	12	6	9	0
238	12	18	3	1	2	8	10	6	0
239	12	19	3	1	2	15	8	9	0
240	12	20	3	1	2	22	12	5	0

Table 19. Simulation Experiment Results, Runs 241-300

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
241	13	1	1	2	2	22	8	8	1
242	13	2	1	2	2	2	4	10	1
243	13	3	1	2	2	14	10	9	1
244	13	4	1	2	2	13	8	12	1
245	13	5	1	2	2	12	11	8	1
246	13	6	1	2	2	7	5	10	0
247	13	7	1	2	2	21	10	4	1
248	13	8	1	2	2	14	9	9	1
249	13	9	1	2	2	7	7	13	0
250	13	10	1	2	2	21	8	4	1
251	13	11	1	2	2	0	7	12	1
252	13	12	1	2	2	18	9	9	0
253	13	13	1	2	2	12	6	11	1
254	13	14	1	2	2	11	13	7	1
255	13	15	1	2	2	13	10	7	1
256	13	16	1	2	2	15	11	5	0
257	13	17	1	2	2	19	10	9	1
258	13	18	1	2	2	11	7	9	1
259	13	19	1	2	2	12	5	9	1
260	13	20	1	2	2	16	8	6	1
261	14	1	2	2	2	2	5	8	1
262	14	2	2	2	2	8	6	10	1
263	14	3	2	2	2	15	5	13	1
264	14	4	2	2	2	9	11	8	1
265	14	5	2	2	2	10	10	8	0
266	14	6	2	2	2	8	3	12	1
267	14	7	2	2	2	8	10	7	1
268	14	8	2	2	2	8	5	11	0
269	14	9	2	2	2	18	11	8	1
270	14	10	2	2	2	21	10	6	1
271	14	11	2	2	2	12	8	9	0
272	14	12	2	2	2	20	9	9	1
273	14	13	2	2	2	6	9	10	1
274	14	14	2	2	2	16	6	10	1
275	14	15	2	2	2	6	4	13	1
276	14	16	2	2	2	7	11	6	1
277	14	17	2	2	2	17	10	8	1
278	14	18	2	2	2	14	14	5	0
279	14	19	2	2	2	8	10	9	0
280	14	20	2	2	2	18	10	7	1
281	15	1	3	2	2	11	2	10	1
282	15	2	3	2	2	4	9	9	1
283	15	3	3	2	2	8	6	11	1
284	15	4	3	2	2	17	7	11	1
285	15	5	3	2	2	10	10	6	1
286	15	6	3	2	2	12	6	11	1
287	15	7	3	2	2	18	8	7	0
288	15	8	3	2	2	5	12	6	1
289	15	9	3	2	2	12	10	6	1
290	15	10	3	2	2	8	4	8	1
291	15	11	3	2	2	9	7	8	1
292	15	12	3	2	2	1	8	7	1
293	15	13	3	2	2	13	4	9	1
294	15	14	3	2	2	14	6	6	1
295	15	15	3	2	2	8	8	8	1
296	15	16	3	2	2	12	5	7	1
297	15	17	3	2	2	9	8	7	1
298	15	18	3	2	2	5	6	10	1
299	15	19	3	2	2	16	4	8	0
300	15	20	3	2	2	8	4	6	1

