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THESIS

SIMULATED LASER WEAPON SYSTEM DECISION SUPPORT TO COMBAT DRONE SWARMS WITH MACHINE LEARNING

by

Daniel M. Edwards

September 2021

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SIMULATED LASER WEAPON SYSTEM DECISION SUPPORT TO COMBAT DRONE SWARMS WITH MACHINE LEARNING

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ABSTRACT

This thesis demonstrates an application of machine learning for enabling automated decision support to warfighters operating laser weapon systems in complex tactical situations. The thesis used the NPS Modeling Virtual Environments and Simulation (MOVES) Institute's Swarm Commander modeling and simulation software environment to develop simulated datasets of wargaming scenarios involving a shipboard laser weapon system defending against drone swarm threats. The simulated datasets were used to train a machine learning algorithm to predict the optimum engagement strategy in a complex battlespace with heterogeneous drone swarms. Multiple machine learning techniques were evaluated, and the classification tree technique was selected as the preferred approach. The final algorithm had an overall accuracy of 96% in correctly predicting engagement outcomes based on drone threat types, quantities, and the laser weapon system attack strategy. The research results demonstrate (1) the utility of modeling and simulation for supporting the development of tactical machine learning applications, (2) the potential for machine learning to support future tactical operations, and (3) the potential for machine learning and automation, in general, to reduce the cognitive load on future warfighters faced with making critical decisions in complex threat environments.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI	artificial intelligence
AUC	area under the receiver operating characteristic curve
CA	classification accuracy
DE	directed energy
DOD	Department of Defense
F2T2E2A	find-fix-track-target-engage-assess
HEL	high energy laser
HELIOS	high energy laser with integrated optical-dazzler and surveillance
ISR	intelligence, surveillance, and reconnaissance
KNN	k-nearest neighbors
kW	kilowatt
LLNL	Lawrence Livermore National Laboratory
LSM	loitering suicide munition
LWS	laser weapon system
ML	machine learning
MOVES	modeling virtual environments and simulation
MW	megawatt
NPS	Naval Postgraduate School
PIB	power in the bucket
SCT	Swarm Commander Tactics
UAS	unmanned aircraft systems
UAVs	unmanned aerial vehicles
U.S.	United States

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EXECUTIVE SUMMARY

Modern tactical warfare is increasingly complex and requires faster and more effective decisions. To support these rapid decisions, the use of automated decision aids to has been proposed as a solution (Johnson 2019, 63). Decision aids require large amounts of data given the complex nature of modern battlefields. To support development of decision aids machine learning represents a potential method to support an effective decision aid. The goal of this research was to conduct experimentation in exploring the application of machine learning to help warfighters in complex laser weapon system versus drone swarm engagement decisions. To accomplish this goal, laser weapons systems and drone threats were studied, and a simulation program was selected to generate engagement data that could be used to train a machine learning algorithm.

This thesis studied the threat engagement methodologies and identified decision factors that must be considered to effectively operate a laser weapon system as well as the applications of artificial intelligence and machine learning in supporting decision making. Base research was conducted into unmanned aerial vehicle, or drone, threats to identify risks and support the development of engagement methodologies. The base research supported the selection and programming of scenarios into wargaming and simulation software, Swarm Commander Tactics, which was used to simulate battles. This study conducted an experiment to develop a machine learning algorithm proof-of-concept by modeling and simulating engagement scenarios to collect training data and use that data to train a machine learning algorithm. The intent of training the algorithm was to identify survivability and successful engagement methodologies when using the simulated shipboard laser weapon. Upon generation of simulated engagement data, multiple machine learning techniques were tested using the simulated engagements to determine if machine learning prediction could support automated decision aids based on simulated data. This research studied machine learning algorithmic methods and the process of developing and training machine learning systems.

Overall, multiple machine learning techniques were evaluated to support prediction of successful drone engagement methodology within the simulated engagements, and the

most suitable was found to be the tree classification technique. The experimentation demonstrated the application of machine learning to this problem domain, through modeling and simulation, and machine learning algorithm training was successful. Results from the final machine learning algorithm predictions had an overall accuracy of 96% in predicting engagement outcomes based on enemy types, quantities, and laser weapon system attack methodology; with a false positive prediction, that is, the algorithm predicted win that was a loss, of 2.1%. These results show that a complex battle space simulation software can be used to accurately train a predictive machine learning algorithm.

This research demonstrated that combining wargaming simulations with machine learning algorithms provides a mechanism for supporting complex decisions and engagements, by laser weapon system, against enemy drone swarms. By implementing a trained machine learning algorithm, it is possible to analyze a complex battlespace with a heterogenous drone swarm so the appropriate engagement technique can be selected thereby optimizing the survivability and effectiveness of target engagement. The thesis addressed the primary research objective of exploring the efficacy of machine learning methods for identifying and supporting effective target selection and engagement methods for a simulated shipboard laser weapon system. This research represents a building block for the generation of decision aids to support drone swarm engagement with a laser weapon system. The complex nature of the modern battlespace requires decision aids to reduce the cognitive loading on the warfighter.

Reference

Johnson, Bonnie. 2019. "Artificial Intelligence—An Enabler of Naval Tactical Decision Superiority." *The AI Magazine* 40 (1): 63–78. https://doi.org/10.1609/aimag.v40i1.2852.

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I. INTRODUCTION

A. OVERVIEW

Modern tactical warfare is increasingly complex and requires faster and more effective decisions (Johnson 2019, 63). The development of transformative and disruptive weapon systems is reshaping the traditional battle space. One example is the Navy's development of high energy laser weapon systems (LWS). The Navy is beginning to install LWS on ships for test and evaluation. While these weapons offer potential improvements to ship and battle group defense, their performance and behavior differ significantly from existing traditional ordinance. Contemporary LWS are based on novel and highly advanced technologies. The complexity of LWS and their departure from traditional ordinance principles and behaviors requires a new methodology to support warfighters in the selection of targets for engagement. The operation of LWS requires the consideration of a complex set of decision factors including how much power will be used (and whether it is available), what the atmospheric conditions are (and how they will affect the laser beam), and what is known about the threat (range, kinematics, characteristics, location of components, material composition and thickness). These factors must be considered to determine at what target range to fire the weapon, to select the target aimpoint, and to predict what the required dwell time needs to be to burn through the target. These factors also inform successful engagement methodologies, for example, whether to prioritize and target specific enemies or engage all targets to achieve the most effective outcome.

Advances in threat technology also contribute to the complexity of the tactical decision space. One type of disruptive weapon that is evolving rapidly is unmanned aerial vehicles (UAVs) (Dunn 2013, 1245). Modern UAVs (or drones) are particularly complex, as they can be deployed as swarms. See Figure 1 which depicts a UAV swarm engagement. The growing threat and prevalence of easy-to-field drone swarms require a change in both conceptual and operational changes (Guitton 2021). Drone swarms introduce a heightened speed of warfare that may exceed the cognitive abilities of human warfighters to make effective decisions in such short timeframes (Galdorisi 2019).

Figure 1. Using Shipboard LWS to Defend Against a UAV Swarm Threat. Adapted from Lockheed Martin (2020).

The use of automated decision aids to support human warfighters has been proposed as a solution to address highly complex tactical decision spaces (Johnson 2019, 17). Extensive research exists concerning algorithms, data fusion, artificial intelligence (AI), machine learning (ML) and automation taxonomies (Save 2013). However, the use of automated methods brings its own challenges. It has been demonstrated that when decision aids have failed to adequately apply cognitive engineering and incorporate the human into the system, operator and system trust issues have arisen (Paradis 1999). Should the aiming system not adequately incorporate the user's skills into account, users may lose trust in the instrumentation system (Mann et al. 2006).

The goal of this research is to conduct experimentation in exploring the application of ML to help warfighters in complex LWS versus drone swarm engagement decisions. To accomplish this goal, multiple ML techniques were tested using simulated LWS engagements to determine if ML could support automated decision aids based on simulated data. The overall intent was to implement ML algorithms to support human warfighters in their use of LWS to defend against drone swarms. This research focused on the use of ML to support effective human-machine teaming in making shipboard LWS engagement decisions to defend against complex UAV swarm threats effectively. This thesis studied the LWS threat engagement methodologies and identified decision factors that must be considered to effectively operate the system. This thesis studied ML algorithmic methods and the process of developing and training ML systems as well as methods for simulating LWS operational scenarios to obtain datasets to train ML algorithms. Finally, this study conducted an ML proof-of-concept by modeling and simulating LWS scenarios to collect training data and using the data to train a ML algorithm for the purpose of identifying survivability and successful engagement methodologies using the simulated shipboard LWS.

B. RESEARCH OBJECTIVES

The primary objective of this research was to determine if AI and ML methods can support more effective rapid target selection and engagement for a simulated shipboard LWS. Additional research goals were:

- To study AI and ML methods to identify and evaluate methods suitable for improving LWS target selection and engagement methodology.
- To study how ML can support a human-machine teaming approach to making complex LWS decisions.
- To study the use of shipboard LWS to defend against complex UAV swarm threats.
- To demonstrate the application of ML to this problem domain through modeling and simulation and ML algorithm training.
- Exploiting the use of a wargaming modeling and simulation environment for use in gathering data sets training to train a ML algorithm.

C. APPROACH

This thesis addressed the research objectives through literature review, development of LWS modeling wargame scenarios, and experimentation using modeling and simulation and the development and evaluation of ML algorithms. The research approach began with a literature review to gather information on laser weapons, automated decision aids (including human-machine teaming, AI methods, and ML), and UAV swarm threats. This information was used as a foundation and basis for developing and modeling LWS operational scenarios and identifying a ML approach. Figure 2 illustrates the process for developing ML algorithms; the process involves gathering data sets that are representative of the operational domain and using the data to train the algorithm.

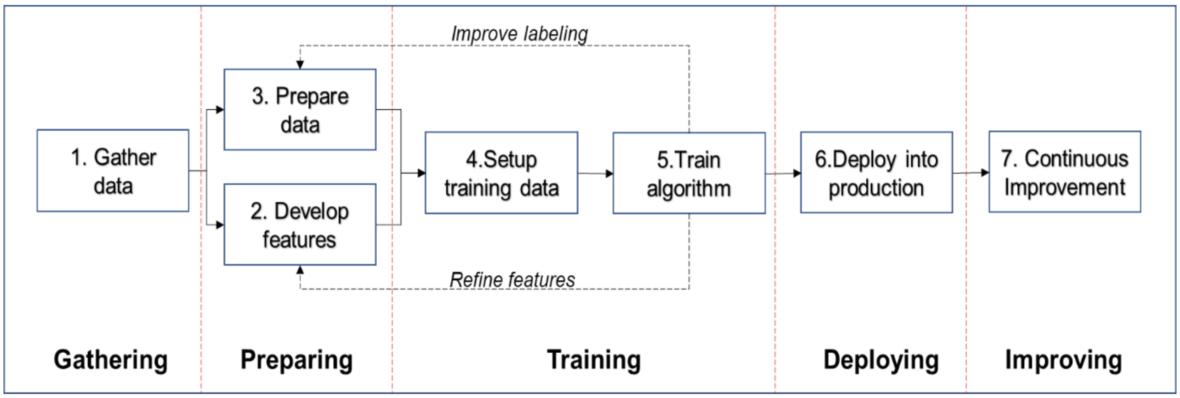

Figure 2. Methodology for Developing ML Systems. Adapted from Kopace (2021).

This study used the Naval Postgraduate School (NPS) Modeling Virtual Environments and Simulation (MOVES) Swarm Commander Tactics (SCT) wargaming software to generate simulated LWS engagement datasets. The SCT software modeled a shipboard LWS system defending against UAV swarm threats. The simulated datasets were used to train an ML algorithm to perform target selection and identify effective ideal engagement methodologies. The ML training process was conducted generally following five phases gathering, preparing, training, deploying, and improving.

This research approach provided limited experimentation into a basic ML algorithm approach to serve as a proof-of-concept and feasibility analysis of the future more full-scale use of AI and ML systems to support and enhance complex LWS engagement decisions.

The research approach followed six primary steps:

1. Identify preferred ML methodology and ML techniques.

2. Develop and run initial LWS engagement simulation test scenarios in SCT.

3. Train ML algorithm based on initial SCT modeling data.

4. Evaluate ML techniques, compare quantitatively, and identify optimal technique for engagement outcome prediction.

5. Use trained ML algorithm to generate scenario predictions and engagement outcome based on enemy or “Red Force” UAV threats and force strength as well as ally or “Blue Force” engagement tactics.

