NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

SYSTEMS ENGINEERING CAPSTONE REPORT

LEVERAGING ARTIFICIAL INTELLIGENCE (AI) FOR AIR AND MISSILE DEFENSE (AMD): AN OUTCOME-ORIENTED DECISION AID

by

Julian I. Jones II, Russell Kress, William J. Newmeyer Jr., and Adam I. Rahman

September 2020

Advisor: Bonnie W. Johnson

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REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
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1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** September 2020	**3. REPORT TYPE AND DATES COVERED** Systems Engineering Capstone Report	
4. TITLE AND SUBTITLE LEVERAGING ARTIFICIAL INTELLIGENCE (AI) FOR AIR AND MISSILE DEFENSE (AMD): AN OUTCOME-ORIENTED DECISION AID			**5. FUNDING NUMBERS**
6. AUTHOR(S) Julian I. Jones II, Russell Kress, William J. Newmeyer Jr., and Adam I. Rahman			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.			**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

The military has recognized the need for automated decision aids to support battle management as warfighters become overwhelmed by shorter decision cycles, greater amounts of data, and more technology systems to manage. To date, much emphasis has focused on data acquisition, data fusion, and data analytics for gaining situational awareness in the battle space. However, a new frontier and opportunity exists for using this data to develop decision options and predict the consequences of military courses of action. This project studied the application of artificial intelligence (AI) to improve battle management decisions in the time-sensitive air and missile defense (AMD) environment. Specifically, this project studied current and future AI applications to the AMD kill chain with a model-based systems engineering (MBSE) approach. The team modeled the AMD kill chain by allocating time to the various kill chain functions and decisions, based on the time afforded by the incoming AMD threat. The team used simulations to analyze and demonstrate the use of automation in the kill chain functions to expedite decisions and improve AMD battle management.

14. SUBJECT TERMS artificial intelligence, AI, decision aids, air and missile defense, AMD, model-based systems engineering, MBSE			**15. NUMBER OF PAGES** 145
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

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Submitted in partial fulfillment of the
requirements for the degrees of

MASTER OF SCIENCE IN ENGINEERING SYSTEMS

and

MASTER OF SCIENCE IN SYSTEMS ENGINEERING

from the

NAVAL POSTGRADUATE SCHOOL
September 2020

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ABSTRACT

The military has recognized the need for automated decision aids to support battle management as warfighters become overwhelmed by shorter decision cycles, greater amounts of data, and more technology systems to manage. To date, much emphasis has focused on data acquisition, data fusion, and data analytics for gaining situational awareness in the battle space. However, a new frontier and opportunity exists for using this data to develop decision options and predict the consequences of military courses of action. This project studied the application of artificial intelligence (AI) to improve battle management decisions in the time-sensitive air and missile defense (AMD) environment. Specifically, this project studied current and future AI applications to the AMD kill chain with a model-based systems engineering (MBSE) approach. The team modeled the AMD kill chain by allocating time to the various kill chain functions and decisions, based on the time afforded by the incoming AMD threat. The team used simulations to analyze and demonstrate the use of automation in the kill chain functions to expedite decisions and improve AMD battle management.

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LIST OF ACRONYMS AND ABBREVIATIONS

AI-AMD	artificial intelligence for air and missile defense
AiTR	aided target recognition
ATCCS	Army Tactical Command and Control System (ATCCS)
AEC	Army Evaluation Center
AD	air defense
AWS	Aegis Weapon System
AI	artificial intelligence
ATLAS	Advanced Targeting and Lethality Automated System
AMD	air and missile defense
BETA	Battlefield Exploitation and Target Acquisition
BFT	blue force tracker
BLUFOR	blue forces
BMDS	Ballistic Missile Defense System
C5ISR	Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance and Reconnaissance
CCDC	Combat Capabilities Development Command
CEC	cooperative engagement capability
CIWS	Close-In Weapon System
COA	course of action
CONOPS	concept of operations
C-RAM	counter-rocket, artillery, mortar
CTA	cognitive task analysis
CTP	common tactical picture
CWA	cognitive work analysis
DAC	Data and Analysis Center
DFIG	Defense Fusion Information Group
DOD	Department of Defense
DODAF	Department of Defense Architectural Framework
DOE	design of experiments

F2T2EA	find, fix target, track, engage, and assess
HPT	high priority target
HSI	human system integration
HVT	high value target
IAMD	Integrated Air and Missile Defense
ICOM	inputs, constraints, outputs, and mechanisms
IPR	in progress review
JAIC	Joint Artificial Intelligence Center
JAMS	Joint Attack Munition System
JDL	Joint Directors of the Laboratories
JP	Joint Publication
LCMR	Light-weight Counter Mortar Radar
LML	Life cycle modeling language
LOAT	level of automation taxonomy
LOE	line of effort
LPWS	Land-based Phalanx Weapon System
M&S	modeling and simulation
MBSE	model-based systems engineering
MDA	Missile Defense Agency
MDAA	Missile Defense Advocacy Alliance
MDO	Multi-Domain Operations
MCPP	Marine Corps planning process
ML	machine learning
NAI	named area of interest
NASA	National Aeronautical and Space Administration
NAVAIR	Naval Air Systems Command
NCARAI	Navy Center for Applied Research in Artificial Intelligence
NPS	Naval Postgraduate School
NVESD	Night Vision and Electronic Sensors Directorate
OODA	observe, orient, decide, act

OPNAV	Office of the Chief of Naval Operations
OV	operational viewpoint
PAC 3	Patriot Advanced Capability 3
REDFOR	red forces
SA	situational awareness
SE	systems engineering
SM	standard missile
SoS	systems of systems
STSS	Space Tracking and Surveillance System (STSS)
SV	system viewpoint
THAAD	Terminal High Altitude Area Defense
TOW	Tube-launched, Optically-tracked, Wireless-guided
TPO	Thesis Processing Office
TRADOC	U.S. Army Training and Doctrine Command
TST	time sensitive target
TTPs	tactics, techniques and procedures
UAV	Unmanned aerial vehicle
UEWR	Upgraded Early Warning Radars
U.S.	United States

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EXECUTIVE SUMMARY

As current trends in Naval Warfare shift toward automated combat weapons systems, the U.S. Navy is focusing its strategies toward artificial intelligence (AI) capabilities that reduce the time a warfighter needs to act decisively. This systems engineering (SE) project represented the human-AI decision process using John Boyd's concept of observe, orient, decide, and act (OODA) and the Marine Corps Planning Process (MCPP) (Angerman 2004; U.S. Department of the Navy 2016). The Air and Missile Defense (AMD) kill chain was represented with a simplification of Joint targeting doctrine, JP 3-60 (Joint Chiefs of Staff 2018). Increased levels of automation for operational activities within the kill chain process were demonstrated to significantly reduce the execution timeframe, which, if further developed and fielded, will provide Sailors and Marines a tactical advantage in air defense. Expediting the kill chain through the use of expert systems and AI will greatly shorten engagement times effectively expanding the battle space.

This project developed the AI for Air and Missile Defense (AI-AMD) architecture which was designed to improve warfighting decisions by prioritizing threats and acting upon them with minimal input from human users. The project focused on understanding and evaluating the Air Missile Defense (AMD) kill chain by identifying steps in the process that can be executed faster using AI-AMD. The project team identified and evaluated risks associated with AI-AMD levels of automation as applied to the various steps in the kill chain process. The team performed a modeling and simulation (M&S) analysis to compare the kill chain at low levels of automation ("without" AI) with the kill chain at high levels of automation ("with" AI), by assessing improvements based on time saved. The team developed concepts for highly automated AI-AMD decision aid operational capabilities based on the M&S analysis and identified existing and future AI methods with potential application to the future AI-AMD architecture.

The team conducted an architecture analysis following the Department of Defense Architectural Framework (DODAF) to determine operational activities of AI-AMD. The team applied a model-based systems engineering (MBSE) approach using the SE tool

Innoslate to develop the conceptual architecture. The architectural analysis combined blue force (BLUFOR) air defense sensors, weaponry, and the Joint network to create an OV-5b/6c action diagram that depicts the AI-AMD decision aid outputs working in conjunction with JP 3-60 Joint Targeting process steps to neutralize enemy threats (Joint Chiefs of Staff 2018). To complete its mission, the BLUFOR system of systems (SoS) executes 36 operational activities: 17 decision points internal to AI-AMD and 19 functions of external systems (including sensor actions and network communication). The team analyzed the results of the architectural analysis using a design of experiment (DOE), discrete event, and stochastic simulation that revealed that high-stress AMD scenarios during the targeting process require full levels of automation while low-stress AMD scenarios require minimum levels of automation. The team developed a decision risk matrix that showed that risks involved with high-stress scenarios can be lowered with full levels of automation. The risk assessment for each of the 17 steps in the targeting process were categorized into four categories: low, moderate-low, moderate, and high. The team developed an associated risk value to make the risk assessment determination. The team leveraged Parasuraman's levels of automation (levels 1-10) to perform the risk assessment which associated decision risk with the levels of automation for individual steps within the targeting process (Parasuraman, Sheridan, and Wickens 2000). The team developed and employed a utility curve to assist in determining the time savings for each level of automation. For example, greater time savings were associated with higher levels of automation.

The project focused on single threat engagements to understand the AI-AMD timing in the kill chain process. The team conducted M&S analyses to demonstrate the capabilities of the AI-AMD architecture. The team performed a discrete event simulation using the Innoslate MBSE tool and Microsoft Excel. The team used Excel to evaluate the meta-model prior to investing heavily in the action diagrams. The primary focus of the simulation was to establish the timing performance of AI-AMD at various stress levels such as low, moderate, and high. The secondary goal was to develop the model as a deliverable design tool to be used at NPS for future studies. The team selected three representative engagements from open source threat data: a low-stress scenario (with a 58.65-minute timeline), a moderate-stress scenario (with a 9.72-minute timeline), and a high-stress scenario (with a 1.51-minute timeline). The results of the team's M&S analysis revealed that human-only decision making (level of automation 1) in the low-stress scenario resulted in a 100% successful AMD kill rate against enemy threats with a fly-in time of 58 minutes or higher. For the moderate threat scenario (representing AI-AMD with various levels of automation (e.g., 6 through 10) for each operational activity decision node), the data results of 1,000 stochastic runs showed an average of 8.08 minutes of completion time for all engagements. When the AI-AMD system was set with the higher levels of automation, the system was successful in its AMD defense in the moderate threat scenario. The decomposed timeline for the high-stress scenario allowed for 0.09 minutes per operational activity decision node. The team set the AI-AMD system to AI-only decision making (level of automation 10) for the high-stress scenario. The results from the high-stress scenario indicated potential success against enemy threats given level 10 automation. The team conducted a sensitivity analysis to explore the impact of alternative underlying representative distributions (baseline, symmetric variable spread, and highly skewed). While changes in distribution shape did impact results, in every case, success within the high-stress scenario only occurred with AI-enabled savings greater than 97%.