Table 20. Simulation Experiment Results, Runs 301-360

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
301	16	1	1	3	2	20	11	7	0
302	16	2	1	3	2	9	8	9	1
303	16	3	1	3	2	2	10	9	0
304	16	4	1	3	2	10	7	12	0
305	16	5	1	3	2	9	6	12	0
306	16	6	1	3	2	8	7	10	0
307	16	7	1	3	2	7	8	11	0
308	16	8	1	3	2	10	10	10	0
309	16	9	1	3	2	12	13	7	0
310	16	10	1	3	2	15	7	9	0
311	16	11	1	3	2	11	11	9	1
312	16	12	1	3	2	16	7	12	1
313	16	13	1	3	2	11	9	10	1
314	16	14	1	3	2	10	9	10	1
315	16	15	1	3	2	15	6	9	0
316	16	16	1	3	2	0	4	12	1
317	16	17	1	3	2	12	6	11	0
318	16	18	1	3	2	17	11	7	0
319	16	19	1	3	2	10	7	11	1
320	16	20	1	3	2	10	8	8	0
321	17	1	2	3	2	15	13	5	0
322	17	2	2	3	2	17	12	8	0
323	17	3	2	3	2	20	9	9	0
324	17	4	2	3	2	12	7	10	1
325	17	5	2	3	2	15	8	10	1
326	17	6	2	3	2	12	6	10	0
327	17	7	2	3	2	17	6	9	0
328	17	8	2	3	2	9	8	11	1
329	17	9	2	3	2	6	7	11	1
330	17	10	2	3	2	17	10	6	0
331	17	11	2	3	2	12	4	13	1
332	17	12	2	3	2	22	11	7	0
333	17	13	2	3	2	0	8	9	0
334	17	14	2	3	2	19	9	6	1
335	17	15	2	3	2	16	6	9	1
336	17	16	2	3	2	10	5	9	0
337	17	17	2	3	2	10	5	13	0
338	17	18	2	3	2	24	9	8	0
339	17	19	2	3	2	13	8	9	0
340	17	20	2	3	2	9	8	7	1
341	18	1	3	3	2	26	12	4	0
342	18	2	3	3	2	11	8	10	0
343	18	3	3	3	2	10	12	8	0
344	18	4	3	3	2	14	12	7	0
345	18	5	3	3	2	6	6	9	1
346	18	6	3	3	2	12	9	9	0
347	18	7	3	3	2	16	8	9	0
348	18	8	3	3	2	8	6	10	0
349	18	9	3	3	2	14	8	7	1
350	18	10	3	3	2	21	8	7	1
351	18	11	3	3	2	12	8	9	1
352	18	12	3	3	2	7	9	8	1
353	18	13	3	3	2	9	9	9	0
354	18	14	3	3	2	7	5	11	1
355	18	15	3	3	2	16	8	9	0
356	18	16	3	3	2	15	5	8	1
357	18	17	3	3	2	11	9	8	0
358	18	18	3	3	2	16	12	4	1
359	18	19	3	3	2	7	12	6	1
360	18	20	3	3	2	17	9	7	0

Table 21. Simulation Experiment Results, Runs 361-420

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
361	19	1	1	1	3	10	6	11	0
362	19	2	1	1	3	18	9	12	0
363	19	3	1	1	3	0	10	14	0
364	19	4	1	1	3	12	9	11	0
365	19	5	1	1	3	22	4	14	0
366	19	6	1	1	3	3	8	14	0
367	19	7	1	1	3	8	5	13	0
368	19	8	1	1	3	8	7	14	0
369	19	9	1	1	3	8	8	13	0
370	19	10	1	1	3	20	8	10	0
371	19	11	1	1	3	2	3	13	0
372	19	12	1	1	3	13	9	13	0
373	19	13	1	1	3	10	7	15	0
374	19	14	1	1	3	15	8	15	0
375	19	15	1	1	3	0	6	15	0
376	19	16	1	1	3	0	4	13	0
377	19	17	1	1	3	5	6	16	0
378	19	18	1	1	3	0	10	9	0
379	19	19	1	1	3	0	9	14	0
380	19	20	1	1	3	16	8	10	0
381	20	1	2	1	3	8	9	11	0
382	20	2	2	1	3	9	10	11	0
383	20	3	2	1	3	0	4	15	0
384	20	4	2	1	3	6	9	9	0
385	20	5	2	1	3	6	4	12	0
386	20	6	2	1	3	6	10	11	0
387	20	7	2	1	3	9	8	12	0
388	20	8	2	1	3	12	5	14	0
389	20	9	2	1	3	5	12	13	0
390	20	10	2	1	3	0	5	15	0
391	20	11	2	1	3	15	8	13	0
392	20	12	2	1	3	5	9	11	0
393	20	13	2	1	3	6	10	12	0
394	20	14	2	1	3	10	10	9	0
395	20	15	2	1	3	8	9	10	0
396	20	16	2	1	3	0	3	15	0
397	20	17	2	1	3	10	4	15	0
398	20	18	2	1	3	3	7	14	0
399	20	19	2	1	3	10	6	14	0
400	20	20	2	1	3	6	4	11	0
401	21	1	3	1	3	8	8	13	0
402	21	2	3	1	3	2	4	16	0
403	21	3	3	1	3	6	13	7	0
404	21	4	3	1	3	8	12	7	0
405	21	5	3	1	3	11	10	8	0
406	21	6	3	1	3	6	3	15	0
407	21	7	3	1	3	21	11	5	0
408	21	8	3	1	3	0	4	14	0
409	21	9	3	1	3	6	6	14	0
410	21	10	3	1	3	9	11	9	0
411	21	11	3	1	3	13	12	6	0
412	21	12	3	1	3	0	5	15	0
413	21	13	3	1	3	13	9	12	0
414	21	14	3	1	3	11	9	11	0
415	21	15	3	1	3	8	8	8	0
416	21	16	3	1	3	0	3	17	0
417	21	17	3	1	3	14	10	11	0
418	21	18	3	1	3	14	12	6	0
419	21	19	3	1	3	8	9	9	0
420	21	20	3	1	3	2	8	10	0