6. Run scenarios with optimized behavior rules to evaluate accuracy of predictions.

D. EXPERIMENT INTRODUCTION

The experimentation for this thesis followed three major phases based on the ML methodology shown in Figure 2.

- Phase 1 (Gathering and Preparing Phase): Developed initial simulations of homogenous and heterogenous threats and collected data on ship survivability and engagement methodology. Subsequently identified priority threats, threats that pose the greatest kill probability to the ship, and engagement methodology most likely to lead to ship survival.

- Phase 2 (Training Phase): Utilized initial data from Phase 1 and trained a ML algorithm to identify Blue Force survivability and engagement strategy based on threat type and significance.

- Phase 3 (Deploying and Improving Phase): Implemented the ML algorithm to predict the outcome of heterogenous attack simulations, compared to actual simulations in SCT and quantified results to demonstrate ML performance.

E. SCOPE AND APPLICABILITY

This research focused on the use of shipboard LWS to defend against UAV threat swarms as a complex tactical operation that could benefit from a human-machine teaming approach. The narrow scope of this thesis was intended to support the investigation of how AI and ML approaches can be applied to complex tactical decisions. The LWS engagement of UAV swarms provides a challenging threat scenario that requires target engagement prioritization. The NPS MOVES SCT system was an appropriate modeling and simulation environment to support this research's ML proof-of-concept demonstration. The scope of this research covered a narrow engagement methodology specifically for engagements within SCT Software version 6.1. Simulations were conducted with one Blue Force Ship and no additional Blue Force assets, at engagement distances of under five kilometers within the simulated ship's radar detection range. Red Force assets consisted of two primary UAV types of fighters and bombers, which are discussed in detail in Chapter III.

F. THESIS ORGANIZATION

This thesis is organized into five chapters. Chapter I provided the thesis overview, research objectives, and general approach. Chapter II highlights the background and literature review for the required relevant elements of this research. Chapter III describes the modeling and ML software used for this experiment and the methodology that was conducted to generate simulated data to train the ML algorithm. Chapter IV discusses the research results as well as the optimization and improvement of the ML process. Chapter V contains the research conclusion and summary and discusses potential future work.

II. LITERATURE REVIEW

This literature review provides background information for the underlying elements required for the implementation of this thesis research. There are three main topics that are relevant to the foundation of this study: (1) an overview of laser weapons and their characteristics; (2) an overview of automated decisions, including AI, ML, and human machine teaming (HMT); and (3) an overview of unmanned aircraft system (UAS) threats and target engagement strategies.

A. LASER WEAPON SYSTEMS

1. Historical Background on Lasers

The term laser is an acronym for light amplification by stimulated emission of radiation (Gould 1959). The first demonstrated laser was produced in 1960 by Ted H. Maiman and was constructed using a ruby rod and flash lamp (Perram et al. 2010, 5). The basic principle of how a laser operates is effectively and simply defined by Lawrence Livermore National Laboratory:

> A laser is created when the electrons in atoms in special glasses, crystals, or gases absorb energy from an electrical current or another laser and become "excited." The excited electrons move from a lower-energy orbit to a higher-energy orbit around the atom's nucleus. When they return to their normal or "ground" state, the electrons emit photons (particles of light). (Lawrence Livermore National Laboratory [LLNL] 2021)

Since the development of that first laser, there have been many other types invented for industrial purposes, consumer electronics, and non-military applications. One of the first research and invention investments into military applications of lasers was a DOD sponsored conference in 1963 to identify potential applications (Perram et al. 2010, 7). An early military application of the laser was its use as a range finder using a ruby and flashlamp laser to irradiate a target and receive the returning signals (Titterton 2016, 8). Additional laser demonstrations were conducted including the destruction of a visible-band camera which led to directed energy studies using newer gas laser to defeat heat seeking missiles in the 1970s (Titterton 2016, 8). Contemporary lasers in use today as full-fledged

LWS are commonly referred to as high energy lasers (HELs) which emit a small spot of light on a target to damage or destroy it (Perram et al. 2010, 10). Advanced laser systems, HELs, are being evaluated, demonstrated, and used by the United States Navy for multiple missions. There are two primary engagement approaches when utilizing a LWS for target neutralization: a soft-kill or a hard-kill. Soft-kills are the disruption of an enemy weapon system by nondestructive means, examples include blinding the sensors or optics on a weapon system rendering the target ineffective. Hard kills from a LWS ablate target components or materials causing the neutralization and physical destruction and of the target. The application of a hard or soft kill may be restricted based on the laser system and target characteristics; if the laser lacks sufficient power to destroy a target a soft kill may still be possible.

2. LWS Characteristics

Power is a primary characteristic which provides a destructive or disruptive capability for an LWS. Laser systems designed for hard kills typically range in power from 50-kilowatt (kW) to one Megawatt (MW) (Perram et al. 2010, 10). A laser's specified power refers to its power at the output of the laser. The power level quickly attenuates as the laser beam travels through the air or atmosphere. Thus, a 100 kW laser does not transmit 100 kW directly to the target being irradiated. The actual damaging power of a LWS is referred to as the power in the bucket (PIB) which is the fraction of total power that can be delivered measured in angular units of λ/D where λ is the laser wavelength and D is the beam size (Slater 2016). Wavelengths for LWS vary depending on their design, construction, and materials, for example a carbon dioxide laser can emit a beam over a wide range of wavelengths and as a result may need to be tuned to facilitate the optimum wavelength for laser efficacy (Titterton 2016, 55). The beam size and quality of the beam are also key characteristics of the LWS. Beam edges are not clearly defined so to effectively quantify beam size one can use the physical space and angular space of the beam to generate a size value (Slater et al. 2010). The beam quality is defined as a measure of excellence of the beam based on the ratio of the actual spot size to the diffraction-limited spot size (Perram et al. 2010, 402).

Additional key system properties for an effective LWS must also consider the operating ranges, target types and atmospheric conditions all of which can greatly reduce system capability if not factored into design and mission profiles. The amount of time that a laser must continuously lase a target is referred to as dwell time, this is a key aspect of system performance as a longer dwell time increases the time to score a target kill. Atmospheric conditions also play a key role in system function due to interference from atmospheric absorption, Rayleigh scattering, and Mie scattering (Titterton 2016, 166–167). Turbulence, the atmospheric motions from planetary waves can also cause system function degradation (Perram et al. 2010, 413). In addition to atmospheric attenuation, target material properties can affect the LWS system performance. To effect total heating of a target the target material there are up to seven material response states: expansion, material property change, melting, vaporization, ablation, spalling, and plasma (Perram et al. 2010, 326). Target hard kill may occur as early as the melt stage; however, this would depend on the aimpoint and the component melting on the target. Target material type, configuration, and properties will dictate the failure modes and the probability of weapon effectiveness (Perram et al. 2010, 326–337).

Overall LWS and target characteristics represent a complex multivariable system interaction. The design of the LWS, atmospheric conditions, and target characteristic can all play a part in the probability of a hard-kill. Further data analysis on atmospheric conditions or intelligence on target types and construction can support a more effective engagement; however, these can be difficult variables to quantify in all scenarios leading to complex challenges that in the event of a real-time threat require fast acting responses from LWS operators. The United States (U.S.) Navy has begun implementation of LWS as part of fleet modernization and advanced ship capabilities, requiring further analysis and effective understanding of the key LWS characteristics.

3. LWS Complex Decision Space

The modern battle space is increasingly complex as new threats continue to develop and advance. The complexity of LWS and their characteristics and their performance indicators can be difficult to quantify, and factors like turbulence effects can impact effective LWS range (Chen et. al. 2018). System and target characteristics greatly influence LWS performance and effectiveness. Tactical decision making must be performed quickly, effectively, and accurately in dynamic high stress environments which sets up the potential for human information overload and operator error (Johnson 2021). Utilization of AI and ML methods to support the warfighter tactical decision-making process, can address information overload by presenting rapid risk analysis and decision aids to the warfighter. Figure 3 highlights factors that contribute to the complexity of tactical decisions. Coupling these inherent factors with LWS complexities creates a complex decision space for operators in the field.

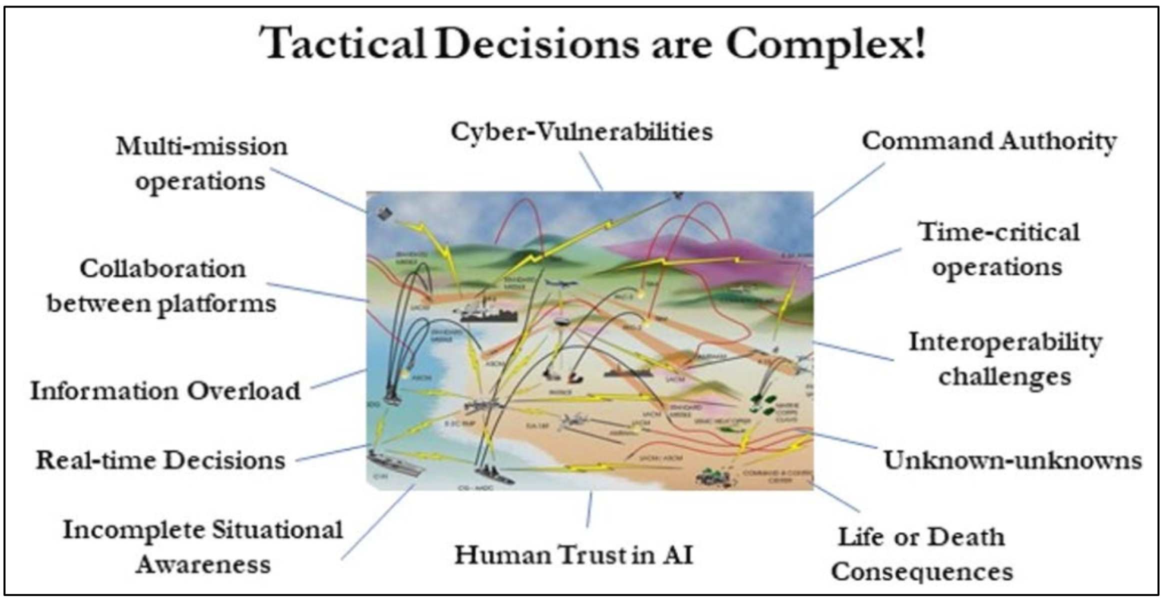

Figure 3. Tactical Decision Complexity. Source: Johnson (2021).

4. Overview of Current Naval Shipboard Laser Weapon Systems

The U.S. Navy is adopting LWS to enhance ship defensive and offensive capabilities. One example is the High Energy Laser with Integrated Optical-dazzler and Surveillance (HELIOS) which has begun permanent deployment on an Arleigh Burke destroyer and has been integrated with its combat system (Magnuson 2021). The HELIOS system is a hybrid adaptable fiber based LWS, with a HEL weapon to effect hard kills and an optical dazzler to effect soft kills. The laser component of HELIOS is a 60kW LWS designed to counter UAS and small craft (Sherman 2021).

B. AUTOMATED DECISION AIDS

Given the complexity of LWS and their departure from traditional kinetic ordnance principles warfighters require support in making rapid effective engagement decisions. Some level of automation is required to ensure tactical superiority with LWS. Humans need support in their LWS engagement decision making. The primary challenge is incorporation automation with the human decision maker, as weapon systems generally have a human-in-the-loop, that is a person that must make the final engagement methodology decision. Automated decision aids can reduce the mental load on the human operator and facilitate more rapid and effective decisions. However, development and understanding of automation within this space require a review of potential the usage of automation methods. This section provides an overview of automation as well as providing detail on ML techniques and human machine teaming considerations.

1. Overview of Automation and Artificial Intelligence

Automated systems operate with little human interaction or input based on a ruleset and standing commands (Johnson 2021). The broader realm of automation covers both ML and AI as visualized in the Venn diagram Figure 4. Specialized AI systems are developed to mimic human intelligence and decision making by developing knowledge from learned behavior or information and applying this knowledge and logic to new information received by the system (Johnson 2021).

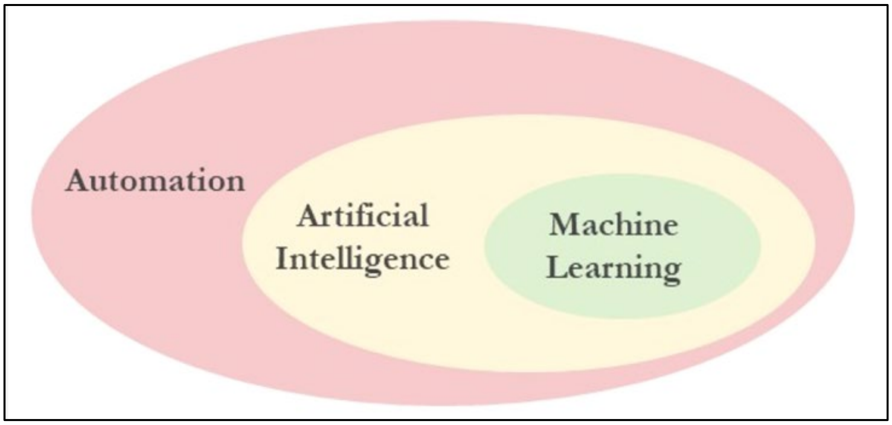

Figure 4. Venn Diagram Automation, Artificial Intelligence and Machine Learning. Source: Johnson (2021).