This project investigated how AI methods can apply to AMD decision making to increase levels of automation and reduce the execution time of a human-AI team (an AI-enabled decision aid). The team analyzed the AMD kill chain from the top down: from OODA to find, fix, track, target, engage, and assess (F2T2EA). The team identified 17 key decision points where increased levels of automation can improve the speed of AMD decision-making. The potential levels of automation were balanced against risks associated with each of the various steps. The team used M&S to evaluate the timeliness of decisions made within the AI-AMD system at low levels of automation ("without" AI) through high levels of automation ("with" AI). The resulting high-level capabilities of the AI-AMD conceptual architecture were documented with recommendations for stakeholder consideration as the system technologies mature. The team identified existing and future AI methods and their potential applications to the AMD kill chain. The team has identified the need for future iterations of AI-AMD to study more complex situations with multiple threats and engagement across the entire battlefield.

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ACKNOWLEDGMENTS

In the hope that the conceptual architecture design herein reduces lives lost on the battlefield and at sea, we dedicate this project to the personnel of the United States Armed Forces. We would like to acknowledge the Office of the Chief of Naval Operations (OPNAV) N2/N6 and Naval Air Systems Command (NAVAIR) Weapons Division for identifying the strategic importance this project could have for our forces and affording us the opportunity to explore its potential. The team would like to recognize the advisors, stakeholders, and professors at the Naval Postgraduate School (NPS); their knowledge and support helped guide this project to success. We appreciate our supervisors and co-workers who facilitated the balancing of this milestone with organizational needs. Lastly, our team would like to deeply thank our families who patiently supported our efforts through the many long days and nights, allowing us to achieve this prestigious goal.

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I. INTRODUCTION

A. STATEMENT OF NEED

The U.S. military has recognized the need for automated decision aids to support battle management as warfighters become overwhelmed with shorter decision cycles, greater amounts of data, and more technology systems to manage (Galdorisi 2019). To date, much emphasis has focused on data acquisition, data fusion, and data analytics for gaining situational awareness in the battle space. However, a new frontier and opportunity exists for using this data to develop decision options and predict the consequences of a military course of action (COA). This project studied the application of artificial intelligence (AI) and cognitive analytics to improve situational awareness and battle management decisions in the air and missile defense (AMD) domain using Boyd's observe, orient, decide, act (OODA) loop.

AI technology has the potential to improve warfighting decisions by prioritizing threats and operational missions; determining COAs based on distributed warfare capabilities and their expected performance; and incorporating predictions of consequences into the decision loop (Cronk 2019). AI predictive analytic methods could form the basis of a near-real-time war-gaming capability to support military tactical operations as well as bridge the gap between the planning and tactical domains. This study developed decision aid capabilities at various levels of automation for conceptual AI-enabled battle management tools. The team studied existing and future AI methods with decision-making application including machine learning, deep learning, cognitive processing, and intelligent data analytics. To create system-level architectures for use in this engineering project, the team drew upon the general knowledge of sensors, air defense systems, the human cognitive / decision-making processes, and the respective performance of each system of systems (SoS) element. The team developed a conceptual decision agent system, referred to as artificial intelligence for air and missile defense (AI-AMD), throughout this document.

1. Problem Statement

There is a need for warfighter decisions to be made faster during AMD operations. The AMD mission space is a complex and time-sensitive arena that requires decisions to be made much faster than when employing traditional methods against advanced threats. Untimely decisions can mean catastrophic results if the threats are not fully addressed. Another area of concern is the limitation on the number of blue force weapons available and the cost of those weapons. With a limited quantity of weapons, decisions and COAs must be made to most effectively and efficiently resolve the threat. The complex battlefield also includes various blue force assets that must be fully coordinated during AMD operations to account for potential friendly fire accidents. Decision making involves a wide range of data that is a combination of known and unknown information, information overload, incomplete data, erroneous sensor data, terrain or environmental limitations, and coordination among various blue force assets in a multi-domain scenario. Each of these data sources continuously evolves throughout the kill chain and it is important to also be aware that the advanced enemy threat is constantly modifying its COAs as new information becomes available. All of these factors led the team to understand how automated decision aids and AI methods can best support and improve AMD decisions.

2. Project Objectives

This project investigated how AI methods can apply to AMD decision making by reducing the execution time of a human-AI team (termed an AI-enabled decision aid). The team leveraged the metrics by which decisions are evaluated to develop conceptual architectures for AI-AMD.

The team developed the following project objectives:

- understand and evaluate the AMD kill chain to identify steps in the process that can be executed faster using AI-AMD
- determine risks associated with AI-AMD levels of automation as applied to the various steps in the kill chain process

- utilize modeling and simulation (M&S) to compare the kill chain at low levels of automation ("without" AI) through high levels of automation ("with" AI), and assess improvements based on time saved.

- develop high level decision aid operational capabilities from the M&S analysis for AI-AMD and conceptual designs for AI-enabled decision superiority

- identify existing and future AI methods and apply them to the AI-AMD kill chain.

B. BACKGROUND AND PROBLEM MOTIVATION

The U.S. Department of Defense (DOD) seeks intelligent machines to enable smarter decision-making capabilities for troops in dynamic combat environments. These capabilities will reduce processing time to "decide faster" by taking advantage of the digital battlefield (Pomerleau 2017). The DOD continues to improve upon its ability to collect data and the next logical step is to process the data to provide near real time COAs to the operator. This will reduce the cognitive burden on the operator and eliminate mundane tasks that can be automated. The DOD emphasizes multi-domain operations (MDO) with the ability to intelligently integrate air, land, sea, and dismount using AI to reduce the kill-chain timeline (U.S. Army Training and Doctrine Command [TRADOC] 2018).

AMD scenarios are of particular interest due to the wide variety of threat characteristics (e.g., tactics, speed, maneuverability, and explosive yield). Per the summary of the 2018 National Defense Strategy regarding missile defense and Joint lethality in contested environments, "Investments will focus on layered missile defenses and disruptive capabilities for both theater missile threats and North Korean ballistic missile threats…The Joint Force must be able to strike diverse targets inside adversary air and missile defense networks to destroy mobile power-projection platforms. This will include capabilities to enhance close combat lethality in complex terrain" (U.S. Department of Defense [DOD] 2018, 6).

The motivation for this project was to apply systems engineering (SE) best practices to understand how increased automation and the application of AI can improve AMD decision-making. The team developed an architecture, framework, and model for analyzing proposed AI-AMD implementation strategies. The project's stakeholders included the Office of the Chief of Naval Operations (OPNAV) N2/N6 (focusing on the use of AI for air and missile defense applications) and Naval Air Systems Command (NAVAIR) Weapons Division (researching the use of AI for automated decision aids for weapon engagements). In a more global sense, the U.S. National Defense Strategy (2018) recognizes the need for AI to compete with near-term competitors who are making significant investments in modernizing their military including the realm of AI. Consequently, the DOD launched its Artificial Intelligence Strategy "to adopt AI to maintain its strategic position to prevail on future battlefields and safeguard a free and open international order" (Cronk 2019). Therefore, the DOD has a vested interest to develop the next generation AI throughout all military branches as an overarching stakeholder.

C. PROJECT PLAN AND DELIVERABLES

1. Work Plan

As this project occurred early in the AI-AMD system life cycle (within the conceptual system engineering design phase, prior to preliminary design), the team's initial task was to create a methodology to support the development of operational system capabilities. To do so, the team leveraged a framework presented by Blanchard and Fabrycky (2011) (refer to Figure 1). The project need was identified by the stakeholders for an approach to support battle management decisions involving many technological systems, large amounts of data, and short timelines. The team performed quantitative and qualitative analysis to develop the representative AMD concept of operations (CONOPS) and to synthesize several alternative conceptual AI-AMD architectures. The team modeled these architectures and ran simulations to facilitate a comparative analysis of capability. The team evaluated results, developed key lessons learned, and fed these results back into the iterative process as appropriate.

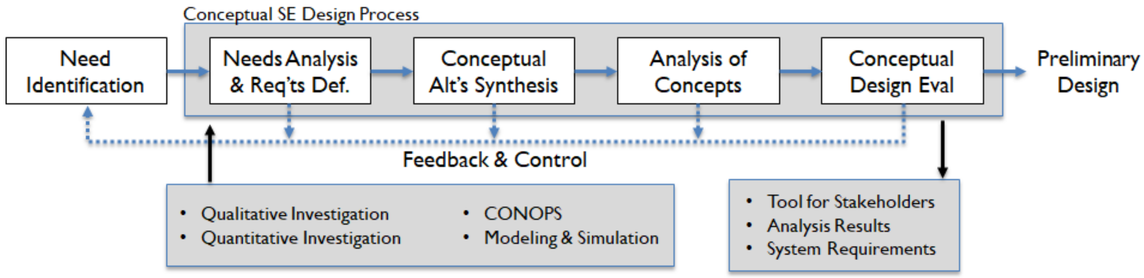

Figure 1. Conceptual Systems Engineering Design Process. Adapted from Blanchard and Fabrycky (2011, 103).

Figure 2 illustrates a harmonized development process within systems engineering: "system design requires both integration and iteration" (Blanchard and Fabrycky 2011, 41). These steps of synthesis, analysis, and evaluation were the feedback relationships across major elements of conceptual system architecting and formed the basis for comparison of potential functional architectures. Outcomes of this portion of the process fed detailed functional analysis and set the foundation for preliminary design baselines in follow-on stages of AI-AMD system development. The stakeholders may choose to reuse the resulting M&S tool with data reflecting their specific combat-oriented scenarios to generate additional unique requirements.

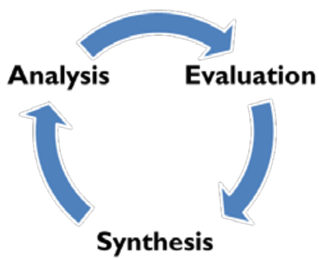

Figure 2. SE Harmonized Development Process. Adapted from Blanchard and Fabrycky (2011, 43).

An implied goal of this project was to develop potential architectures for an AI-AMD system to inform system capabilities by reducing the time it takes for AMD execution. To achieve this deliverable, the project activities with defined inputs, constraints, outputs, and mechanisms (ICOM) were derived from the conceptual SE design process elements. The project activities are illustrated in Figure 3.