Table 22. Simulation Experiment Results, Runs 421-480

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
421	22	1	1	2	3	14	4	11	1
422	22	2	1	2	3	24	9	8	1
423	22	3	1	2	3	7	6	12	1
424	22	4	1	2	3	6	7	12	1
425	22	5	1	2	3	0	8	11	1
426	22	6	1	2	3	0	0	14	1
427	22	7	1	2	3	0	8	12	1
428	22	8	1	2	3	8	9	9	1
429	22	9	1	2	3	0	3	16	1
430	22	10	1	2	3	15	6	12	1
431	22	11	1	2	3	0	2	15	1
432	22	12	1	2	3	7	8	11	1
433	22	13	1	2	3	9	7	8	1
434	22	14	1	2	3	12	11	6	1
435	22	15	1	2	3	0	2	13	1
436	22	16	1	2	3	0	6	12	1
437	22	17	1	2	3	0	5	12	1
438	22	18	1	2	3	11	4	13	1
439	22	19	1	2	3	0	6	6	1
440	22	20	1	2	3	0	6	14	1
441	23	1	2	2	3	13	4	13	1
442	23	2	2	2	3	0	4	11	1
443	23	3	2	2	3	13	6	7	1
444	23	4	2	2	3	9	6	13	1
445	23	5	2	2	3	0	5	16	1
446	23	6	2	2	3	10	8	12	0
447	23	7	2	2	3	14	3	13	1
448	23	8	2	2	3	11	7	12	1
449	23	9	2	2	3	1	3	14	1
450	23	10	2	2	3	13	7	11	1
451	23	11	2	2	3	0	9	10	1
452	23	12	2	2	3	0	3	16	1
453	23	13	2	2	3	0	8	10	1
454	23	14	2	2	3	0	4	12	1
455	23	15	2	2	3	12	7	9	1
456	23	16	2	2	3	4	6	12	1
457	23	17	2	2	3	6	3	17	1
458	23	18	2	2	3	15	12	6	1
459	23	19	2	2	3	0	6	10	0
460	23	20	2	2	3	16	4	12	1
461	24	1	3	2	3	8	5	9	1
462	24	2	3	2	3	2	4	12	1
463	24	3	3	2	3	9	4	13	1
464	24	4	3	2	3	0	4	12	1
465	24	5	3	2	3	12	9	10	1
466	24	6	3	2	3	7	3	15	1
467	24	7	3	2	3	20	8	10	1
468	24	8	3	2	3	6	4	16	1
469	24	9	3	2	3	16	4	13	1
470	24	10	3	2	3	2	7	9	1
471	24	11	3	2	3	8	12	6	1
472	24	12	3	2	3	7	7	14	1
473	24	13	3	2	3	16	7	9	1
474	24	14	3	2	3	12	11	6	0
475	24	15	3	2	3	11	9	7	1
476	24	16	3	2	3	19	10	6	1
477	24	17	3	2	3	8	7	9	1
478	24	18	3	2	3	6	7	8	1
479	24	19	3	2	3	6	8	10	1
480	24	20	3	2	3	12	7	7	0