2. Machine Learning

Within the domain of AI, ML develops algorithms that optimize decisions based on available data (Mitchell 1997). ML is considered a subset of AI and can be used to identify patterns, learn from the patterns, and then make decisions as a result of the information learned to optimize the intended outcome (Shah 2018). Complex scenarios in warfighter engagements can benefit from decisions aids driven by ML applications because the systems experience can provide better background for target engagement based on the target goals. According to Taiwo Oladipupo Ayodele’s chapter in *New Advances in Machine Learning,* there are multiple types of ML methodologies including supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and transduction (Ayodele 2010, 19–22). Ayodele (2010) states supervised learning consists of an ML algorithm generated function which uses user labeled datasets to learn and generate desired result and outputs based on the labeled examples. The author asserts unsupervised learning is a more complex ML algorithm based on inputs without labeled examples, the ML algorithm attempts to learn how to do a task that the user does not define for it. A semi-supervised ML algorithm combines both supervised and unsupervised methods to create both labeled and unlabeled examples. Reinforcement learning consists of an algorithm which is given a policy of how to behave in a system where actions have defined impacts and the algorithm can then learn based on feedback to identify which impacts to avoid or to initiate. Lastly, transduction is based on a system learning based on training inputs outputs instead of starting with a constructed function (Ayodele 2010, 19). Upon reviewing these methods supervised learning was selected as the desired approach for this thesis.

Supervised learning provides a methodology for the inference of a learning algorithm based on labeled data (Mark et al. 2015, chap. 1). The SCT modeling software outputs labeled data which allows for the use of supervised ML allowing a training data set to be developed. With the methodology selected the next step in conducting supervised ML is to select one or more techniques to execute the learning process.

3. Machine Learning Techniques

Supervised learning has multiple techniques, which support the ML process; they are classified into two main categories linear regression and classification techniques (Mark et al. 2015, chap. 1).

a. Linear Regression

Linear regression uses prediction and forecasting to identify connections and dependencies between data and is one of the oldest learning techniques (Mark et al. 2015, chap. 1). Linear regression is used when there is one independent variable with a linear relationship between the independent and dependent variables (Gandhi 2018). Examples of suitable linear regression use cases include advertising budget and sales relationships or radiation therapy type and tumor sizes (Mark et al. 2015, chap. 1), Linear regression is not a suitable technique for use with SCT due to multiple variables, which will be discussed in Section 3, and as a result classification is a more suitable technique for this experiment.

b. Classification Techniques

Classification is a pattern recognition technique that analyzes data inputs and develops a qualitative response, an example of this is identifying fraudulent credit card purchases based on multiple variables (Mark et al. 2015, chap. 1). There are many forms of classification techniques including logistic regression, decision trees, random forest, K-nearest neighbor (KNN), and neural networks. Logistic regression is a technique that is used when the target variable is categorical, for example if you wanted to identify email that was spam or not and had multiple factors, like sender, subject, links, etc., a logistic regression technique would be well suited for this (Swaminathan 2019). Decision trees group items with similar features and can be one of the fastest classification methods, they also provide a clear visualization of the data (Ayodele 2010, 25). Random forest is a multi-decision tree collection which provides a more generalized solution (Varghese 2019). Provided that KNN is a technique that deals with proximity of data points and requires a clear understanding of the inputs, as a result this method was not ideal for this experiment (Varghese 2019). Neural networks are multi-node systems where each node is its own linear regression model and require very large quantities of training data which could not be supplied by SCT given the scope and timeframe of this study (IBM 2020). For this experiment three classification techniques will be used and compared: logistic regression, decision tree, and random forest, these methods were selected based on the data generated from SCT and each respective techniques attributes.

4. Human-Machine Teaming and Trust Considerations

Data analysis is conducted by AI to generate and assess decisions in complex situations and ML can be used to train a system to better identify tactical courses of action in complex systems (Johnson 2019, 1). Multiple types of data can be processed with ML, from images and speech to objects and patterns. Naval warfighters must process a large amount of data for decision making and will require AI and ML to highlight the most relevant information to inform faster and better decisions in the stress of combat (Galdorisi 2019). One end state for AI and ML implementation in tactical decisions making is in support of automated and semi-automated decision aids. Two major challenges in implementing an intelligent battle decision aid are to create an effective human-machine teaming relationship and to create an effective human-machine trust dynamic.

Implementation of ML as a decision support tool methodology is ongoing in multiple fields including the healthcare industry. There has been a trend to generate ML driven diagnosis tools in clinical settings for patient diagnosis. Increasingly, ML is used to support clinical decisions to improve human diagnostic performance; however, a study of ML based clinical support decision systems found that these ML systems were at a high risk of bias and that for better results, a supported human decision should be considered above standalone

ML diagnostic systems (Vasey et al. 2021, 1–2). This highlights the need for a human to be part of the decisions aid system that can leverage the ML data support to make rapid, and effective assessments and take data driven action. Fully automated or heavily automated military decision aids that do not properly integrate the operator can lead to failure by operator over-reliance on, or lack of trust in, decision aids (Paradis 1999). The balance of an effective AI or ML decision support requires proper user integration and effective data analysis to ensure it is a net benefit to the system it is implemented in.

Utilizing ML to better prioritize LWS targets and inform the operator of the greatest threat is one method where the user and ML system could work in harmony to inform an expedient and effective kill. The complexity of LWS characteristics and drone threats provide a prime example of the need for ML supported decision making by the warfighter.

C. DRONE SWARM THREATS

Drone swarm threats were selected as the simulated enemy because of the complex nature and wide range of capabilities which can be countered by effective LWS. Usage of drones have greatly increased in the last twenty years with multiple mission capabilities including surveillance, reconnaissance, and direct-action combat support (Guitton 2021, 26). Drones have become more prevalent, cheaper, and more capable requiring specific anti-drone strategies as drones may appear in any conflict (Guitton 2021, 26).

1. Swarm Considerations

Drones represent a dynamic and scalable threat that can drastically change the battle space. Single drone attacks like the explosive laden drone used to attack the Erbil Airport in Iraq, which consisted of a single drone carrying explosives, detonated targeting U.S. forces. (Reuters 2021). Single drones are a threat; however, multi drone attacks represent a greater challenge and threat to military forces. When multiple drones are operating together, either autonomously or manually controlled, they can perform multi-unit assaults referred to as drone swarms (Guitton 2021, 28). These drone swarms can be homogenous, multiple drones of one type, or heterogenous where there are multiple types of drones all in the same swarm. Figure 5 shows a SCT screenshot with four types of drones attacking a Blue Force vessel: fighter drones, intelligence, surveillance, and reconnaissance (ISR) drones, bomber drones, and Loitering Suicide Munition (LSM) drones.

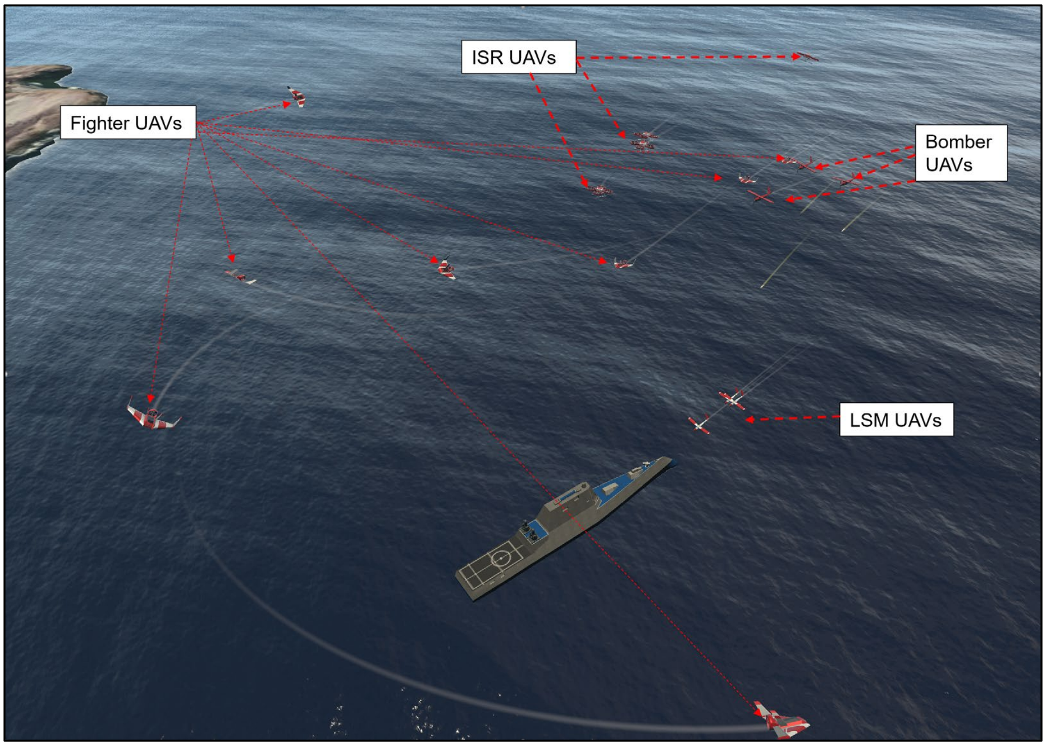

Figure 5. Heterogenous Swarm Attack Scenario. Source: MOVES (2021).

The wide array of drone types and functions create challenging battlefield conditions as operators need to assess and engage hostile drones quickly and effectively. Shipboard LWS allow for rapid target engagement and can support hard and soft kills. Additionally, a LWS with a decision support aid would further support the warfighter and ensure more successful drone swarm engagements.

Drone swarms pose a significant threat and need to be adequality accounted for in risk assessments because of the inexpensive cost and ease of use (Dunn 2013, 1245). Drones can be procured and assembled easily and then laden with explosives, or they can be used their kinetic energy to mechanically damage planes or systems (Dunn 2013, 1245). Drone swarms of sufficiently large quantities have the potential to overwhelm a ship's defensive capabilities (Laird 2016). Utilizing decisions aides or modeling to optimize engagement of the drone swarm can support an operator to engage the drone threats quickly and more effectually (Laird 2016). Because of their potential in anti-drone operations LWS are being researched and designed to detect, track, and neutralize drone threats for ground troops on mobile vehicle platforms (Eckstein 2013). Advanced LWS are becoming more prevalent in effective anti-drone warfare because they can scale to meet the needs of the warfighter from shipboard lasers to small mobile vehicle lasers there is a high degree of scalability allowing for a relevant set of solutions to address drone threats.

2. Target Engagement Methodology

Targeting is a key step in the kill chain process especially when utilizing LWS because of the necessity of a clear risk assessment, deconfliction, and identification of viable LWS targets. Decision aids for the huma-machine team can support more effective targeting and by extension enhancing the engagement success probability. Targeting was selected as a key area for decision support because of the complex and relatively new implementation of LWS. Targeting is one step in the overall kill chain cycle process of Find-Fix-Track-Target-Engage-Assess (F2T2E2A) kill chain cycle pictured in Figure 6.