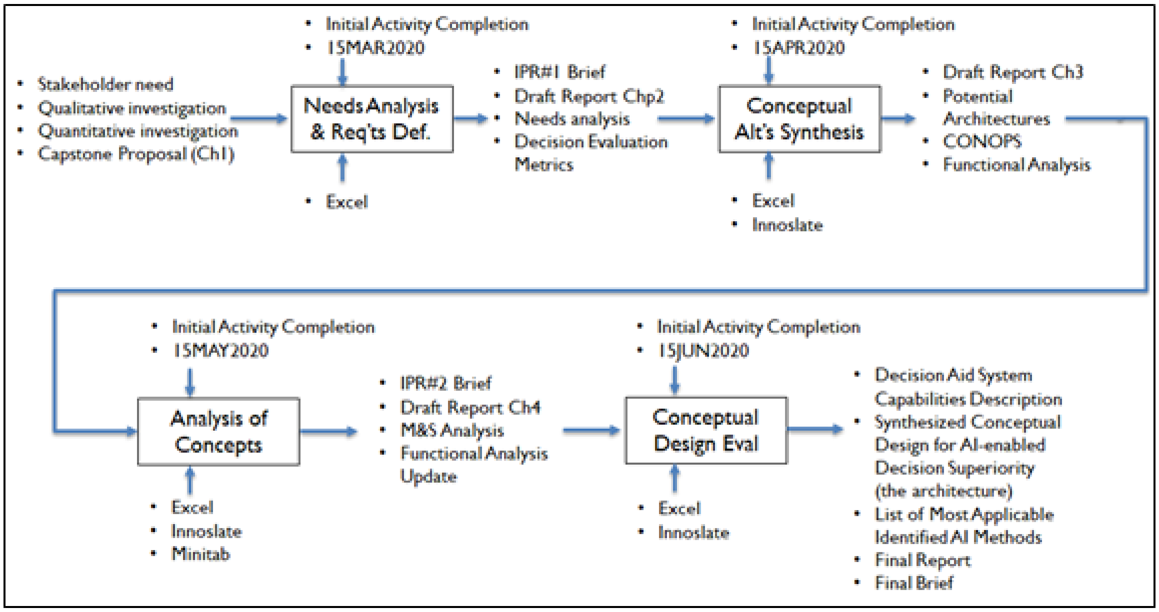

Figure 3. AI-AMD Project Activities ICOM

2. Project Milestones and Timeline

The project milestones for the team are shown in Table 1. The winter quarter focused on understanding the problem, preparation for the first in progress review (IPR), Chapter I, and an outline of the report. The spring quarter focused on an expanded literature review, architecture analysis, Chapter II, and the second IPR. The summer quarter focused on the design of experiments (DOE), M&S, analysis, and finalizing the project report.

Table 1. Project Milestones

Task Name	Duration	Start	Finish
Artificial Intelligence - Outcome Oriented Decision Aid (AI-OODA)	**186 days**	**Thu 1/9/20**	**Fri 9/25/20**
Weekly Group Meetings (2100 EST)	**171 days**	**Mon 1/27/20**	**Mon 9/21/20**
Weekly meetings with advisor (1300 EST)	**186 days**	**Thu 1/9/20**	**Thu 9/24/20**
Winter Quarter	**57 days**	**Thu 1/9/20**	**Fri 3/27/20**
Name/Roles/Initial Investigation Due	7 edays	Thu 1/9/20	Thu 1/16/20
Background/Schedule	7 edays	Thu 1/16/20	Thu 1/23/20
Complete Project Proposal to Advisor	7 edays	Thu 1/23/20	Thu 1/30/20
Finalize Project Proposal for Approval	8 edays	Thu 1/30/20	Fri 2/7/20
Proposal Approved	0 days	Tue 2/18/20	Tue 2/18/20
Needs Analysis	14 edays	Fri 2/7/20	Fri 2/21/20
Define Decision Metrics	14 edays	Thu 2/27/20	Thu 3/12/20
In Progress Review (IPR) #1 Preparation	7 edays	Thu 3/12/20	Thu 3/19/20
IPR #1	0 edays	Thu 3/19/20	Thu 3/19/20
Report Outline and Chapter 1 Draft	25 edays	Mon 3/2/20	Fri 3/27/20
Spring Quarter	**75 days**	**Thu 4/2/20**	**Thu 7/16/20**
Report Chapter 1	14 edays	Thu 4/2/20	Thu 4/16/20
Literature Review	27 edays	Thu 4/2/20	Wed 4/29/20
Report Chapter 2	41 edays	Thu 4/2/20	Wed 5/13/20
Model Development in Innoslate	28 edays	Wed 5/13/20	Wed 6/10/20
Scenario Development	14 edays	Wed 6/10/20	Wed 6/24/20
DoDAF Architecture Development	14 edays	Wed 6/10/20	Wed 6/24/20
Report Chapter 3	14 edays	Thu 7/2/20	Thu 7/16/20
IPR #2 Preparation	7 edays	Thu 6/25/20	Thu 7/2/20
IPR #2	0 days	Thu 7/2/20	Thu 7/2/20
Summer Quarter	**56 days**	**Thu 7/9/20**	**Fri 9/25/20**
Finalize Innoslate Model	14 edays	Thu 7/2/20	Thu 7/16/20
Modeling and Simulation	15 edays	Thu 7/9/20	Fri 7/24/20
Refine Decision Aid Capabilities	11 edays	Mon 7/13/20	Fri 7/24/20
Identify AI Methods	11 edays	Mon 7/13/20	Fri 7/24/20
Report Chapters 4 and 5 Draft	22 edays	Thu 7/2/20	Fri 7/24/20
Draft Complete Report to Advisor	33 edays	Thu 7/9/20	Tue 8/11/20
Initial Draft to Thesis Processing Office	11 edays	Mon 7/13/20	Fri 7/24/20
Editing as required	18 edays	Fri 7/24/20	Tue 8/11/20
Final Draft to Heather Hahn	0 days	Tue 8/11/20	Tue 8/11/20
Final Editing	31 edays	Tue 8/11/20	Fri 9/11/20
Final Draft to Thesis Processing Office	0 days	Fri 9/11/20	Fri 9/11/20
Final Briefing Preparation	70 edays	Thu 7/9/20	Thu 9/17/20
Final Briefing	0 days	Thu 9/17/20	Thu 9/17/20
Graduation	0 days	Fri 9/25/20	Fri 9/25/20

The timeline for the project can be seen in Figure 4. The project began in January 2020 starting with initial investigation and project refinement and concluded in September 2020 with the completion of this document.

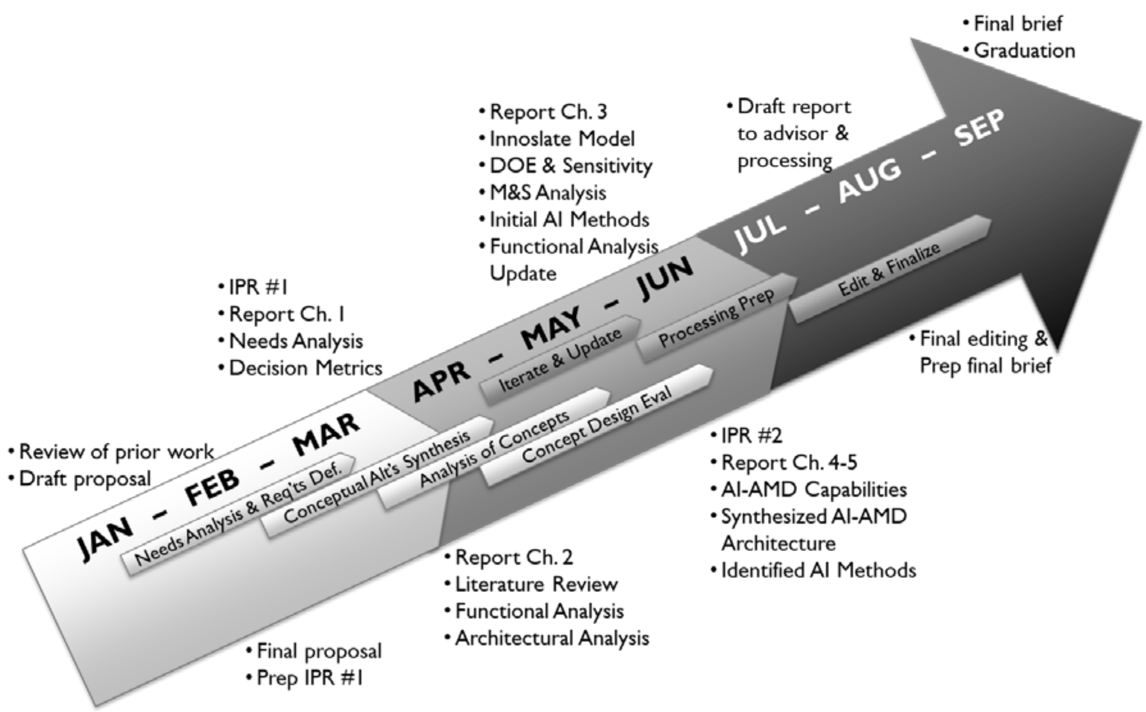

Figure 4. Project Timeline

3. Team Structure

Table 2 outlines the team members supporting the project, the roles of each member, and their respective organizations. The team consisted of a diverse group of engineers who provided a wide range of expertise in the systems engineering field and specialty areas. Roles included team lead, systems engineering lead, chief editor, and architecture lead; all conducted supporting analysis.

Table 2. Project Team Membership

Team Member	Role	Organization
J. Isaac Jones	Team Leader	Mechanical engineer and data scientist at the Combat Capabilities Development Command (CCDC) Data and Analysis Center (DAC) in Aberdeen Proving Ground, MD
Russell Kress	Systems Engineering Lead	Mechanical engineer and senior test manager at the Army Evaluation Center (AEC) in Aberdeen Proving Ground, MD
William Newmeyer	Chief Editor	Quick Response Branch Chief at the CCDC Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance and Reconnaissance (C5ISR) Center Night Vision and Electronic Sensors Directorate (NVESD) in Fort Belvoir, VA
Capt Adam Rahman	Architecture Lead	Communications Officer, Marine Wing Communications Squadron-38, Marine Air Control Group-38, 3rd Marine Air Wing, United States Marine Corps

4. Team Roles

Figure 5 depicts the organizational structure for the team along with specific responsibilities for each member of the group. The team recognized that all members were critical to executing this project involving analysis, M&S, and documentation.