Table 23. Simulation Experiment Results, Runs 481-540

Run	Treatment	Replicate	AloneLevel	CoopLevel	AdaptLevel	BomberHit	BlueKilled	RedKilled	PopUpKilled
481	25	1	1	3	3	16	11	8	0
482	25	2	1	3	3	12	5	14	1
483	25	3	1	3	3	6	2	16	1
484	25	4	1	3	3	13	6	12	1
485	25	5	1	3	3	12	12	8	0
486	25	6	1	3	3	7	7	13	1
487	25	7	1	3	3	11	8	11	0
488	25	8	1	3	3	12	7	14	0
489	25	9	1	3	3	13	7	11	1
490	25	10	1	3	3	8	8	11	0
491	25	11	1	3	3	14	9	9	1
492	25	12	1	3	3	8	3	17	1
493	25	13	1	3	3	0	7	12	1
494	25	14	1	3	3	12	8	11	0
495	25	15	1	3	3	11	5	11	0
496	25	16	1	3	3	14	6	8	1
497	25	17	1	3	3	10	7	14	0
498	25	18	1	3	3	25	7	8	1
499	25	19	1	3	3	13	7	11	1
500	25	20	1	3	3	7	12	6	0
501	26	1	2	3	3	0	3	14	0
502	26	2	2	3	3	8	7	12	1
503	26	3	2	3	3	8	4	14	1
504	26	4	2	3	3	12	8	12	0
505	26	5	2	3	3	13	11	11	1
506	26	6	2	3	3	13	7	13	0
507	26	7	2	3	3	7	4	13	0
508	26	8	2	3	3	0	5	13	1
509	26	9	2	3	3	4	6	13	1
510	26	10	2	3	3	20	12	8	0
511	26	11	2	3	3	10	5	16	0
512	26	12	2	3	3	7	7	15	0
513	26	13	2	3	3	4	7	16	0
514	26	14	2	3	3	10	8	8	1
515	26	15	2	3	3	14	8	10	1
516	26	16	2	3	3	13	6	11	1
517	26	17	2	3	3	10	10	9	0
518	26	18	2	3	3	14	10	11	1
519	26	19	2	3	3	0	5	14	1
520	26	20	2	3	3	5	10	9	1
521	27	1	3	3	3	13	8	8	1
522	27	2	3	3	3	3	12	8	1
523	27	3	3	3	3	10	7	9	0
524	27	4	3	3	3	7	13	7	0
525	27	5	3	3	3	10	9	10	1
526	27	6	3	3	3	2	6	11	0
527	27	7	3	3	3	10	5	14	0
528	27	8	3	3	3	8	8	11	0
529	27	9	3	3	3	11	14	8	0
530	27	10	3	3	3	15	9	7	0
531	27	11	3	3	3	9	13	8	0
532	27	12	3	3	3	6	6	13	1
533	27	13	3	3	3	20	8	10	1
534	27	14	3	3	3	7	5	15	0
535	27	15	3	3	3	21	9	8	0
536	27	16	3	3	3	0	2	14	0
537	27	17	3	3	3	12	8	7	1
538	27	18	3	3	3	23	10	8	1
539	27	19	3	3	3	2	10	10	0
540	27	20	3	3	3	1	6	11	1

Bibliography

1. *A Framework for Autonomy: A Short Paper on the First Principles of Autonomous Design* [2019], Technical report, Lockheed Martin.

2. *Air Force Doctrine Publication 1, The Air Force* [2021].

3. Banks, J., Carson II, J. S., Nelson, B. L. and Nicol, D. M. [2010], *Discrete-Event System Simulation*, 5 edn, Prentice Hall, Upper Saddle River, NJ.

4. Boskovic, J. D., Knoebel, N., Moshtagh, N., Amin, J. and Larson, G. L. [2009], Collaborative Mission Planning & Autonomous Control Technology (CoMPACT) System Employing Swarms of UAVs, *in* "AIAA Guidance, Navigation, and Control Conference", AIAA, pp. 1–24.

5. Bruns, R. D. [2020], Simulation and Analysis of High Value Airborne Asset Defense Effectiveness With Kinetic Weapons and Noise Jamming, Master's Thesis, Air Force Institute of Technology (AFIT), Wright-Patterson Air Force Base, OH.

6. Carter, A. B. [2012], *Department of Defense Directive 3000.09, Autonomy in Weapon Systems*, Washington, DC.

7. Ciaravino, M. A. [2020], Simulation and Analysis of Cyber Operations for A2AD using AFSIM, Master's Thesis, AFIT, Wright-Patterson Air Force Base, OH.

8. *Defense Science Board Summer Study on Autonomy* [2016], Technical report, Department of Defense, Washington, United States.

9. *Defense Science Board Task Force Report: The Role of Autonomy in DoD Systems* [2016], Technical report, Department of Defense ,Washington, United States.

10. Douchette, E. [2019], Networked Weapon Effects, Technical report, Air Force Research Laboratory Weapons Directorate.

11. Giles, K. and Giammarco, K. [2019], "A Mission-Based Architecture for Swarm Unmanned Systems", *System Engineering* **22**, 271–281.

12. Hartman, J. [1997], *High Resolution Combat Modeling*.

13. Hill, R. R. and Miller, J. O. [2017], A History of United States Military Simulation, Air Force Institute of Technology, Department of Operational Sciences, Winter Simulation Conference.

14. Huang, H.-M. [2004], "Terminology for Specifying the Autonomy Levels for Unmanned Systems Version 1.0", *NIST Special Publication* **1011**, 1–32.

15. Johnson, J. [2017], “Washington’s Perceptions and Misperceptions of Beijing’s Anti-Access Area-Denial (A2-AD)‘Strategy’: Implications for Military Escalation Control and Strategic Stability”, *The Pacific Review* **30**(3), 271–288.