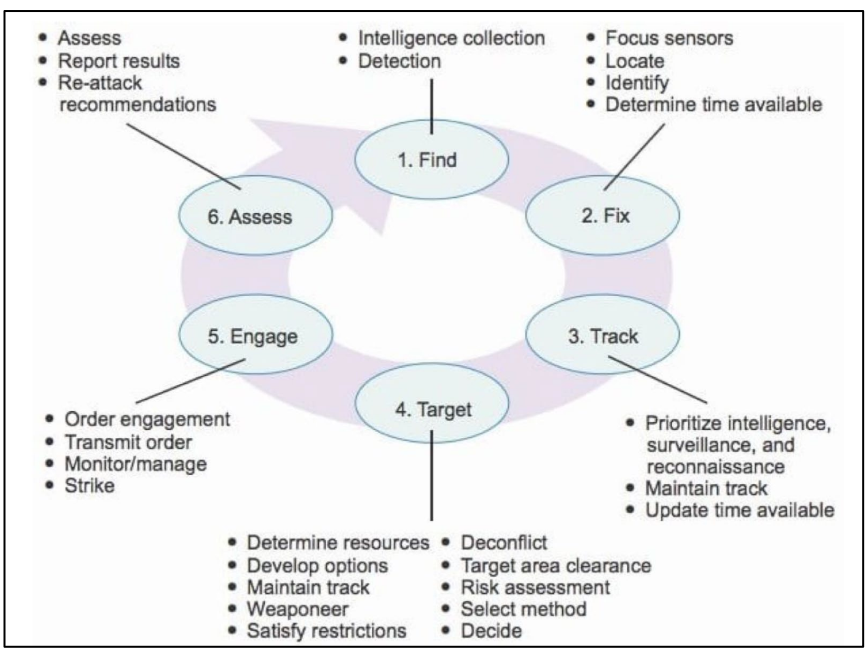

Figure 6. Find-Fix-Track-Target-Engage-Assess Kill Chain Cycle. Source: U.S. Joint Chiefs of Staff (2013).

Per the United States Armed Forces Joint Chiefs of Staff Joint publication 3–0, Joint Operations Targeting is defined as "the process of selecting and prioritizing targets and matching the appropriate response to them, taking account of command objectives, operational requirements, and capabilities" (Joint Chiefs of Staff 2018).

Target prioritization is key to successful operations by the U.S. Armed Forces. Drone swarms pose a unique threat in modern warfare as they are large inexpensive groups of hostile forces that can fulfil multiple roles ranging from reconnaissance to direct action attacks. Knowing which drones to target and engage may mean the difference between a ship's survival. Countries like China are interested in using drone swarms for U.S. Aircraft Carrier targeting (Kallenborn and Bleek 2018, 524). Drone swarms are not necessarily homogenous, and proper identification, targeting, and engagement of the drones that pose the greatest risk to ship survivability is paramount. When implementing a new LWS on ship having a system that can support effective and risk-based targeting can improve LWS performance in terms of ship survivability. The primary goal of this research is to determine if ship survivability can be maximized by using ML in simulated LWS engagements with heterogenous drone swarms to optimize targeting and engagement methodology while maximizing kills of enemy forces.

III. SWARM COMMANDER TACTICS AND MACHINE LEARNING EXPERIMENTATION

Experimentation based on simulated ship LWS and drone swarm engagements provides a simple and effective method for evaluation the efficacy of ML in supporting target engagement methodology. The beginning of this section describes the software elements and their features for simulation and machine learning and is designed to provide sufficient background as well as the experimental approach. After the background overview the experiment is detailed, following the three-phase method outlined in section 1.A Approach: Phase 1 gathering and preparing, Phase 2 training, and Phase 3 deploying and improving.

A. SWARM COMMANDER TACTICS SOFTWARE OVERVIEW

The NPS MOVES Institute has created a software program called SCT which generates simulated engagements between Red and Blue forces. SCT was originally designed as a tactics' "game" where NPS Students could develop their strategies in a simulated battle space. Over time, the model began to grow and include directed energy (DE) systems, atmospheric data, and more realistic simulation elements. SCT will serve as the virtual simulation test environment LWS UAV swarm engagements. This section is designed to provide better understanding of SCT and its capabilities.

1. Relevant Software Program Organizational Elements and Overview

The SCT software contains elements to allow for multi-user game play, player editing and setup, development of combat scenarios, development of system element behaviors called "plays," and scenario simulations or "runs." This thesis focuses on the scenario development in the scenario editor function, scenario runner, and plays. The title screen for software commander is shown in Figure 7.

Figure 7. Swarm Commander Tactics Main Menu. Source: MOVES (2021).

a. Scenario Editor

Scenario Editor is the primary menu for setting up a simulated battle within a battle space, players are established with player assets including asset types, quantities, positioning, and asset goals. The editor is used to generate a unique environment where simulations can be established in a controlled environment. The scenario editor allows for mission objectives based on plays to be attributed to each entity, for example the Blue Force ship entity can be programmed to hold (defend) a position while the Red Force UAV can be programmed to attack the Blue Force ship entity. Figure 8 shows a sample scenario editor with Red and Blue Force elements.

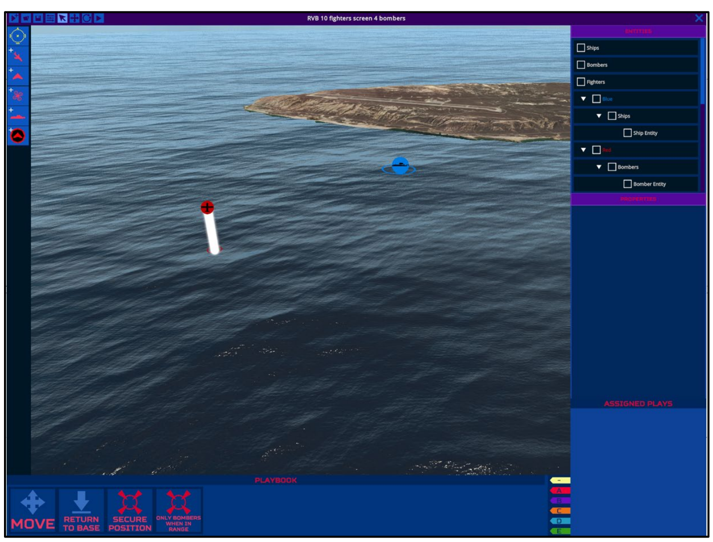

Figure 8. Sample Swarm Commander Tactics Scenario Editor. Source: MOVES (2021).

b. *Scenario Runner*

The scenario runner is the actual simulation of the developed scenario with programmed entities. The simulation is conducted in real-time and each entity attempts to execute their programmed mission. The software logs data during the engagement including time, entity location, damage taken or health of entity, ship LWS power level, and entity status (alive or killed). The software outputs a .csv data file after each simulation which allows for data harvesting and analysis. Figure 9 shows an active shot of a red team versus blue team simulation scenario.

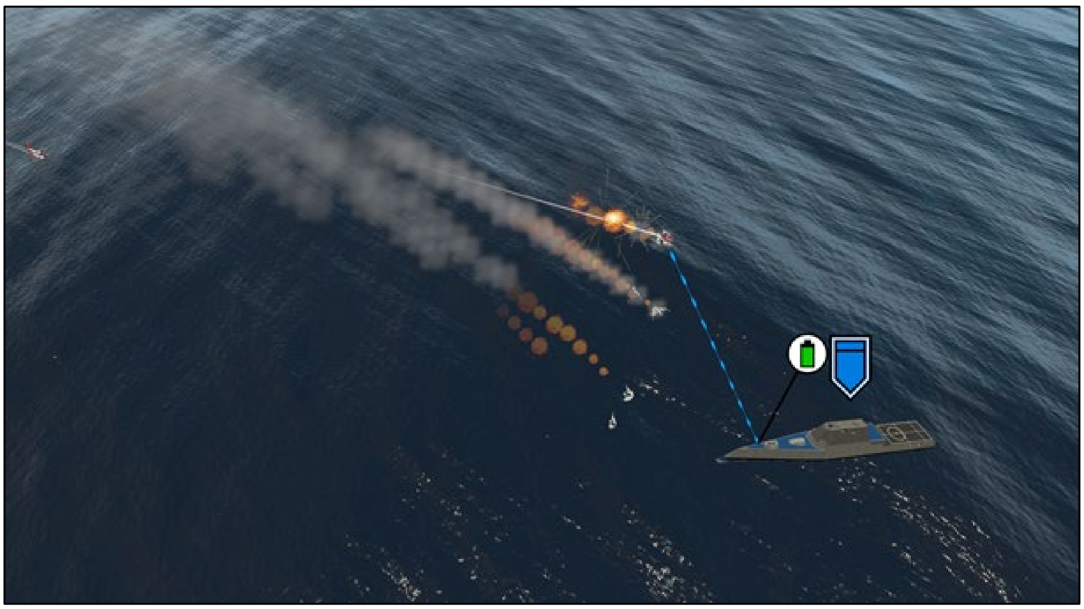

Figure 9. Sample Scenario Running. Source: MOVES (2021).

c. *Play Designer*

The play designer software element allows for behaviors to be developed for entity attribution in the scenario editor, this allows experimentation with entity behavior to model the effects of various behaviors like target prioritization. This designer allows for the addition of rulesets to identify optimized behavior in the scenario ruins. Figure 10 shows a sample play behavior development tree representing the command to attack when enemies are within weapons range. The default settings for target engagement behavior in SCT is proximity based, meaning the nearest enemy target is the default engagement regardless of the target's actual threat level, as an example, a Red Force ISR drone in closer proximity to a blue Force ship would be targeted over a bomber drone even though the bomber drone poses a greater potential threat to the ship. The ability to modify entity behavior allows for more optimized engagement methodology to be implemented. The second engagement methodology developed to support this research was the threat prioritization play which is a Blue Force command to ignore non-offensive capable enemy units and target and engage only UAVs which pose a damage threat.

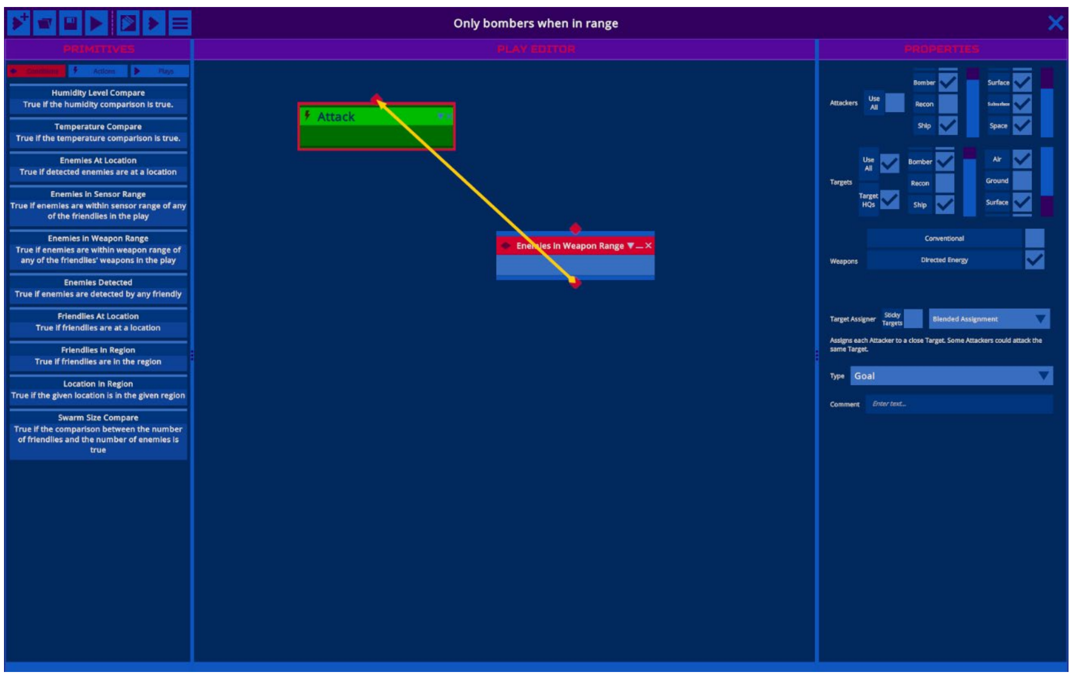

Figure 10. Swarm Commander Tactics Play Designer Attack Behavior When Enemies in Weapons Range. Source: MOVES (2021).

2. Swarm Commander Tactics Software System Entities

a. UAVs

The software program has five different UAV systems, each with unique qualities and functions:

1. ISR UAVs, a small UAV which does not pose a damage threat to any systems.

2. Fighter UAVs poses a damage threat to aircraft (1 unit), and no threat to ships, its primary function is air to air drone warfare. The fighter UAVs are not capable of sinking the ship.

3. Bomber UAV Variant 1 standard drops ordinance onto ships and causes poses a moderate damage threat (1 unit of damage). Multiple ordinance impacts are required to sink the ship.

4. Bomber UAV Variant 2 Loitering Suicide Munition (LSM) represents a suicide UAV laden with explosives which rams into and detonates itself on the ship target this causes a damage (5 units of damage). Multiple impacts are required to sink the ship.

5. Bomber UAV Variant 3 Missile Platform, This UAV deploys an anti-ship cruise missile which causes significant damage (25 units of damage) to the ship, a single missile impact sinks the ship.

The UAVs specific damage characteristics are summarized in Table 1 and pictured in Figure 11, Figure 12, and Figure 13, note that the bomber variant is represented by one figure type as all three share the same general aesthetic model.