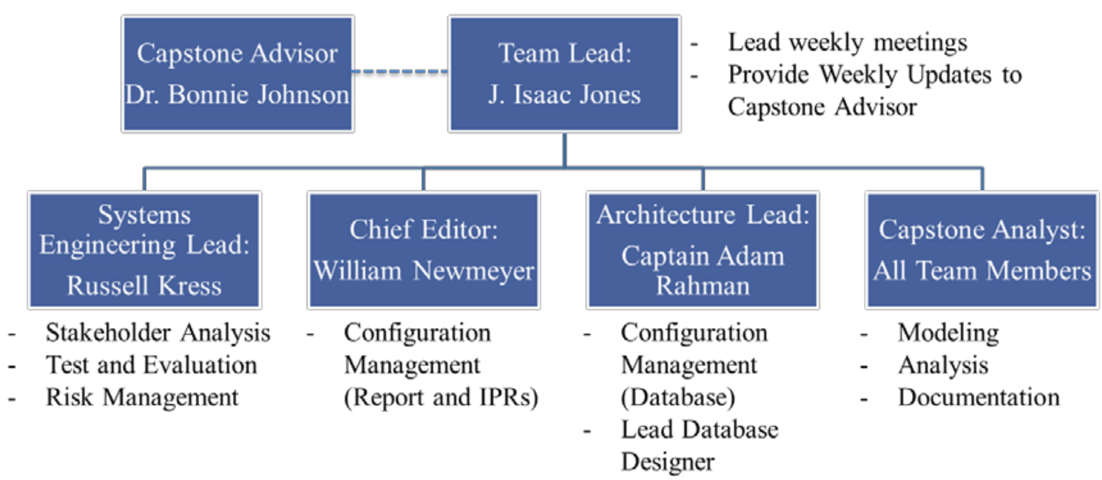

Figure 5. Team Roles

D. BENEFIT OF THE STUDY

The DOD seeks to use AI capabilities to increase the operational effectiveness of the military by addressing critical challenges that the United States is facing in today's modern combat scenarios. Per the DOD AI strategy, the key areas of AI applications are to "improve situational awareness and decision-making," "increase safety of operating equipment," "implement predictive maintenance and supply," and "streamline business processes" (Cronk 2019).

The U.S. Navy is addressing how to utilize its collected data and to pursue the next logical progression of analyzing the data to inform decisions. In an article from the U.S. Naval Institute, "the Navy knows it needs big data, artificial intelligence, and machine learning, but it still is grappling with what it wants AI to do. This must change if the Navy is going to reap the benefits of these emerging technologies" (Galdorisi 2019). To achieve this goal, The Navy established *A Design for Maintaining Maritime Superiority 2.0* which outlines a line of effort (LOE) to achieve high velocity outcomes (Office of the Chief of Naval Operations [OPNAV] 2018). To prioritize the LOE, the U.S. Navy focused "efforts for fielding AI/ML algorithms on areas that most enhance warfighting, training, and corporate decisions," and prioritizing the top five problems that each wish to resolve (OPNAV 2018, 11).

For the Navy, automated machines using AI will help reduce manpower requirements, increase operational effectiveness, and help maintain maritime superiority. The Navy has recognized the need for automated decision aids to support battle management as warfighters become overwhelmed with shorter decision cycles, greater amounts of data, and more technology systems to manage. The U.S. Navy Center for Applied Research in Artificial Intelligence (NCARAI) has active research groups in "adaptive systems, intelligent systems, interactive systems, and perceptual systems" to meet the need for AI (NCARAI 2020). The results of this project can be used by the Navy to inform future requirements as AI system development continues.

E. REVIEW OF PRIOR WORK

AI and automated information management has been a DOD goal dating back to the 1970s (Government Accountability Office [GAO] 1981). Tasks to collect, process, analyze, exchange, and transform data into information, including methods of AI, are areas of ongoing research. However, with the growing emphasis on the DOD's utilization of AI comes a growing public concern for empowering computers to fight our wars. Concerns include soft sciences (ethics and trustworthiness) alongside traditional hard sciences (algorithm development and implementation).

State-of-the-art implementations include improving the rate of the Warfighter's ability to learn and to train (Army Research Lab 2018), decision-making frameworks for casualty care (Wong 2019), and data gathering and reasoning systems for making recommendations in near real time (Pomerleau 2017). Investigations conducted to date revealed several DOD projects including the Army's Project Convergence and Advanced Targeting and Lethality Automated System (ATLAS) as well as the Air Force's Project Maven. In the recently published Department of Defense Artificial Intelligence Strategy, the Joint Artificial Intelligence Center (JAIC) has been defined as the focal point for AI, providing the mission, vision, and coordination of AI related efforts (Cronk 2019). Additionally, the U.S. Air Force is pursuing a Joint All-Domain Command and Control (JADC2) whose "fundamental premise is to evolve from today's highly centralized and outdated command and control architecture to a more distributed system that connects every sensor to every shooter and blends artificial Intelligence (AI) with human judgment to accelerate decision making" (Birch 2020). During the review of prior work, the team determined an opportunity exists to reduce the overall kill chain timeline by increasing the level of automation.

F. SCOPE, DEFINITIONS, AND CONSTRAINTS

1. Scope

Using the OODA loop, the team used time as the primary metric to determine if an AI-AMD system could allow the operator to observe faster, orient faster, decide faster, and act faster. In a complex battlespace against an advanced threat, greater amounts of data will need to be analyzed, but the decision cycles will become shorter. The need highlights that an AI-AMD system must be trustworthy and provide understandable guidance to the operator in order to reduce the time required to engage. Mission success is timely defeat of threats across an operational scenario with multiple potential threats. Figure 6 depicts the Operational View (OV-1) high-level graphic of the AMD operation with AI-AMD performing the OODA loop.

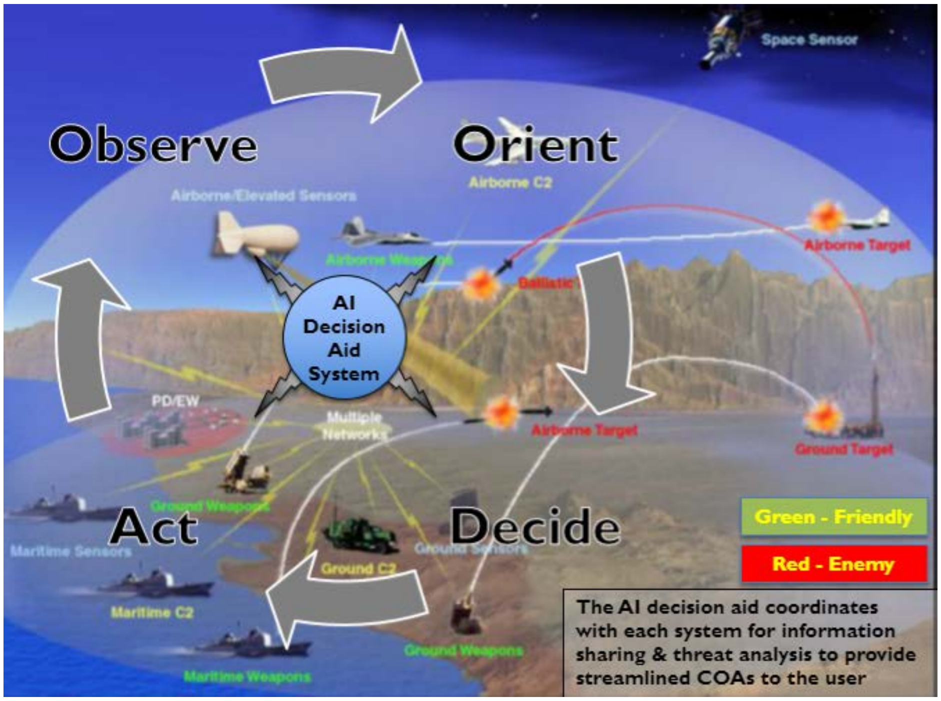

Figure 6. OV-1 High-Level Operational Concept Graphic. Adapted from Skidmore (2012, 3).

2. Definitions

There are several key terms used throughout this project that can be interpreted in various ways. To ensure that the reader understands the team's interpretation, the following key terms have been defined. These key terms were derived from multiple sources.

- An algorithm is "a procedure for solving a mathematical problem in a finite number of steps" (Merriam-Webster 2020).

- “Automated Decision Aid or battle management aid (BMA) is a device that uses AI method to improve process speed of large amounts of data to improve tactical knowledge” (Johnson, forthcoming).

- Automation is a “device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator” (Parasuraman, Sheridan, and Wickens 2000).

- Artificial Intelligence is “the ability of machines to perform tasks that normally require human intelligence—for example, recognizing patterns, learning from experience, drawing conclusions, making predictions, or taking action—whether digitally or as the smart software behind autonomous physical systems” (DOD 2018).

- Data Fusion Information Group (DFIG) model is the Joint Directors of the Laboratories (JDL) information fusion model outlining six different levels of data fusion; Level 0 Data Assessment, Level 1—Object Assessment, Level 2—Situation Assessment, Level 3—Impact Assessment, Level 4—Process Refinement, Level 5—User Refinement, and Level 6 Mission Management (Blasch 2015).

- Expert systems are AI systems that use reasoning to solve complex problems (Nikolopoulos 1997).

- Levels of automation characterize human interaction “from fully manual to fully automatic” (Parasuraman, Sheridan, and Wickens 2000).

- ICOM refers to inputs, controls, outputs, and mechanism. It is used to generate the OV-5b operational activity model.

- Marine Corps Planning Process (MCPP) is a planning process used by all command echelons for military planning and operations (U.S. Department of the Navy [USN] 2016).

- Machine learning is one critical component of artificial intelligence wherein a computer system can adapt and improve on its own without human correction (Salazar 2018).
- Predictive analytics is a capability that can take into account possible consequences and effects into the process of decision making (Johnson, forthcoming).

3. Assumptions and Constraints

The project focuses on the AMD operations based on *Joint Targeting Joint Publication (JP) 3–60* (Joint Chiefs of Staff 2013) kill chain for an efficient Human-AI cooperation and execution. In order to set the scope of the project several assumptions and constraints were generated and used throughout the modeling and analysis. These assumptions and constraints were used to simplify calculations in determining threat timelines and blue force timelines. A summary of assumptions and constraints follows:

- Detection capabilities for Blue Force (BLUFOR) were assumed to be 100% accurate at maximum effective range.
- Threats from Red Force (REDFOR) and defeat mechanisms for BLUFOR were assumed to follow a linear trajectory.
- Speed was assumed to be constant.
- Distance was assumed linear.
- Maximum operational range was assumed to be constant.
- Defeat speeds for BLUFOR were assumed to be constant.
- Network latency was assumed to be 250 milliseconds for each message crossing the network (send and receive).

- BLUFOR engagement reaction time was assumed to be 1 second (i.e., the weapon system fires against the threat within 1 second after receiving orders).
- Detection probability was assumed to be 100% at maximum effective range.
- Sensors were assumed to be local to the BLUFOR defeat mechanisms.
- Utility curve was assumed to be consistent across all AI steps in the kill-chain.
- Automation levels 1–3 and levels 8–10 were assumed to provide marginal changes in utility with a linear rate of change between levels 3–8.
- Hypersonic and cruise missile threats were far more challenging than enemy drone threats due to speed of the threat and associated time to respond.

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II. LITERATURE REVIEW

In order to adequately understand the AMD decision-making process and operational context, a literature review was conducted focusing on four main areas of interest to include psychology of decision making, the tactical planning process, blue force sensor performance, and artificial intelligence techniques. Each of these areas were then used to further refine constraints, assumptions, M&S parameters, and the overall kill-chain timeline. The following sub-sections detail the literature review and how the information was used for the project.