16. Macal, C. M. [2016], “Everything You Need to Know About Agent-Based Modelling and Simulation”, *Journal of Simulation* **10**(2), 144–156.

17. Maloney, J. B. [2020], Simulating a Hypersonic Intelligence Surveillance and Reconnaissance (ISR) Aircraft’s Military Utility in an Anti-Access Area Denial (A2AD) Environment, Master’s Thesis, AFIT, Wright-Patterson Air Force Base, OH.

18. Mattis, J. [2018], Summary of the 2018 National Defense Strategy of the United States of America, Technical report, Department of Defense ,Washington, United States.

19. Montgomery, D. C. [2020], *Design and Analysis of Experiments*, 10 edn, Wiley, Hoboken, NJ.

20. Pelosi, M. and Honeycutt, A. K. [2017], “Cruise Missile Integrated Air Defense System Penetration: Modeling the S-400 System”, *International Journal of Aviation, Aeronautics, and Aerospace* **4**(3), 2.

21. Pollack, N. A. [2021], Simulation and Analysis of High Value Airborne Asset Defense With Autonomous Systems, Master’s thesis, AFIT, Wright-Patterson Air Force Base, OH.

22. Sanchez, S. M., Sanchez, P. J. and Wan, H. [2020], Work Smarter, Not Harder: A Tutorial on Designing and Conducting Simulation Experiments, *in* “2020 Winter Simulation Conference (WSC)”, pp. 1128–1142.

23. Spiegel, C. S. [2020], Simulation and Analysis of Cruise Missile Autonomous Behaviors, Master’s Thesis, AFIT, Wright-Patterson Air Force Base, OH.

24. United States Joint Chiefs of Staff [2017], *Joint Publication 3-01: Countering Air and Missile Threats*, Washington, DC.

25. United States Joint Chiefs of Staff [2019], *Joint Publication 3-09: Joint Fire Support*, Washington, DC.

26. *United States Air Force Science and Technology Strategy* [2019], Technical report, Department of the Air Force, Washington, United States.

27. Weimer, C. W., Miller, J. O. and Hill, R. R. [2016], Agent-Based Modeling: An Introduction and Primer, *in* “2016 Winter Simulation Conference (WSC)”, IEEE, pp. 65–79.

28. West, T. D. and Birkmire, B. [n.d.], "AFSIM", *Cyber Security and Information Systems Information Analysis Journal* **7**(3), 50.

29. Williams, A. [2015], *Autonomous Systems: Issues for Defence Policymakers*, NATO Capability Engineering and Innovation Division, Norfolk, VA.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704–0188

1. REPORT DATE *(DD–MM–YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From — To)*
24–03–2022	Master's Thesis	August 2020 — March 2022

4. TITLE AND SUBTITLE

Simulating Autonomous Cruise Missile Swarm Behaviors in an Anti-Access Area Denial (A2AD) Environment

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Goggins, Kyle W., Captain, USAF

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Way
WPAFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT-ENS-MS-22-M-132

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Strategic Development Planning & Experimentation
U.S. Air Force Research Laboratory
Bldg 620
Wright-Patterson AFB, OH 45433
COMM: 937-255-5474
EMAIL: howard.emsley@us.af.mil

10. SPONSOR/MONITOR'S ACRONYM(S)

SDPE

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

DISTRIBUTION STATEMENT A:
APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The increasing A2AD threat imposed by the modern IADS, coupled with the decreasing advantage provided by high-end stealth platforms, has prompted Air Force senior leaders to invest in radically changing the nature of air power. A prominent element of this new vision is weapon swarming, addresses this challenge by overwhelming the IADS with huge numbers of attritable aerial assets emboldened by autonomous capabilities. This research proposes a framework for classifying the different levels of autonomy along three independent dimensions—namely ability to act alone, ability to cooperate, and ability to adapt. A virtual combat model is constructed using the AFSIM in order to simulate the engagement between a blue strike package, featuring a manned bomber and an autonomous cruise missile swarm, and a red IADS. The influence of varying levels of autonomy on the strike package's performance is evaluated by using the autonomy framework as the basis for a designed experiment. Analyzing the results reveals which dimensions and levels of autonomy are most impactful in promoting survivability and lethality for this simulated scenario.

15. SUBJECT TERMS

Autonomous Teaming, Anti-Access Area Denial, Agent-Based Modeling and Simulation, Combat Modeling, Design of Experiments

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Dr. Lance E. Champagne, AFIT/ENS
					19b. TELEPHONE NUMBER *(include area code)*
U	U	U	UU	69	937-255-3636, x4646; lance.champagne@afit.edu