Table 1. Swarm Commander Tactics UAV Damage and Speed Characteristics

UAV Type	**Damage units to ship**	**Cooldown (seconds)**	**Speed (m/s)**
UAV Fighter	0	5	100
UAV Bomber Variant 1 (air to ground bomber)	1	5	80
UAV Bomber Variant 2 (loitering suicide munition)	5	N/A	80
UAV Bomber Variant 3 (cruise missile platform)	25	30	80
UAV ISR	0	N/A	120

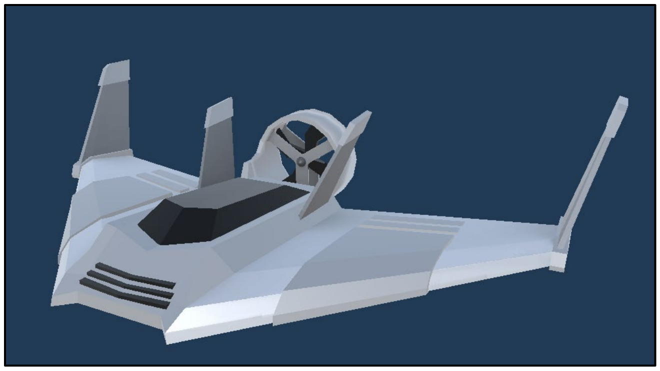

Figure 11. Red Force Fighter UAV. Source: MOVES (2021).

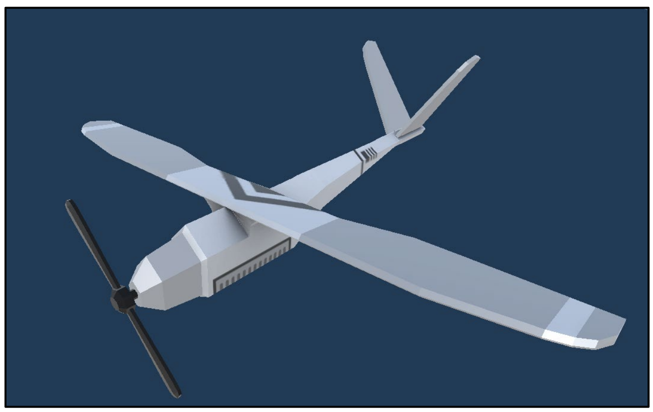

Figure 12. Red Force Bomber UAV General Representation. Source: MOVES (2021).

Figure 13. Red Force ISR UAV. Source: MOVES (2021).

b. Simulated Ship

The Blue Force general representation of a ship for surface to air engagements. Simulated DE weapon system with which includes atmospheric attenuation using NPS ANCHOR, a laser performance scaling code that provides rapid estimates of laser performance in the given conditions (Collins 2016). The ship laser directed energy weapon defines inputs to its firing calculation including output power, wavelength, beam diameter, jitter, and atmospheric data when targeting and engaging a hostile target (MOVES 2021). The ship's laser is a 10,000-watt system with a wavelength of 1.0642e-06 meters. The total energy battery for the system is 300 simulated units with a 1 unit per second power usage rate (MOVES 2021). This Ship model and LWS is a simplified representation of a shipboard LWS and does not match real-world systems, it is simply used for simulation purposes. The Blue Force ship model is pictured in Figure 14.

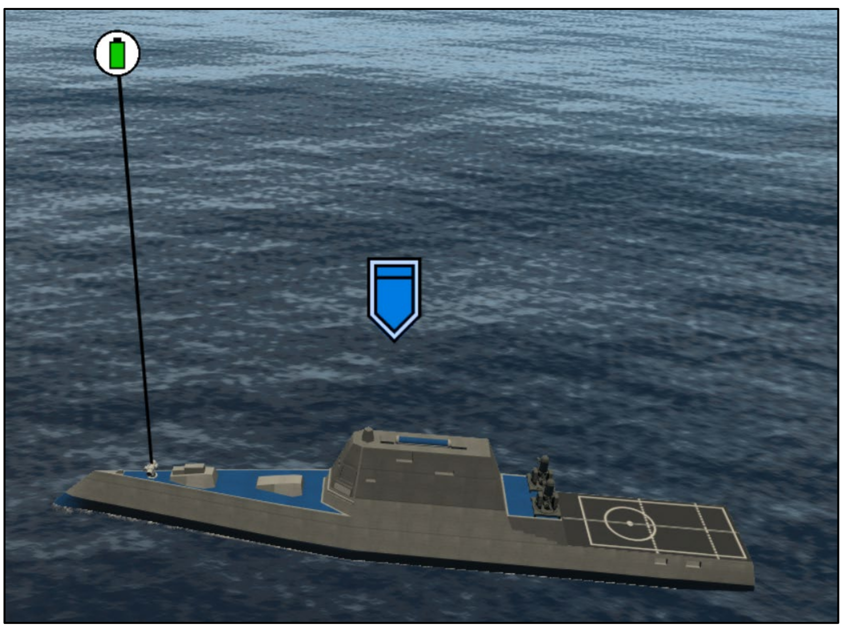

Figure 14. Blue Force Ship. Source: MOVES (2021).

B. ORANGE ML SOFTWARE APPLICATION OVERVIEW

Implementation of ML based on the simulation data from SCT required a programming environment, to facilitate the ML execution the software program Orange was selected to conduct the ML portion of the experiment. Orange software was selected to be the ML software suite because it is an open-source software for ML and data visualization that has a user interface with a widget toolbox (Orange Data Mining [Orange], n.d.). Orange software allows users to conduct ML by setting up a graphical interface instead of having to code multiple elements in the computer language Python. The ML interface is referred to as a project workflow, a sample workflow is presented in Figure 15 which shows the file linkage to a classification decision tree, distribution statistics, and a scatter plot.

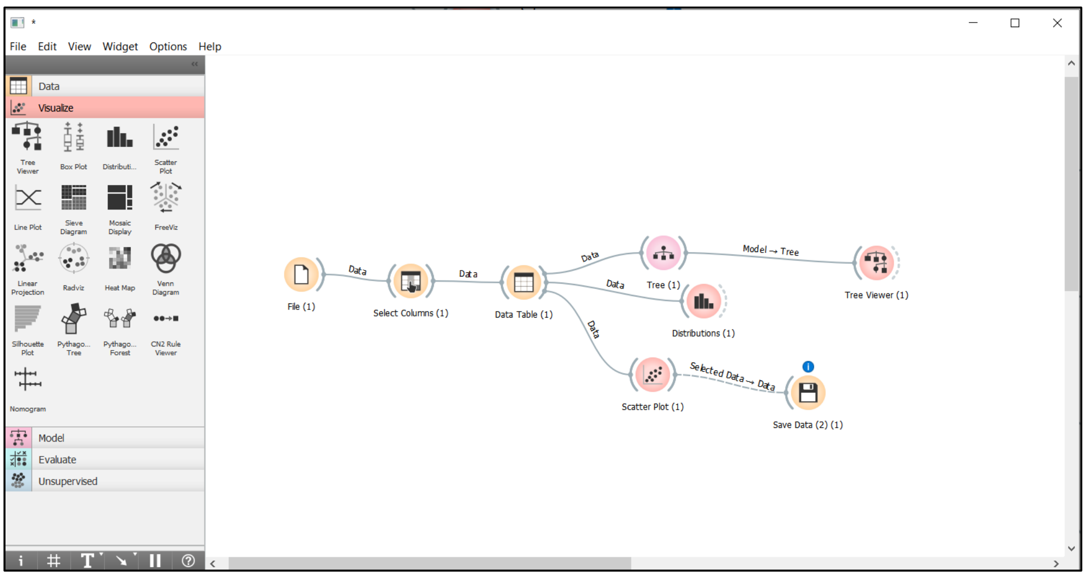

Figure 15. Sample Workflow from Orange v3.26. Source: Orange (2021).

The Orange software be programmed to take data inputs and group based on the data attributes. During the initial familiarization with Orange, a group of UAVs was imported and the system was able to learn which UAVs are attributed with certain speed levels and damage capabilities. Subsequently, a blind import excluding the UAV type was put into Orange and the system generated a grouping scatter plot correctly identify the UAVs by attributes, this is shown in Figure 16. The Orange software project also generated a classification tree for UAV types based on attributes, as shown in Figure 17, which shows how the grouping was performed based on learned attributes. This exercise provides background for how the overall experiment was conducted using initial data to support learning

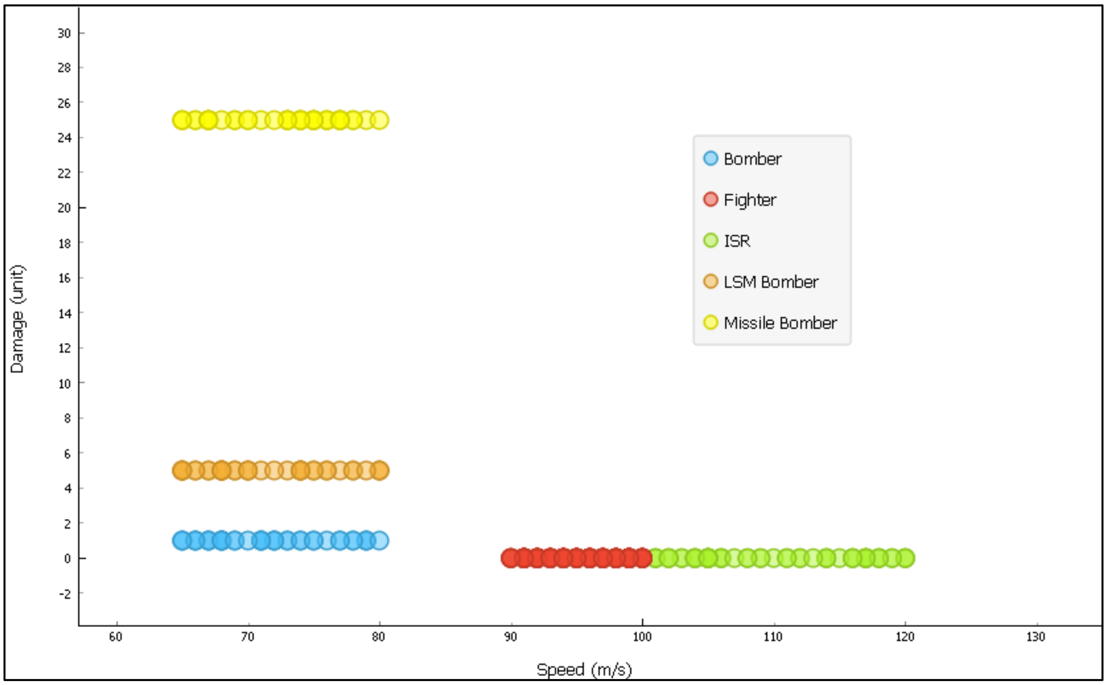

Figure 16. Trained ML UAV 2 Factor Scatter Plot Sample Workflow from Orange v3.26. Source: University of Ljubljana (2021).

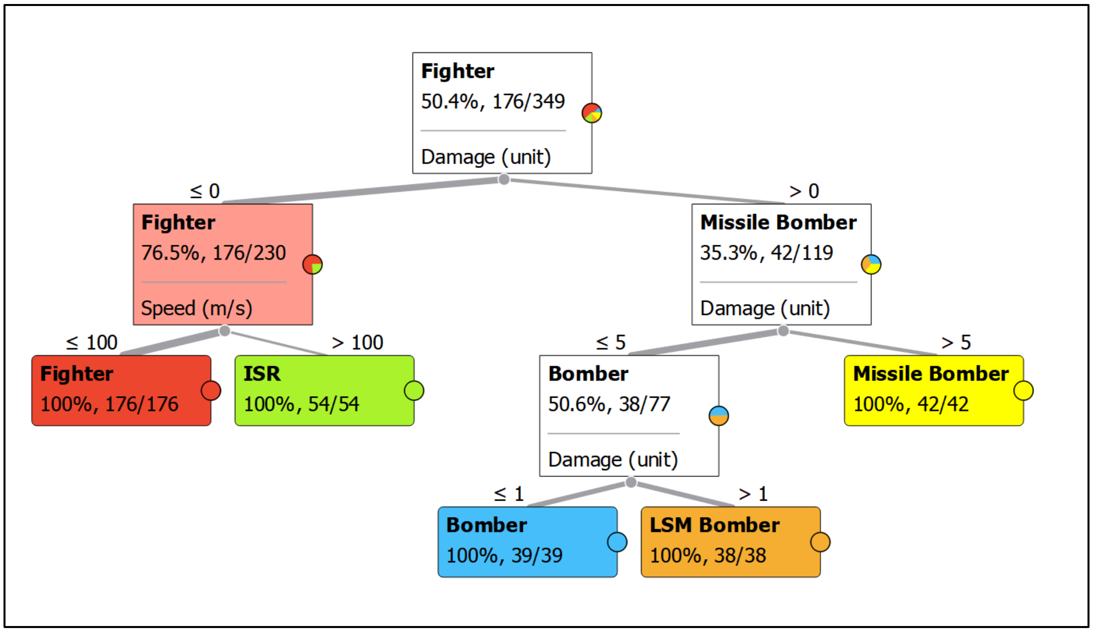

Figure 17. Trained ML UAV Type Classification Tree from Orange v3.26. Source: Orange (2021).