A. PSYCHOLOGY OF DECISION MAKING

In proposing AI-enabled systems, numerous research papers initially present the role of the machine as a supplement to the human element. Elsewhere, human behaviors were considered in the development frameworks for classifying various decision strategies and characteristics, in terms of both outcome and process metrics, with potential applications in designing decisions support systems (Riedl, Brandstätter, and Roithmayr 2008). Decision making has been modeled from an outcome-oriented multi-attribute evaluation perspective (Chen 2010), and “net benefit” methods of evaluating decisions in balance of risks and benefits have been presented (Vickers and Elkin 2006). Likewise, to begin the process of developing an AI architecture for an AMD decision support application, this project also started with consideration of the human decision-making process.

The use of human system interface (HSI) methodologies can drive reductions in the manning requirements of a fire control system by broadening the mission concept and extending the use of automation in the total fire control system and not just the human interface with the weapons (Kennedy, Thomas, and Green 2004). Additionally, the authors provide simplifying assumptions for hostility posture driving levels of automation. Several levels of functional flow and decomposition of OODA are presented through six major functions: 1) search, 2) detect, 3) track, 4) classify, 5) resolve, and 6) shoot. Multiple references to Parasuraman, Sheridan, and Wickens (2000) exist for the foundations of ten levels of automation and associated risks regarding mental workload, situational awareness, complacency, and skill degradation. Parasuraman, Sheridan, and Wickens (2000) proposed that automation can be applied to four broad classes of functions, as shown in Figure 7. The team also recognize that the four broad functions are analogous to the OODA loop commonly used by DOD personnel across all U.S. military Services.

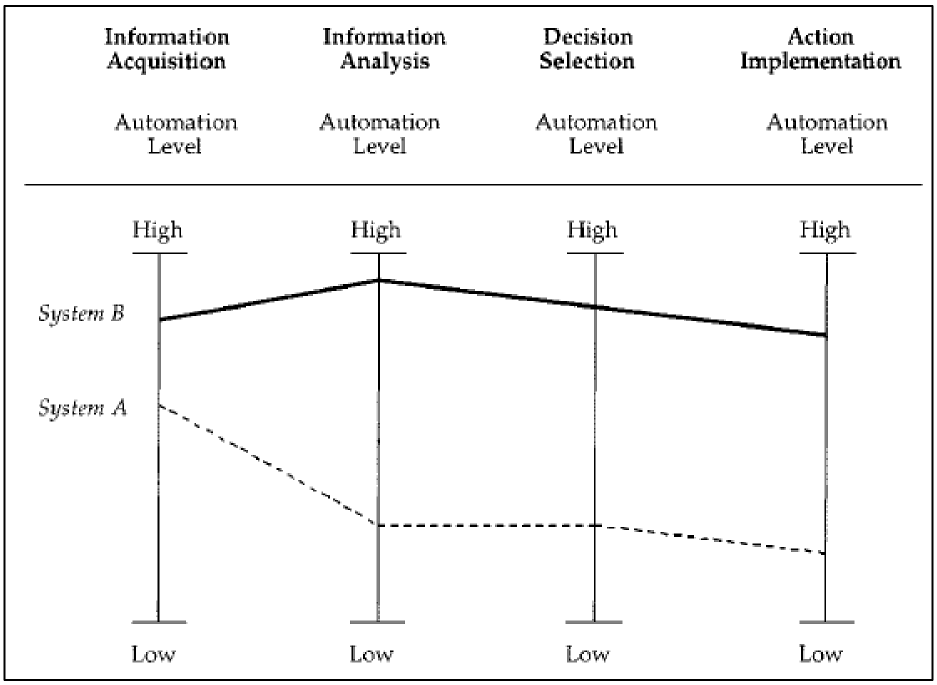

Figure 7. Examples of Systems with Different Levels of Automation. Source: Parasuraman, Sheridan, and Wickens (2000, Figure 2).

In *A Model for Types and Levels of Human Interaction with Automation*, the authors provided a framework for answering the question "which system functions should be automated and to what extent?" (Parasuraman, Sheridan, and Wickens 2000). It is notable that automation does not just augment human decision making, but it actually changes the decision-making process. These 10 levels of automation are listed in Table 3. The authors' examples include "an air defense operator given various sensor readings who has to decide whether to shoot down a potentially hostile enemy aircraft" (2000). This example has a direct application to the AI-AMD problem set, and the team used the levels of automation to define the appropriate levels of automation within the AMD kill chain.

Table 3. Levels of Automation. Source: Parasuraman, Sheridan, and Wickens (2000, Table 1).

HIGH	10. The computer decides everything, acts autonomously, ignoring the human.
	9. informs the human only if it, the computer, decides to
	8. informs the human only if asked, or
	7. executes automatically, then necessarily informs the human, and
	6. allows the human a restricted time to veto before automatic execution, or
	5. executes that suggestion if the human approves, or
	4. suggests one alternative
	3. narrows the selection down to a few, or
	2. The computer offers a complete set of decision/action alternatives, or
LOW	1. The computer offers no assistance: human must take all decisions and actions.

Furthermore, the four categories of functions referenced in Figure 7 can be simplified to represent human cognitive decision-making processes, as depicted in Figure 8. There are many similarities across the many references consulted for this project:

- Sensory processing
  - Acquisition and registration from multiple sources
  - Information acquisition function
  - “Observe” phase
- Perception/working memory
  - Conscious perception/manipulation of information
  - Information analysis function
  - “Orient” phase
- Decision making
  - Decisions based on cognitive processing

- Decision and action selection function
- “Decide” phase

- Response Selection
    - Implementation of response
    - Action implementation function
    - Similar to “Act” Phase

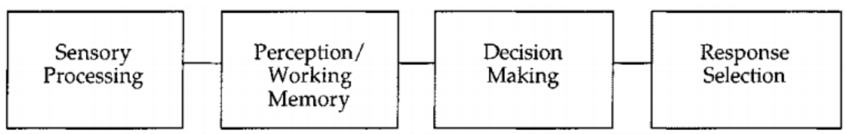

Figure 8. Simplified Human Cognitive Process for Decision Making. Source: Parasuraman, Sheridan, and Wickens (2000, Figure 1).

This project used Parasuraman’s 10 levels of automation as a guide to aid in the determination of what functions should be automated and to what extent. This project also used this framework with an emphasis on human performance consequences (mental workload, situational awareness, complacency, and skill degradation) as well as decision/action consequences (reliability and costs of decisions/action outcomes). Figure 9 illustrates this decision framework flow chart used to guide the team in determining the appropriate levels of automation within the kill chain.

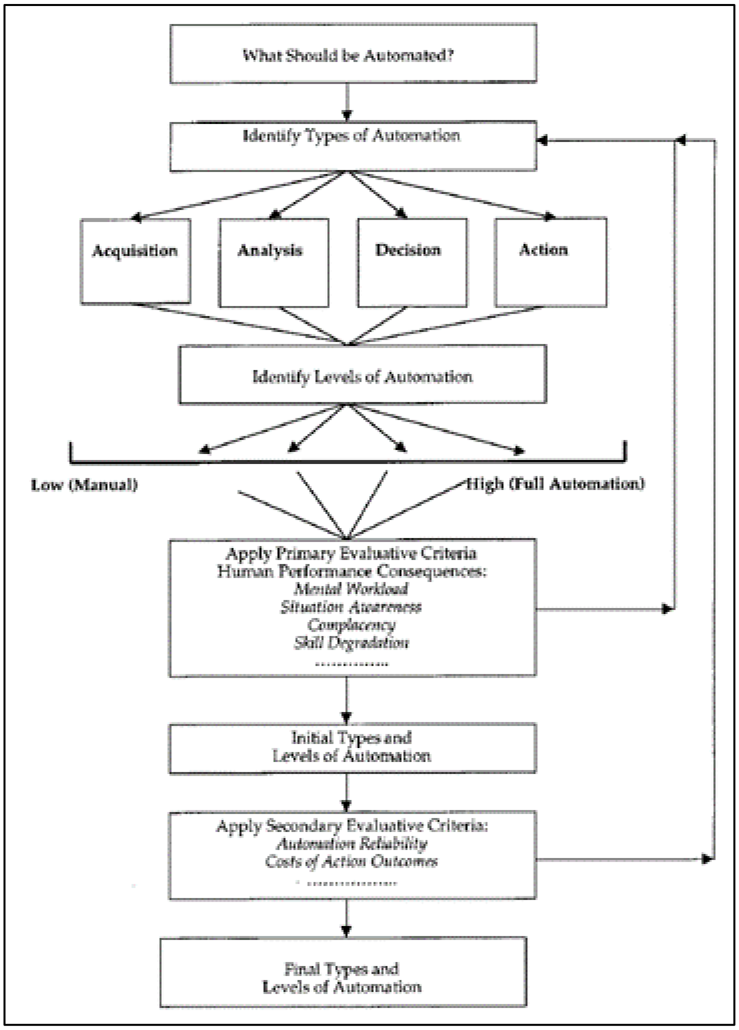

Figure 9. Flow Chart Application of the Mode of Types and Levels of Automation. Source: Parasuraman, Sheridan, and Wickens (2000, Figure 3).

Authors Save, Feuerberg, and Avia (2012), in citing several flight crew and air traffic control examples where historic taxonomies fall short of full characterization, further developed the four functions (information acquisition, information analysis, decision and action selection, action implementation—herein analogously "OODA") by utilizing the 10 levels of automation from Parasuraman, Sheridan, and Wickens (2000). Owing to prior human-based psychological factors, "[other] authors (Hollnagel 1999) have clarified that the decision on what to automate cannot be based simply on a 'Function allocation by substitution'. This approach was applied in the past also by means of the so-called MABA-MABA lists (Men are better at—Machines are better at) (Fitts 1951)" (Save, Feuerberg, and Avia 2012). This led to the development of their 26-element level of automation taxonomy (LOAT) matrix; three principles are provided:

- An automated system cannot have one "overall" level of automation. In other words, a statement about a level of automation for a system always refers to a specific function being supported;
- One automated system can support more than one function, each having a different level of automation;
- The description of each automation level follows the reasoning that automation is addressed in relation to *human performance*, i.e., the automation being analyzed is not just a technical improvement but has an impact on how the human is supported in his/her task accomplishment. (Save, Feuerberg, and Avia 2012)

In *Situation Awareness, Mental Workload, and Trust in Automation: Viable, Empirically Supported Cognitive Engineering Constructs* (Parasuraman, Sheridan, and Wickens 2008), the authors identify three main research areas of decision making over the preceding three decades: situational awareness (SA), mental workload, and trust. Empirical data behind these three areas is provided in lieu of qualitative analysis. Comparisons of learning about decision making to human factors engineering techniques are made (Fitts' Law, stimulus-response compatibility, visual search models, and crossover model for tracking performance). In attempting to solve human factors engineering problems for automated systems, the authors counter the argument that these three areas are "folk psychology" as claimed by previous articles (Parasuraman, Sheridan, and Wickens 2008).