C. PHASE 1: DEVELOPMENT OF INITIAL SIMULATION SCENARIOS

Phase 1 of the experiment serves a baseline for comparison of the basic engagement logic in SCT. The simulation scenario types and methodologies are discussed below in tow primary subsections the threat scenarios and the engagement methodology. The threat scenarios consist of two primary categories, homogenous and heterogeneous drone swarms. The engagement methodology section breaks out the two primary methodologies studied in this experiment proximity-based engagement and threat-based engagement. Simulation scenarios were generated based on the threat scenarios and engagement methodologies to create a baseline data set to train the ML algorithm.

1. Blue Force Engagement Mythology Variables

Blue Force engagement methodology consists of two primary methods, proximity engagement and threat engagement. Engagement methodology is the target variable for the experiment as it represents the decision required to ensure maximum combat effectiveness. The entire experiment is designed to provide decision support recommendation to the LWS operator based on the battlespace conditions and variables. The proximity methodology will command the ship to attack all targets and prioritize the closest target first. The proximity method is effective provided the ship can destroy all enemies, meaning no enemies would need to be engaged by other Blue Force assets in a real-world scenario freeing other assets up to continue their missions. However, should the ship be overwhelmed due to the number or types of enemy UAVs there is greater risk of loss of the ship when implementing the proximity engagement methodology. The threat engagement method prioritizes the most dangerous enemies only, this could require other Blue Force assets to engage fighter drones or other non-offensive damage capable UAVs. The threat priority method ignores ISR or Fighter drones, which pose no damage threat to the ship. These two engagement methods were selected based on the current capabilities of the SCT software as they can be programmed in the current version and allow for two distinct approaches to a simulated engagement. The optimal engagement methodology must be selected based on the UAV types and quantities present in the battlespace. The variables which the ML software must assess are the variable type numerical or categorical, and whether the variable is a feature or the target variable, the goal variable. Variable classifications in the simulation scenarios are defined in Table 2.

Table 2. Relevant Simulation Scenario Variable Types and Descriptions for ML

Variable	**Variable Type**	**Feature or Target Variable**	**Description**
Fighter Quantity	Numeric	Feature	Number of fighters in the simulated scenario
Bomber Type	Categorical	Feature	Type of bombers in simulated scenario
Bomber Quantity	Numeric	Feature	Number of bombers in the simulated scenario
Engagement Methodology	Categorical	Feature	Proximity Engagement fire on closest enemy or Threat Engagement fire on offensive threat enemies only (i.e., bombers)
Win or Loss	Categorical	Target Variable	End state for simulation Blue Force win or loss

2. Homogenous and Heterogenous Threat Scenarios

Initial threat scenarios were simulated to build user knowledge of the SCT software and the data outputs generated each time a scenario was simulated. Initial simulation scenarios involved Red and Blue Force engagements with one Red Force threat type, this means varying quantities of homogenous UAVs attacked the Blue Force Ship, see Figure 18 for a sample attack wave. The data generated in these basic scenarios shows the approximate quantity of homogenous UAVs required to destroy the Blue Force Ship regardless of engagement strategy. The total quantity by UAV type required to kill the Blue Force Ship is summarized in Table 3.

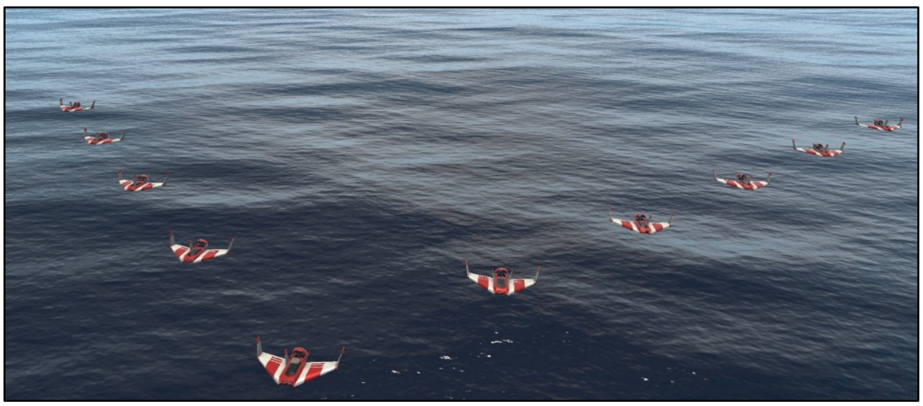

Figure 18. Homogenous UAV Wave Swarm Commander Tactics. Source: MOVES (2021).

Table 3. Homogenous UAV Units Required to Destroy Blue Force Ship

UAV Type	Quantity Needed to Destroy Blue Force Ship
UAV Fighter	N/A- Non-Offensive to Ship
UAV ISR	N/A- Non-Offensive to Ship
UAV Bomber Variant 1 (air to ground bomber)	**90**
UAV Bomber Variant 2 (loitering suicide munition)	N/A-Maximum simulated wave was 300 units, failed to destroy Ship
UAV Bomber Variant 3 (cruise missile platform)	**29**

Homogenous attacks for each UAV type listed in Table 2 were simulated with up to three hundred units to determine the quantity of each UAV type required to overwhelm the Blue Force defenses. Losses to homogenous waves represent enemy UAV quantities that, regardless of engagement tactics, would overwhelm the Ship defenses. These homogenous scenarios were run to develop a baseline for UAV type lethality. The Fighter UAV type though non-offensive was simulated as they were used in heterogeneous attack waves to represent non direct threat UAVs. The most devastating UAV was the UAV Bomber Variant 3 which fires an anti-ship missile, when 29 units fire in concert the ship is unable to destroy all the incoming missiles and is destroyed. The UAV Bomber Variant 1 air to ground bomber can overwhelm the Blue Force with a wave of 90 or more units. The UAV Bomber Variant 2 LSM was unable to reach the ship prior to being destroyed even at the maximum wave size of 300 units.

Heterogenous simulation scenarios involved Red and Blue Force engagements with multiple Red Force threat types, this means varying quantities of heterogenous UAVs were simulated attacking the Blue Force Ship, see Figure 19 for a sample attack wave. The data generated in these basic scenarios was used to see the damage taken and power utilized by the Blue Force Ship. Like the homogenous scenarios, heterogenous threat attacks were conducted until the destruction of the Blue Force Ship or until the attacks rendered the laser system inert through power drain (which did not occur in any of the simulations).

Figure 19. Heterogenous UAV Wave Swarm Commander Tactics. Source: MOVES (2021).

D. PHASE II: ML TRAINING

Training of ML algorithm in this experiment was conducted using supervised learning because of the availability of labeled simulation data. The initial simulations generated in SCT were used to train the ML algorithm and training was conducted in multiple iterations to optimize the algorithm. This section discusses the training as well as the comparison and selection of the optimum ML technique classification process.

1. Machine Learning Training Process Overview

Training the ML algorithm began with the generation of baseline data simulations in SCT. The baseline scenarios needed to be random to avoid bias and to ensure this initial training scenario parameters were generated in an Excel sheet built with a random number generation set for each variable provided in Table 2. These generated conditions including UAV types and quantities and the random engagement methodology were input and simulated in SCT. The output simulation data was from SCT was input into Orange and evaluated with multiple ML technique evaluation methods including forest, random forest, and logistic regression. The ML algorithm training was conducted in two iterations to determine if there was an increase in optimization. The workflow package developed in Orange for initial ML training and an additional iteration are shown in Figure 20 and Figure 21, respectively. The results of the training are discussed in Chapter IV.

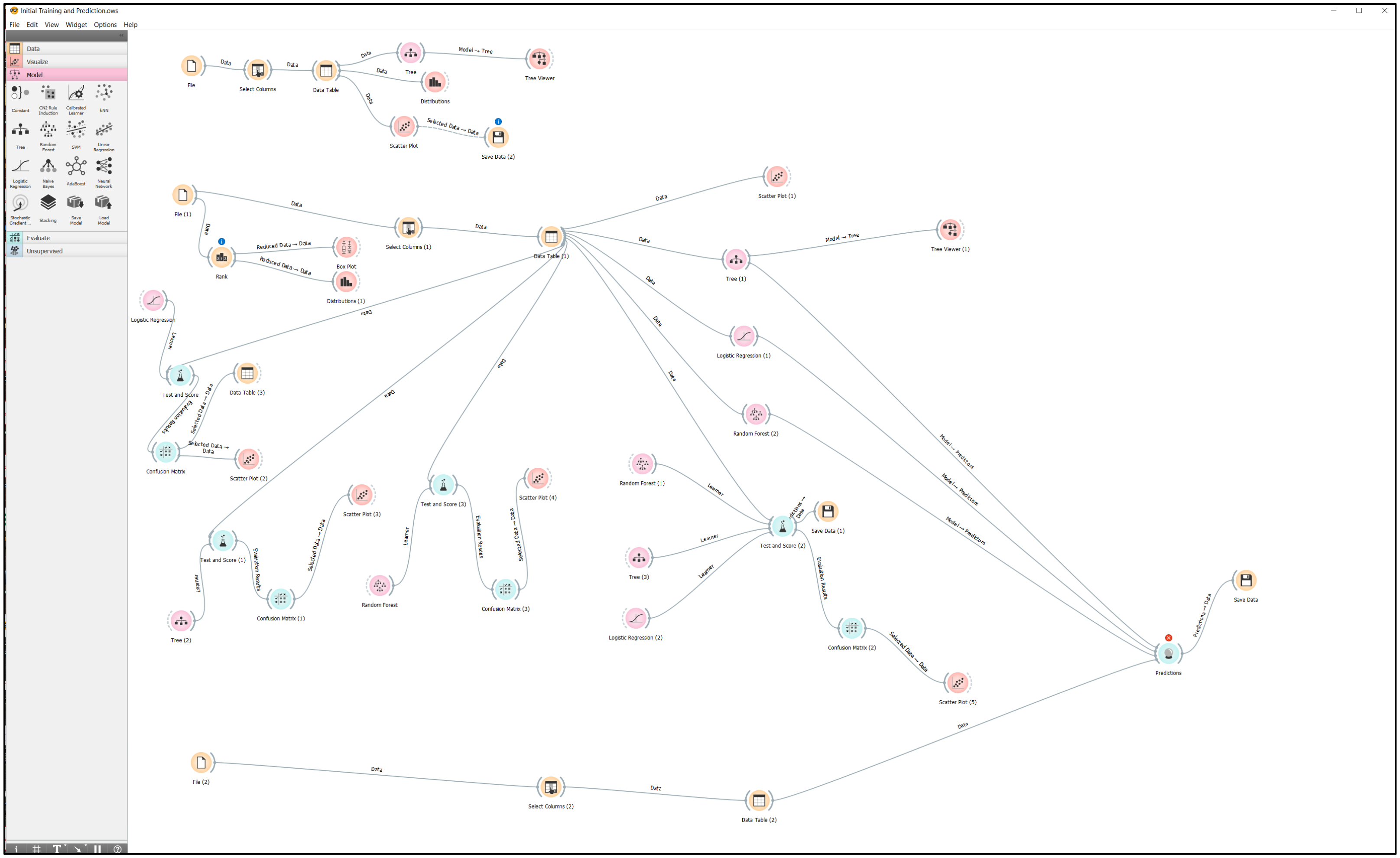

Figure 20. Initial Experiment Workflow from Orange v3.26. Source: Orange (2021).

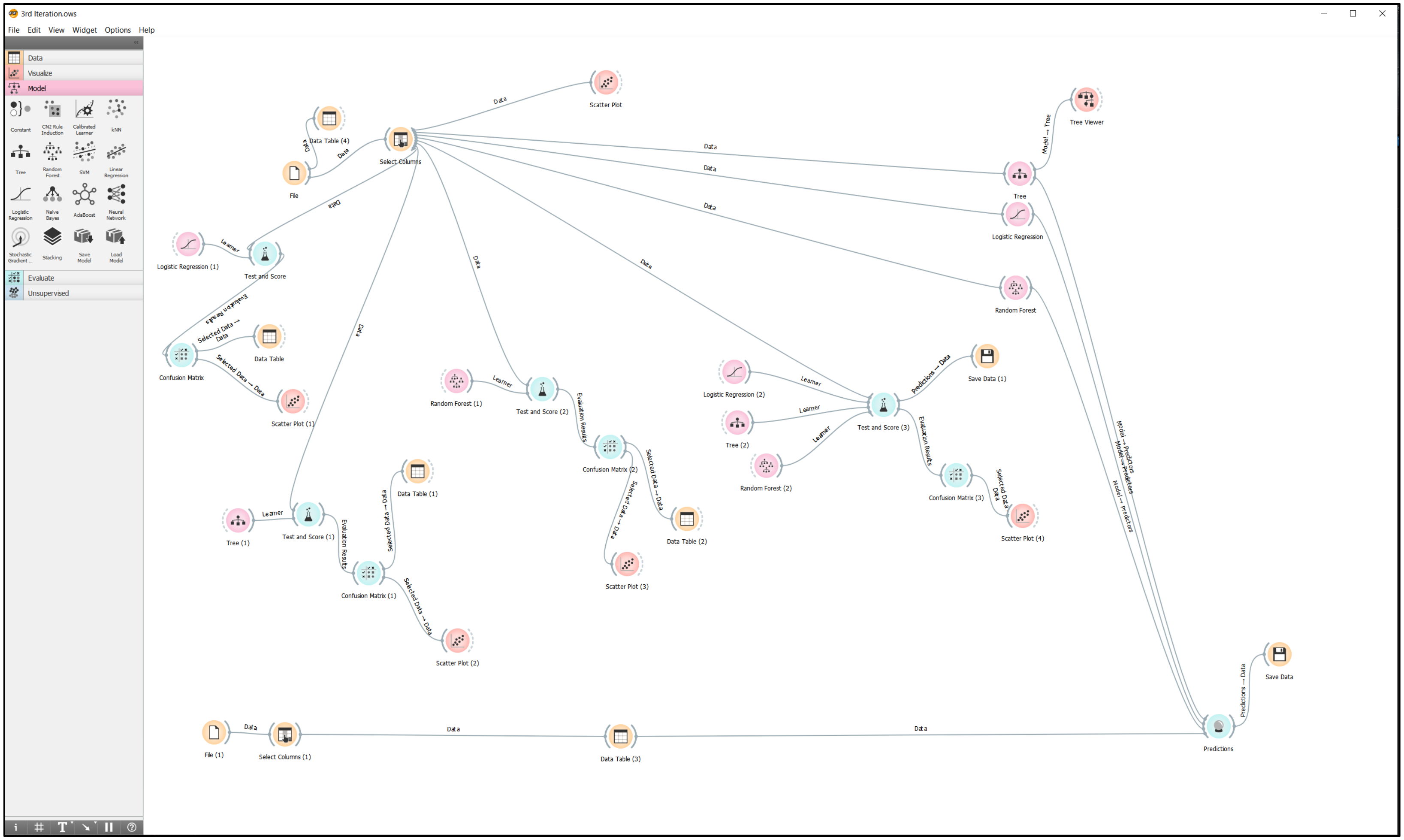

Figure 21. Iterative Workflow from Orange v3.26. Source: Orange (2021).

2. Comparison and ML Technique Evaluation

Multiple ML techniques (forest, random forest, and logistic regression) were utilized to identify the most effective technique in the ML algorithm for predictions supporting decisions on future ship engagements. Each ML technique needed to be tested and scored allowing for comparison using evaluation metrics. Common evaluation metrics include:

- Classification accuracy (CA) is the overall accuracy of the model, meaning how frequently will the ML model be correct.
- Area under the receiver operating characteristic curve (AUC) "provides an aggregate measure of performance … One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example." (Google 2020)
- Precision is a helpful metric "when the costs of false positives are high" (Nicholson, n.d.).
- Recall is beneficial "when the cost of false negatives is high" (Nicholson n.d.).
- F1 is a combination of precision and recall which can provide insight to false positives and false negatives (Nicholson n.d.).

Each evaluation metric has advantages and disadvantages, but overall, the CA is an effective general method as it denotes the true accuracy of the model which informs the viability of using the classification technique for prediction future outcomes. Using the AUC gives the correct proportion of correctly classified data instances. The precision and recall metrics are beneficial depending on the criticality of false positives or false negatives. For the SCT simulations, a false positive would mean the engagement method selected for the incoming swarm was predicted to lose the battle and in fact the Blue Force would have won. False negatives would be predicting the Blue Force victory when in fact the Blue Force would lose, false negatives are more costly in the ML algorithm because a false negative provides the LWS operator bad information which jeopardizes the Ship's survivability. The F1 metric combines precision and recall mathematically as shown in Figure 21, and is a helpful amalgamation of precision and recall.

$$\boxed{F1 = 2 \times \frac{precision \times recall}{precision + recall}}$$

Figure 22. F1 Metric Equation. Source: Nicholson (n.d.).

E. PHASE III: DEPLOYING AND IMPROVING PROCESS

After the training process in Phase II the deploying and improvement process occurred consisting of two main tasks, deployment of the ML algorithm using a selected classification ML technique to predict future engagement outcomes and to iteratively train the ML model to see if further optimization is achievable. Utilizing the metrics for ML technique evaluation the most effective classification technique was found to be tree classification due to the combination of its CA, precision, recall and F1 performance. Random forest classification was the second most effective method with slightly smaller CA, precision, recall and F1 performance. Logistic regression was not nearly as effective as tree or random forest with a lower CA, precision, recall and F1 score. The complete scoring of each ML method is summarized in Figure 23.

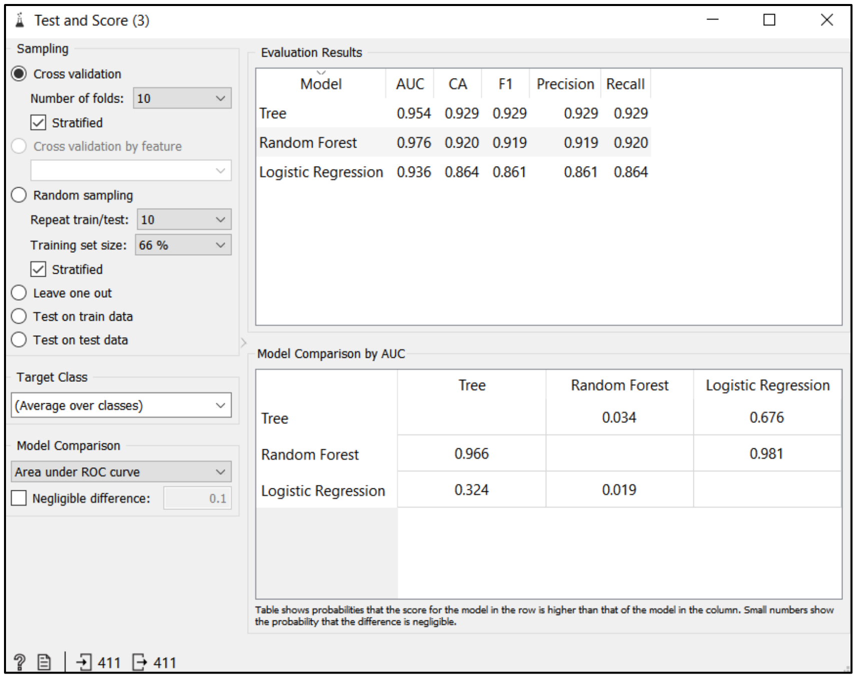

Figure 23. ML Technique Comparison Metrics Orange v3.26. Source: Orange (2021).

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IV. RESULTS AND DATA OPTIMIZATION

A. INITIAL SIMULATION RESULTS SUMMARY

Initial homogenous and heterogenous simulations were generated at random to develop the baseline data to train the ML algorithm, in total 273 simulated baseline battles were run in the SCT software. Overall, the threat engagement methodology is more effective in ensuring a Blue Force victory in terms of ship survival as seen in Table 4. The primary drawback of the threat engagement methodology is that enemy fighters and ISR UAVs are left alone by the Blue Force Ship which in a complex battlespace with multiple Blue Force assets another Blue Force entity would need to engage them tying up additional resources. Ideally, the Proximity engagement would be used to neutralize all enemies provided the Blue Force Operators could determine survivability and success rates prior to the engagement which is the purpose of prediction modeling with ML.

Table 4. Baseline Simulation Scenarios Based on Randomized Engagement Methodology

Engagement Methodology	Number of Simulations	Blue Force Wins	Blue Force Losses	Win Percentage
Proximity	161	106	55	66%
Threat	112	100	12	89%

The initial simulation data was fed into the ML algorithm to train it to identify optimum strategies for successful engagements where the Blue Force survived and while maximizing enemies destroyed. Using the training data, a first iteration model algorithm was developed to serve as a prediction and decision support tool. The ML model provides predictions of combat scenarios and would allow the Blue Force to select the appropriate engagement methodology. Results from the ML optimization follow in Section IV.B.

B. ML ALGORITHM RESULTS

Optimization of engagement methodology using the ML model occurred in two iterations, the first after initial training and the second using the data from the first iteration. Initially, a series of new Blue Force versus Red Force engagements was generated in Excel, again using random quantities and types of UAVs and fed into a prediction tool within Orange which draws on the learned data to provide expected win or loss conditions based on the Blue Force's engagement methodology.

1. First Iteration of ML Prediction

The initial ML prediction based on trained data generated a classification tree sowing the probabilities of Blue Force winning engagements based on the types and quantities of enemy UAVs and the Blue Force engagement methodology (threat or proximity). The classification tree shown in Figure 24 provides a graphical representation of the potential engagement outcomes. This classification tree was generated based on the training data from Table 4.

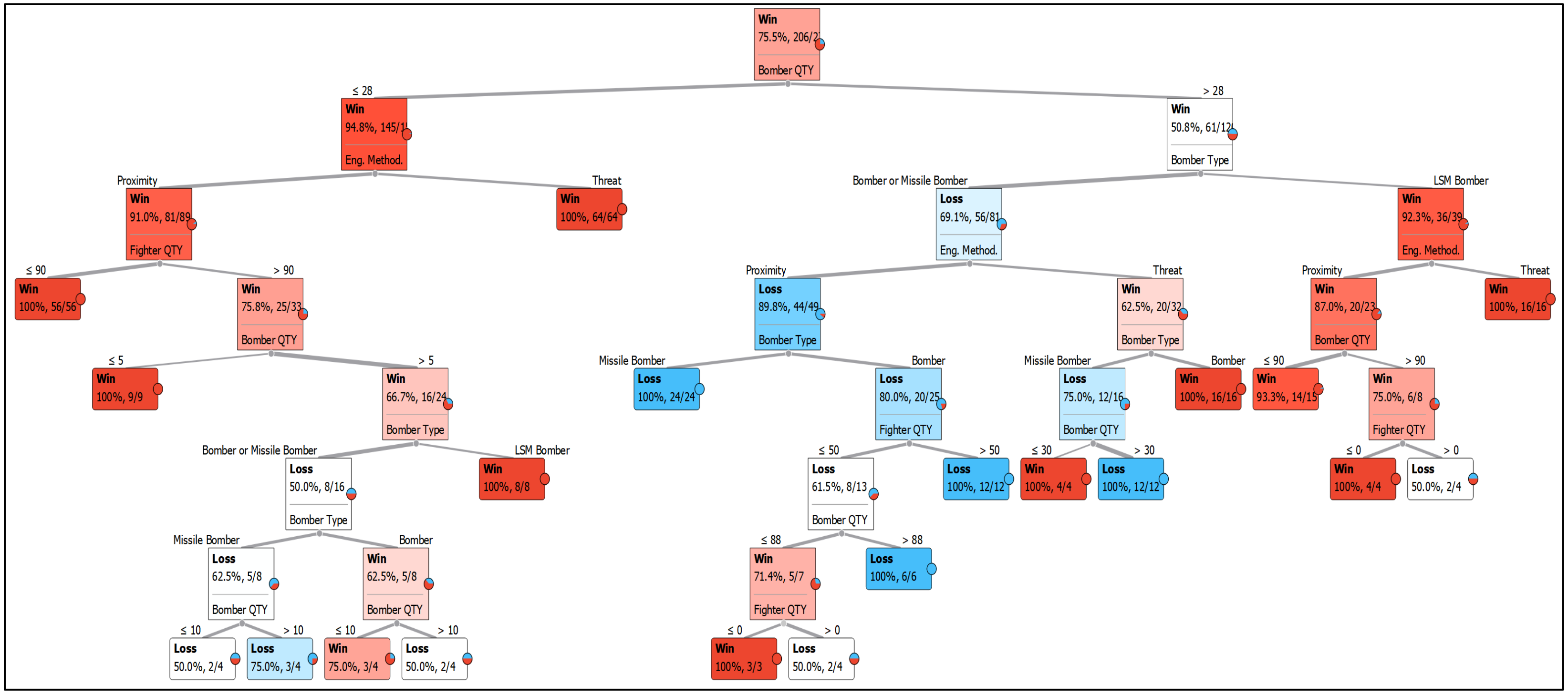

Figure 24. 1st Iteration ML Classification from Orange v3.26. Source: Orange (2021).