A key ability of SA is to diagnose different operator states and responses. The author states, "SA represents a continuous diagnosis of the state of a dynamic world. As such, there is 'ground truth' against which its accuracy can be assessed" (Parasuraman, Sheridan, and Wickens 2008). The authors go on to discuss the difference between SA and choice, where SA has ground truth and choice does not. Choices are made based on the diagnosis of the consequence of each of the potential choices. Therefore, choices vary from person to person. It is important to also understand that SA is not performance. For example, auto-pilot works well when the route is followed but may not work that well for emergency rerouting. Supporting SA is essential to the performance characteristics. There are three levels of SA:

- Level 1—seeking information
- Level 2—integrating information
- Level 3—predicting outcomes

Mental workload is defined as “the relation between the function relating the mental resources demanded by a task and those resources available to be supplied by the human operator” (Parasuraman, Sheridan, and Wickens 2008). Many parallels exist between SA and mental workload. Neither are measures of performance or knowledge (e.g., two people performing the same task can have same outcome, but one may have more attention left for follow-on tasks than the other). The diagnosis of excess cognitive workload will suggest different COAs.

Misuse and disuse of automation is a result of operator trust. There were many empirical data references in the literature review on modeling the psychological decision-making model and finding balance between trust, misuse, disuse, and overuse. High false alarm rates lead to disuse, high levels of trust leading to overreliance, so finding the right balance of AI is critical. This project leveraged the article’s many different references to empirical data sources for SA, workload, and trust to characterize the architecture of the AI-AMD decision support aid.

B. TACTICAL PLANNING PROCESS, KILL CHAIN, AND BATTLEFIELD MANAGEMENT

In the NPS capstone, *Artificial Intelligence Applications for Solving Combat Identification Problems Concerning Unknown Unknowns* (2019), Wood describes the implementation of AI at the different levels of war and the methodology used at different levels of implementation for sea-based warfare (Wood 2019). At the lowest level, ship-based implementation represents the tactical equivalent of ground warfare. Within the ship-based level:

> The amount of information collected from on-board sensors provides an opportunity to better manage and quickly CID potential targets and develop data to help find unknown-unknowns. AI integrated into the combat system may also add automation alleviating the demands placed on crews and offering better and more timely decision making. (Wood 2019, 30)

However, due to limitations of current systems, the Aegis Weapon System (AWS) as an example, only allows for the data to be available for a limited time on an operator's display as long as the target falls within the sensor ranges of the system.

The Naval Task Forces represent the operational level of AI implementation, designed to inform decision makers of known threats in the area of operations while limiting the space of unknown-unknowns. The ability to integrate and share data of the battlespace helps create a single integrated common tactical picture (CTP) that extends the usage of resources efficiently and decreases accidental civilian engagements. Due to differences among the classes of ships and the technological hardware capability, AI implementation is limited at the Task Force level. However, with hardware and software modernizations within the aging ships, fused AI implementations provide a potential solution to the problem. From a prior NPS capstone, "The Navy is already developing and implementing a program known as cooperative engagement capability (CEC) to similarly integrate data shared via datalinks into a single CTP" (Wood 2019, 35). This will allow for the efficient use of AI implementation across the Task Force to be integrated into a single-source CTP available for all sea and land-based assets.

The highest level is cloud-based AI systems on shore-based network infrastructure that will be implemented at all levels. This will allow for all levels to view the same information from multiple different locations. However, due to datalink capabilities and limited bandwidth within different classes of ships, at this time, cloud-based AI systems are not the most efficient systems for AI implementation. A great number of technological advances will be needed in tactical clouds and cloud computing algorithms to support AI implementation for combat identification of the unknown-unknowns.

AI implementation at the Task Force based level of war is best suited for strategic thinking skills that incorporate the OODA loop created by John Boyd. The execution of military missions starts at up front with decision makers creating COAs for the commander to implement in the battlespace. The team reviewed the tactical planning process from the Marine Corps, the Army, the Navy, and the Joint Planning Process. The Marine Corps Planning Process (MCPP) is used by Marines at all echelons of command to conduct range of military operations. Based on the operational view and project objectives, it was determined that the MCPP would be the most suitable doctrine for the project, as shown in Figure 10. It is the fundamental responsibility of decision makers to design a well-executed plan that not only conveys the commander's intent, but also receives guidance from the Commander at all phases. The MCPP uses the fundamental idea of the OODA loop to design a framework for solving a problem, developing COAs, war gaming the desired COAs, and transitioning into implementing the commander's intent.

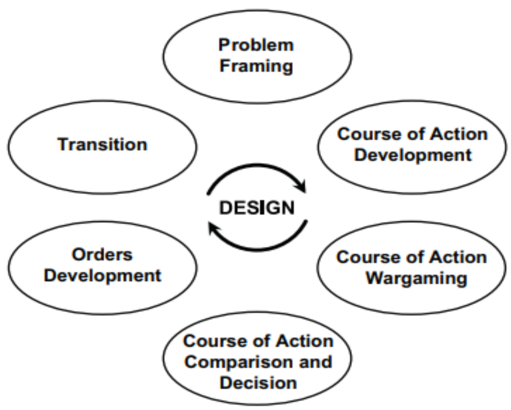

Figure 10. Marine Corps Planning Process.
Source: USN (2016, Figure 1–1).

Within the overall design framework, COA development based on the OODA loop process becomes integral to the planning process. COA development is designed to be a top-down planning process, while creating an operational battlespace that incorporates the idea of a single-battle concept with an integrated planning process. The MCPP framework is a crucial part of AI implementation. Therefore, in a Task Force based AI implementation, it is imperative that the human process of the OODA loop reduces the time required to generate desired courses of action that will aid the joint target cycle.

The AI implementation within the joint targeting cycle can be achieved through systematic joint processes with human-machine interaction that uses the OODA process in a cooperative manner. In the research paper "*Interactive OODA Processes for Operational Joint Human-Machine Intelligenc*e" Blaha (2018) proposes an effective human-machine teaming effort to create a joint decision-action process using a human-machine OODA technique. The author states:

> For human and machine OODA loops acting as a team through concurrent processes, communication between the two processes is critical for each agent providing input to the other. Communication from the other agent constitutes one of the inputs to the human or machines Observe stage of processing. That is, it behaves as just one of the many potential input streams within the Outside Information observations. (Blaha 2018, 3–12)

Characterizing and conceptualizing the OODA framework provides a key strategic advantage for systematically outpacing the decision-making processes of an adversary or threat. Current OODA concepts have framed cognitive decision processes in support of agile and competitive warfighters and human-centric operations. As noted in *Interactive OODA Process for Operational Joint Human-Machine Intelligence*, "future military decision making based on human-machine teaming relies on technology and interaction concepts that support joint human-machine intelligence, not just human capabilities. This requires new OODA concepts" (Baha 2018). In addition to the traditional human-centric OODA loop Figure 11, the author defines a machine-centric OODA loop Figure 12 with notable similarities. The author considers

> how advances in artificial intelligence and cognitive modeling can be integrated within the machine-orient stage, providing the machine a unique advantage over humans in that the machine can integrate a level of understanding and prediction about human operators together with predictions about machine behaviors and data analytics. (Blaha 2018)

Recognizing this, the author proposes an augmented, joint human-machine teaming OODA loop in Figure 13.

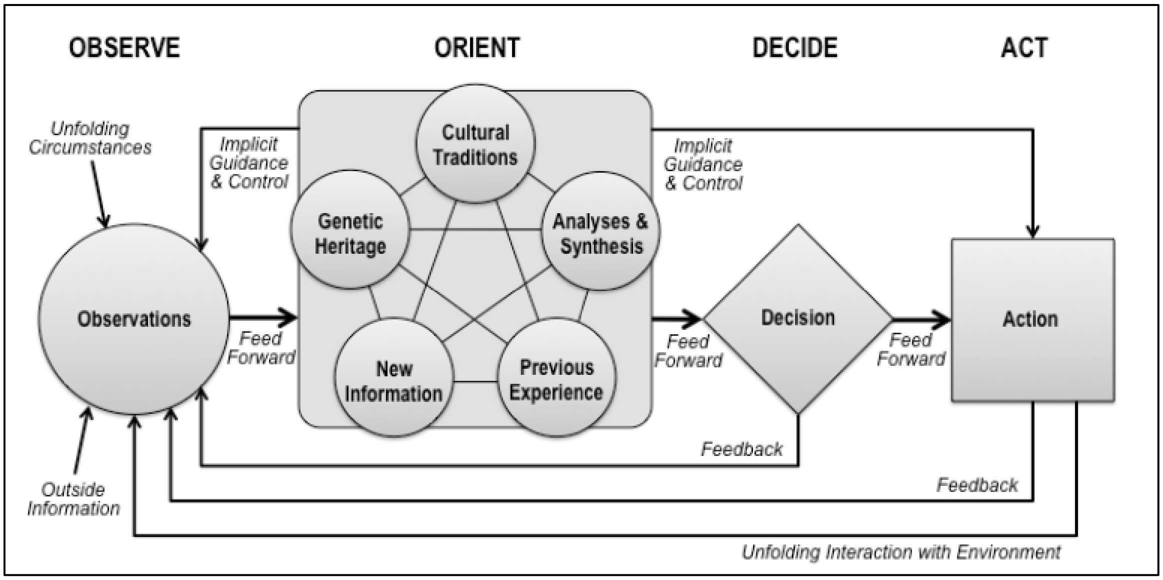

Figure 11. Human Centric OODA Loop. Source: Blaha (2018, Figure 1).

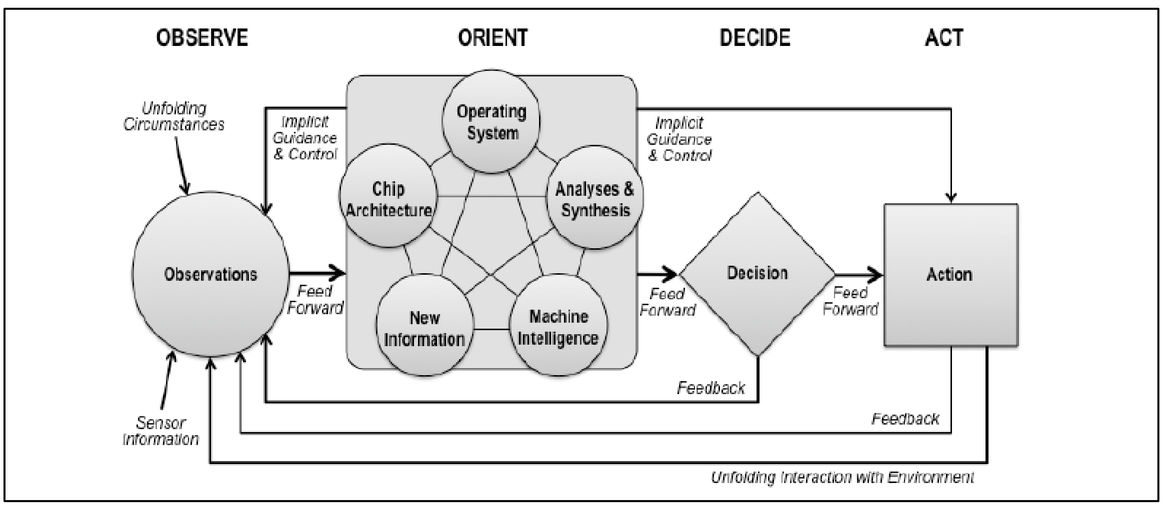

Figure 12. Machine Centric OODA Loop. Source: Blaha (2018, Figure 2).