Using the randomized Excel generator 69 new scenarios were generated and tested in the ML prediction algorithm in Orange. For the initial prediction run all three classification techniques tree, random forest, and logistic regression were analyzed to confirm that tree classification was in fact the most effective ML technique for simulated SCT data analysis. The results of the ML predictions are presented in Table 5. Overall, the tree classification technique had the fewest false negatives and highest correct threat engagement methodology predictions. The tree classification was less accurate for proximity engagement methodology; however, the ML technique was more conservative than the random forest and logistic regression as evidenced the eight false positives (losses predicted when wins occurred). Overall tree classification is still the most desirable ML technique for predictions of SCT engagements.

Table 5. Initial ML Prediction Results of Simulation Scenarios

Tree Classification						
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positive (predicted loss and win occurred)	False Negative (predicted win and loss occurred)
Proximity	35	27	8	77%	8	0
Threat	34	33	1	97%	0	1
Random Forest						
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positive (predicted loss and win occurred)	False Negative (predicted win and loss occurred)
Proximity	35	29	6	83%	5	1
Threat	34	32	2	94%	0	2
Logistic Regression						
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positive (predicted loss and win occurred)	False Negative (predicted win and loss occurred)
Proximity	35	30	5	86%	3	2
Threat	34	27	7	79%	4	3

2. Second Iteration of ML Predictions

Upon completion of the initial prediction run the model was re-trained using the results from the additional scenarios to ensure the algorithm had access to additional scenarios. The second iteration of predictions was executed using another randomized group of scenarios and the ML algorithm was used to predict the outcome of the simulated engagements. The results of the predictions are provided in Table 6. Once again, a classification tree was generated to provide a graphic representation of what the algorithm had learned, this is shown in Figure 25.

The second iteration prediction run increased the overall correct percentage of Proximity engagement predictions and slightly decreased the threat engagement predictions. Overall, there was also an increase in false negatives. After reviewing the scenario specifics, it was determined that some of the newly developed test scenarios were outside the range of what the ML algorithm had seen. For example, there was a scenario with a large quantity of LSM Bombers with Fighter UAVs which effectively screened the LSM bombers long enough for them to execute a ship kill. Another scenario had twenty-three missile platform bombers and a large quantity of fighters again acting as a screen allowing the ship to be overwhelmed in proximity engagement mode. Both false negative examples represent a gap in the ML algorithm's training, the ML incorrectly predicted victory based on the training data which included homogenous scenarios where both bomber types were easily defeated based on the quantity present. As a result of the decrease in performance the ML algorithm was subsequently trained again with a larger data set to attempt to improve performance.

Table 6. Second Iteration ML Prediction Results of Simulation Scenarios

Tree Classification						
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positive (predicted loss and win occurred)	False Negative (predicted win and loss occurred)
Proximity	43	39	5	91%	1	4
Threat	26	21	4	81%	0	4

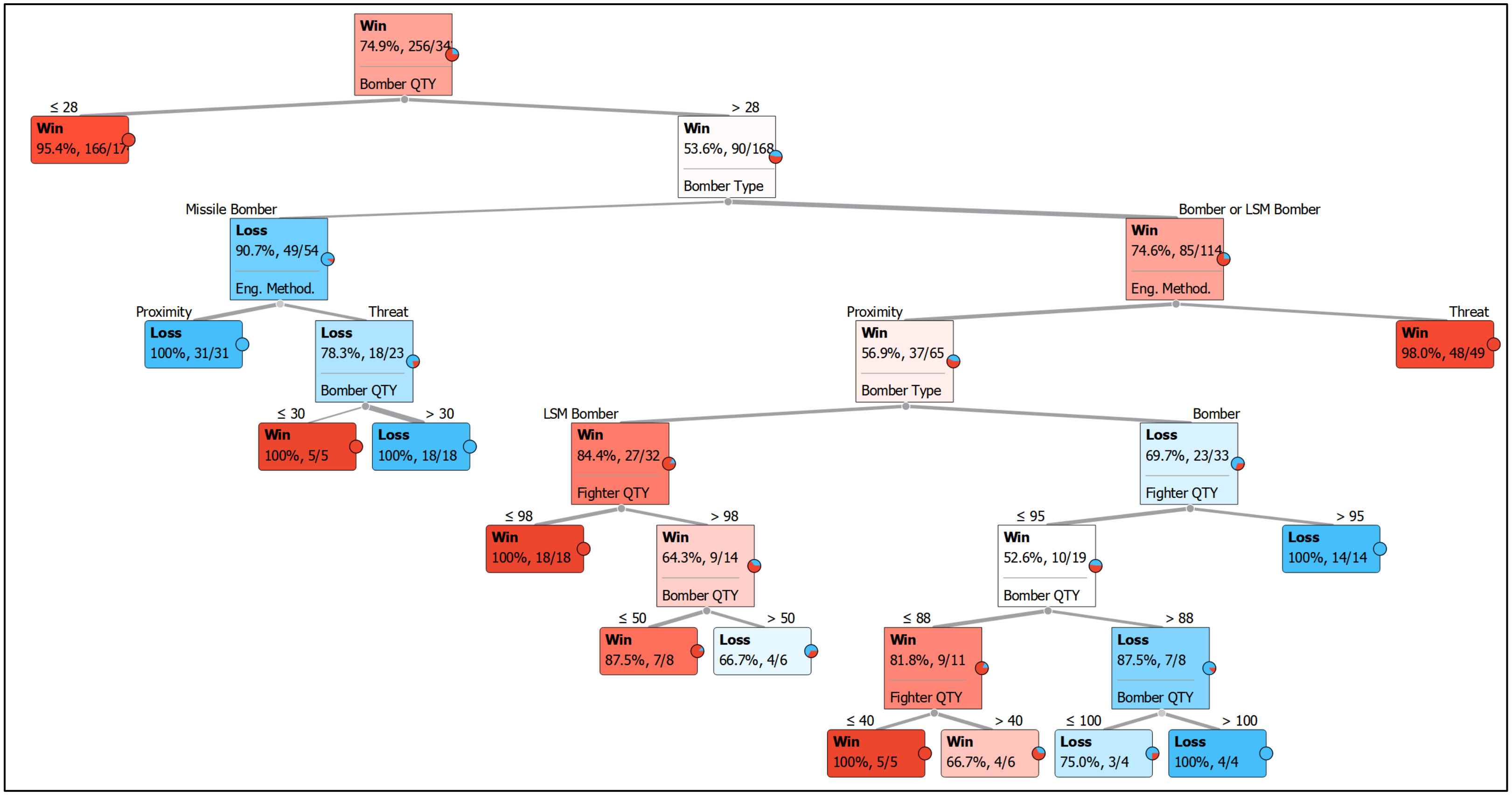

Figure 25. 2nd Iteration ML Classification from Orange v3.26. Source: Orange (2021).

3. Additional ML Optimization and Evaluation

The ML algorithm was retrained using a larger set of simulation data including multiple scenarios where Red Force drone swarm attacks were heterogenous and fighter UAVs were effectively screening for Bomber UAVs. In total, 420 simulation scenarios were used to train the algorithm including all of the baseline scenarios and previously tested prediction scenarios. To demonstrate the improvement in the ML Algorithm, a comparison of the initial ML model and the final ML model is provided below in Table 7 and Table 8. The increased training data and multiple iteration approach greatly improved the prediction accuracy of the ML algorithm. Overall, the multiple iteration approach improved the overall accuracy and reduces the total false negatives and positives.

Table 7. Comparative Results for Prediction of Simulation Scenarios in Orange

Initial Model Accuracy								
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positives	False Positives %	False Negatives	False Negatives %
Proximity	244	218	26	89.3%	22	9.0%	4	1.6%
Threat	176	167	9	94.9%	0	0.0%	9	5.1%
Final Model Accuracy								
Engagement Methodology	Number of Simulations	ML Correct Prediction	ML Incorrect Prediction	Percentage Correct	False Positives	False Positives %	False Negatives	False Negatives %
Proximity	244	229	15	93.9%	8	3.3%	7	2.9%
Threat	176	175	1	99.4%	1	0.6%	0	0.0%

Table 8. Overall Summary ML Model Prediction Accuracy

Model Comparison Summary			
Model	**Accuracy**	**False Negative Occurance**	**False Positive Occurance**
Initial Model	92%	3.1%	5.2%
Final Model	96%	1.7%	2.1%

C. ML ALGORITHM PREDICTIONS AS A DECISION AID SUPPORT TOOL

The training and optimization of the ML provides the foundation for a user decision aid in selecting engagement methodology for SCT simulations. By implementing the ML algorithm to assess an approaching drone swarm, the appropriate engagement technique can be selected. The ML algorithm provides the user with insight as to the optimal engagement strategy. The user would determine based on the ML prediction whether to target the threats, the UAV bombers, or target all enemies based on proximity and this engagement decision would support the most enemy kills while prioritizing the ship's survival. The ML algorithm has reduced the cognitive load on the system user by quantifying the courses of action in terms of most likely outcome for complex heterogenous drone swarms.

V. CONCLUSION

A. SUMMARY

This research studied the combination of simulated wargaming and ML as a proof of concept and as a foundation for a decision support tool. To accomplish this goal multiple ML techniques were tested using simulated LWS engagements to determine if ML could support automated decision aids based on simulated data. Overall, ML techniques were evaluated to support engagement methodology analysis for use with a simulated LWS to defend against complex drone swarm threats effectively. Experimentation demonstrated the application of ML to this problem domain through modeling and simulation and ML algorithm training. Results from the ML algorithm predictions had an overall accuracy of 96% in predicting engagement outcomes based on enemy types and quantities, and LWS attack methodology. The ML algorithm predictions had false positives (a predicted win that was actually a loss) 2.1% of the time. These results demonstrate that a complex battle space simulation software can be used to accurately train a predictive ML algorithm.

The thesis demonstrates that a research approach that combines wargaming simulations with the development of ML algorithms provides a mechanism for studying and supporting the use of automation and AI techniques for supporting complex decisions and engagements. By implementing a trained ML algorithm, it is possible to analyze a complex battlespace with a heterogenous drone swarm so the appropriate engagement technique can be selected thereby optimizing the survivability and effectiveness of target engagement. The thesis addressed the research objective by demonstrating the efficacy of ML as a method to identify and support effective target selection and engagement methods for a simulated shipboard LWS defending against UAV swarm threats. This research represents a fundamental building block for the development of an automated decision aid to support future warfighters operating laser weapon systems.

B. FUTURE RESEARCH OPPORTUNUTIES

There are multiple future research opportunities in the implementation of ML to support warfighter engagement decisions, the two primary areas are testing expanded simulations and engagements to create more complex ML algorithms and developing ML optimized decision aids integrated with user interfaces that can be tested in simulated wargaming environments.

Expansion of the ML training and simulated engagements could be conducted in SCT to generate scenarios on a larger scale with multiple Blue Force assets with distinct missions. Multi-ship engagements and multi-domain engagements with land, sea, and air systems working together could be developed to support large scale wargaming scenarios which create an opportunity to generate complex data. The more complex multi-asset simulations could be used to train ML algorithms to support target engagement decisions across multiple platforms (ships, aircraft, and ground systems). The SCT software is constantly growing and expanding as it is upgraded with new systems, capabilities, and enticements. The adaptability of SCT allows for programming to establish specific environments including blue ocean, islands, and land engagements.

Development of decision aids using trained ML algorithms presents a unique opportunity to test the utility of ML algorithms in a tactical application. Further research could be conducted to take a ML algorithm and build it into the wargaming software to provide a user interface for making tactical decisions in a simulated environment. This represents the next step in bringing this research into practical applications by providing mock warfighters with tactical decision aids based on simulated engagements with the objectives of reducing the cognitive load on warfighters and ensuring they have the tools and capabilities to execute missions rapidly and effectively.

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