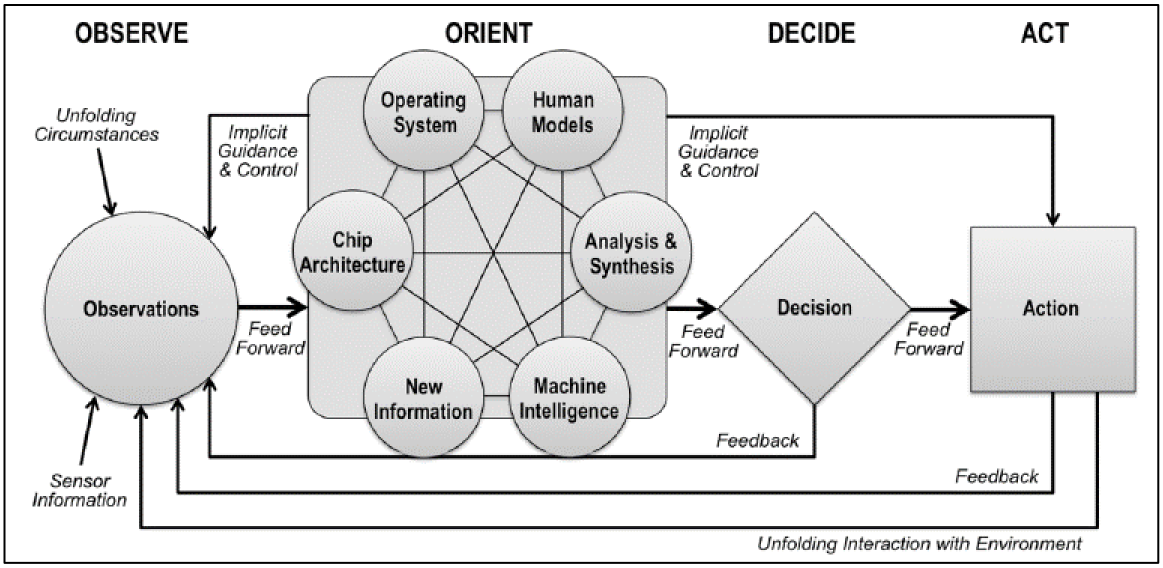

Figure 13. Joint Human and Machine Teaming OODA Loop. Source: Blaha (2018, Figure 3).

As the project integrated the OODA loop process into automated battle management aid, it was imperative that the human-machine concept was present for all decision-making outcomes. From Task Force based operations, it is crucial to implement the AI in the appropriate kill chain process directed by the JP 3-60. As targets come in all shapes, size, and numbers; the design of the AI within the project focuses on deliberate targeting (planned) and dynamic targeting (targets of opportunity) based on time sensitive targets and component critical targets with the commander's end state and objectives. Based on the targeting steps depicted in Figure 14, the AI OODA process focused on step 1–4. During these steps, the targeting acquired through on-board sensors are able to provide the AI with sufficient information to allow for machine learning and cognitive processes to decipher targets and provide the user with possible COAs to engage the enemy targets.

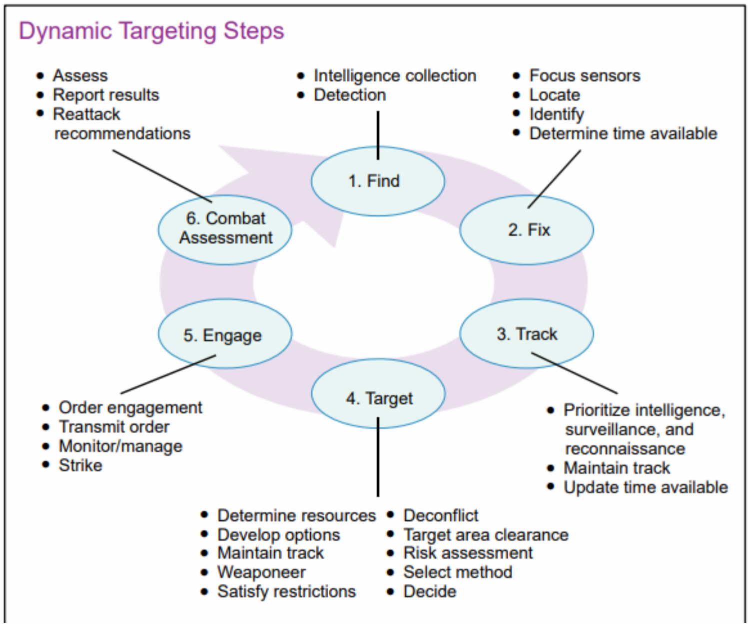

Figure 14. Joint Targeting Steps. Source: Joint Chiefs of Staff (2018, Figure II-10).

C. SENSORS, RESOURCE MANAGEMENT, AND DATA FUSION

1. Blue Force Sensor Systems and Characteristics

Sensor capabilities are a critical component of the AMD operation. There are various sensor modalities each capable of detecting, recognizing, and identifying targets of interest. Examples of sensors include radars, infrared sensors, multi-spectral sensors, acoustic sensors, and radio frequency sensors. Each of these sensors have their own unique performance characteristics, detect, identify, and recognize probabilities, and modeling characteristics. Some environmental considerations that need to be accounted for include time of day, time of year, starlight, moonlight, spectrum interference, and terrain features that play a significant role in adequately defining the performance of the sensor. These types of sensors form the basis of the U.S. AMD system portfolio.

United States AMD capabilities consist of a layered approach across multi-domains, the DOD services, and the U.S. Missile Defense Agency (MDA). Navy AMD systems include the AWS and Phalanx Close-In Weapons System (CIWS). The AWS uses an automated control system to detect, track, and engage the targets using a high-powered radar called the AN/SPY capable of detecting over 100 targets simultaneously (USN 2019). The Phalanx CIWS provides a similar capability, but for close-in targets as a last line of defense with an effective range of just under a mile and an estimated six seconds to engage the target (Hutchison 2017). The Army also has a significant land-based AMD capability with an Integrated Air and Missile Defense (IAMD) effort that seeks to integrate sensors, launchers, missiles, and control systems using a set of standard interfaces and networks (U.S. Department of the Army [USA] 2020). Examples of Army land based systems include close combat systems such as the Tube-launched, Optically-tracked, Wireless-guided (TOW) systems, cruise missile defense systems such as the Sentinel radar and Stinger systems for short to medium range defense, counter-rocket, artillery, mortar (C-RAM) systems such as the Land-based Phalanx Weapon System (LPWS) and the AN/TPQ series of radars, and lower-tier capabilities such as the Patriot system for high-value assets (USA 2020). The MDA also has a layered sensor network for detecting and tracking threat missiles through a Ballistic Missile Defense System (BMDS) (Missile Defense Agency [MDA] 2020). These sensors include the Upgraded Early Warning Radars (UEWR) for long range coverage managed by the U.S. Air Force, the Cobra Dane radar for mid-course tracking managed by the Air Force, Sea-Based X-Band Radar for wide area early warning detection over the ocean, and the Space Tracking and Surveillance System (STSS) satellite constellations using visible and infrared sensors to detect threats (Missile Defense Agency 2020). In addition, there are also Joint Attack Munition Systems (JAMS) designed across services, platforms, and coalitions for use on aviation platforms. Some examples include the Hydra rockets, Hellfire missiles, and the JAGM air-to-ground weapon system (USA 2020).

By understanding the capabilities that exist today, the team was able to better develop architectures that can be used to augment the various systems and aid in the decision-making process. The team recognizes that the physics of sensor performance plays a significant role in AMD operations. Rather than address time savings associated specifically with sensor performance, the project focuses on the role that AI plays in improving AMD decision making in a multi-domain, highly complex battlespace. M&S of the architectures normalized the sensor performance characteristics to constrain the scope of the project but allows for advanced M&S specifically for the sensors to be added in the future. With many sensors and systems across services and coalition partners capable of detecting and defeating enemy threats each with their own specific mission areas, AI can be used to make efficient and intelligent COAs in a SoS construct to reduce the overall kill chain timeline.

2. Sensor Data Fusion

The Joint Directors of the Laboratories (JDL) created the Defense Fusion Information Guide (DFIG) as a means to standardize on the definitions of data fusion. The DFIG defines six different levels of data fusion consisting of level 0—Data Assessment, Level 1—Object Assessment, Level 2—Situation Assessment, Level 3—Impact Assessment, Level 4—Process Refinement, Level 5—User Refinement, and Level 6 Mission Management (Blasch 2015). These levels can be mapped to the various steps in the kill chain as well as the OODA loop and each step can independently have a different level of data fusion based on the situation and risk associated with the decision. To assist with defining the levels of data fusion within the kill chain, first it was critical to understand how the kill chain currently functions and how the operators perform each function in the process. From there, the team used existing research on data fusion support to decision making to address system level data fusion and SoS level data fusion (Paradis, Breton, Elm, and Potter 2002). There are certain tasks within the kill chain that, under most circumstances, should not be automated due to the risks involved without a human in the loop. However, suppose a Navy ship is under fire from multiple enemy missiles. If time is critical, the decision aid may be allowed to decide to engage those threats without a human in the decision loop as a last resort method once certain predefined gates are reached without operator involvement. Comparisons of the various data fusion frameworks can be found in Table 4, Table 5, and Table 6.

Table 4. Imperfect Data Fusion Frameworks.
Source: Khaleghi et al. (2010, Table 1).

Framework	Characteristics	Capabilities	Limitations
Probabilistic [32,40,45]	Represents sensory data using probability distributions fused together within Bayesian framework	Well-established and understood approach to treat data uncertainty	Considered incapable of addressing other data imperfection aspects
Evidential [36,54–56,58]	Relies on probability mass to further characterize data using belief and plausibilities and fuses using Dempsters' combination rule	Enables fusion of uncertain and ambiguous data	Does not deal with other aspects of data imprecision, inefficient for fusion of highly conflicting data
Fuzzy reasoning [160,66,67]	Allows vague data representation, using fuzzy memberships, and fusion based on fuzzy rules	Intuitive approach to deal with vague data esp. human generated	Limited merely to fusion of vague data
Possibilistic [29,72,64]	Similar in data representation to probabilistic and evidential frameworks and fusion to fuzzy framework	Allows for handling incomplete data common in poorly informed environment	Not commonly used and well understood in fusion community
Rough set theoretic [35,97,75,77]	Deals with ambiguous data using precise approximate lower and upper bounds manipulated using classical set theory operators	Does not require any preliminary or additional information	Requires appropriate level of data granularity
Hybridization [78,38,67,79]	Aims at providing a more comprehensive treatment of imperfect data	Deploys fusion framework in a complementary rather than competitive fashion	Rather ad hoc generalization of one fusion framework to subsume other(s), extra computational burden
Random set theoretic [20,16,85,39]	Relies on random subsets of measurement/state space to represent many aspects of imperfect data	Can potentially provide a unifying framework for fusion of imperfect data	Relatively new and not very well appreciated in fusion community

Table 5. Correlated Data Fusion Methods.
Source: Khaleghi et al. (2010, Table 2).

Framework	Algorithms	Characteristics
Correlation elimination	Explicit removal [105,107,108]	Usually assumes a specific network topology and fixed communication delays
	Measurement reconstruction [106,109]	Applicable to more complex fusion scenarios
Correlation presence	Covariance Intersection [98,110]	Avoids the covariance underestimation problem, yet computationally demanding and rather pessimistic
	Fast CI [112,113]	Enhanced efficiency through alternative non-linear optimization processes
	Largest Ellipsoid [114]	Provides a tighter (less pessimistic) covariance estimate, yet limited to KF-based fusion like the others

Table 6. Inconsistent Data Fusion Methodologies.
Source: Khaleghi et al. (2010, Table 3).

Inconsistency aspect	Problem	Resolution strategy	Characteristics
Outlier	If fused with correct data, can lead to dangerously inaccurate estimates	Sensor validation techniques [118–120]	Identification/predication and subsequent removal of outliers, typically restricted to specific prior-known failure models
		Stochastic adaptive sensor modeling [121]	General framework for detection of spurious data without prior knowledge
Disorder	Update current estimate using old measurements (OOSM)	Ignore, reprocess, or use backward/forward prediction [124,125,123,128,146]	Mostly assume single-lag delays and linear target dynamics
	Update current estimate using old track estimates (OOST)	Use augmented state framework to incorporate delayed estimates [133,134]	Much less understood and studied in the literature
Conflict	Non-intuitive results while fusing highly conflicting data using Dempsters' combination rule	Numerous alternative combination rules [137–140]	Mostly ad hoc in nature without proper theoretical justification
		Apply corrective strategies while using Dempsters' rule [141,142,39]	Defend validity of Dempsters' rule provided that certain constraints are satisfied

D. AUTOMATION AND ARTIFICIAL INTELLIGENCE TECHNIQUES

Automation and AI often go hand in hand. AI is a higher order domain of automation where automation refers to the concept of mimicking the human thought process and rational action. Stuart Russell and Peter Norvig (2015) provide many additional definitions of AI, shown in Figure 15.

Thinking Humanly	**Thinking Rationally**
"The exciting new effort to make computers think . . . *machines with minds*, in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . ." (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole *et al.*, 1998) "AI . . . is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Figure 15. Artificial Intelligence Definitions. Source: Russell and Norvig (2015, Figure 1.1).

AI applications in the DOD look to expedite information, increase situational awareness, and aid in decision making. AI development started post-World War II when Warren McCulloch and Walter Pitts proposed a model of artificial neurons characterized by a switch being either on or off (Russell and Norvig 2015). DOD's work on automation dates back to projects like Battlefield Exploitation and Target Acquisition (BETA) (GAO 1981) and Army Tactical Command and Control System (ATCCS) (GAO 1990).

In its inception, automation has mainly applied to the dull, dirty, and dangerous jobs to allow humans to work on safer and more complex tasks. Advancements in computing power has opened the door to developing algorithms to model more complex tasks. The DOD is investing in such technologies to assist in various applications on the battlefield. Automation can come in various forms: from simple items such as a toaster, to robots in factories, autonomous automobiles, and game winning artificial intelligence. As described earlier in Table 3, automation can be described in 10 levels and the levels dictate the ratio of control between machine and human operator.

1. Algorithms and Machine Learning

Algorithms are key to computer logic. These are essential mathematical models processing inputs into a desired output. While traditionally programmed and iterated by humans, automation has been applied in the form of machine learning. Machine learning is essentially the automation of algorithm development. Concepts such as neural networks are built to statically break down data and develop or train a model from the data fed into the system. Machine learning can occur at various levels from supervised (where humans assist in feeding the data and running the iterations) to levels of no supervision (where raw data can be fed and the network self-iterates to construct the algorithm).

While machine learning looks to use computational power to accelerate algorithm development, there can be some difficulties such as developing bias based on the limitation on the input data, collecting and preprocessing data, running hundreds to thousands of iterations, and having the computational power to produce. Trust and transparency must be considered when accepting an AI-AMD decision. Often the final product does not contain the details behind the algorithms' determination (Zhao and Flenner 2019). The methods and theories that guide development of these algorithms is a critical component of machine learning.

2. Data Fusion, Decision Theory, and Predictive Analytics

Predictive analytics is a means to evaluation COAs. The DOD currently employs two generations of analytics which are descriptive and diagnostic. Descriptive analytics can be used to provide hindsight to better understand what has happened. Diagnostic analytics look to provide insight into events that occurred. The next generation of analytics is predictive analytics. Predictive analytics takes what we have learned from the past to provide foresight into what will likely happen, as depicted in Figure 16.

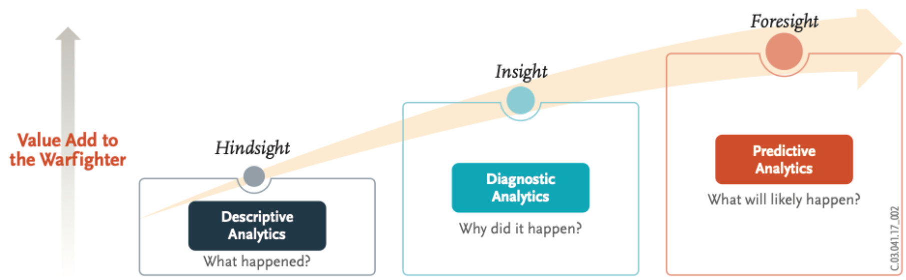

Figure 16. Hindsight, Insight, and Foresight Analytical Value to the Warfighter. Source: Booze Allen Hamilton (2017, 3).

There are several AI techniques that were reviewed to support this project including predictive analytics, decision theory, Bayesian networks, game theory, and decision theory. Predictive analytics has the potential to assist in automated decision aids by providing second and third order effects to COAs. These COAs assist development of military wargaming to determine effects and responses. Predictive analytics have the ability to expedite this process in Naval planning (Johnson, forthcoming). Bayesian networks are a type of graphical statistics model; these networks are good for reviewing the probabilities of the relations of contributing factors to an event (Johnson, forthcoming). Many reasoning methods are carried out using a Bayesian network. A belief network is a type of Bayesian network that captures uncertainty to carry out a sensitivity analysis (Ang 2004). Decision Theory is a framework for decision made under uncertainty, built on utility theory (Russell and Norvig 2015). It provides a method for selecting actions based on desired outcomes (Johnson, forthcoming). Game Theory is an evolution on decision theory with multiple agents where the relationship between the actions of players effect the others (Russell and Norvig 2015). Game theory is broken down further into descriptive and normative interpretations. Description focus on the adversary's response while normative looks more at the optimal action the player should make.

The program BETA, which was mentioned earlier, was a project that collected data from a set of ground station sensors, processed the data autonomously, and displayed the data on a central terminal. Poor performance led to the cancellation of the project around 1980 (GAO 1981). Another project mentioned, ATCCS, was an attempt at a decision aid with the Army, however the network bandwidth and its large size made the system unusable (GAO 1990). Data collection methods have advanced over the last few decades and now is the time to apply advances in the AI domain to provide automated decision aids to the Warfighter.

The DOD is collecting more data than ever before that can be used to feed and to train machine learning processes to develop defense algorithms. Those same sensors, combined with data fusion, will help create models of the enemy, the blue forces, and the operating environment. Methods in decision theory will create COAs based on these models, and predictive analytics will look at the 2nd- and 3rd-order effects. These AI methods and concepts can be used to develop AI-AMD systems to provide optimized, prioritized COAs for warfighters and commanders to accelerate and improve the kill chain to expand the battlespace. A sampling of the various methods obtained from the literature review are listed in Table 7.

Table 7. AI Methods

Methods		Description
Theories	Probability Theory	Considers the actions degree of belief (Russell and Norvig 2015)
	Utility Theory	Considers agents degree of usefulness (Russell and Norvig 2015)
	Decision Theory	Considers both probability and utility (Russell and Norvig 2015)
	Game Theory	Described rational behavior of multiple agents in the same situation (Russell and Norvig 2015)
Data Analytics	Descriptive Analytics	Analytics that provide hindsight into what happened (BAH 2017)
	Diagnostic Analytics	Analytics that provide insight into why it happened (BAH 2017)
	Predictive Analytics	Analytics that provide foresight into what will likely happen (BAH 2017)
Reasoning	Deductive Reasoning	Reasoning based on known premises (BAH 2017)
	Inductive Reasoning	Reasoning based of patterns for uncertain inferences (BAH 2017)
	Spatial Reasoning	Reasoning Used to navigate the world (Russell and Norvig 2015)
	Evidential Reasoning	Fusion of uncertain and ambiguous data (Khaleghi et al. 2010)
	Case-based Reasoning	Recall similar cases from experience (Hopgood, 2016)
	Fuzzy Reasoning	Intuitive approach to vague data (Khaleghi et al., 2010)
Other	Event Procedure	Based on criteria selection, a triggered event occurs automatically
	Templating Filling	Based on decisions selected, a form can be autopopulated

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III. AI-AMD ARCHITECTURE AND KILL CHAIN ANALYTICAL FRAMEWORK

This chapter presents the AI-AMD systems architecture and kill chain analytical framework. The team conducted a model-based systems engineering (MBSE) analysis to understand how a future automated decision aid capability could support AMD systems. The team used a SE tool called Innoslate to conduct the MBSE analysis and capture architectural models based on the DOD Architectural Framework (DODAF). The team analyzed AMD systems from an operational viewpoint and a systems viewpoint to understand how an AI-AMD decision aid might function operationally and to understand its system characteristics, properties, boundaries, and interactions.

This chapter also contains the team’s analytical framework for studying kill chain automation. As AMD is a time-critical mission, the team studied AMD kill chain functions in terms of timing to understand how much time it takes to perform each function. The team developed an analytical framework for studying the AMD kill chain based on the operational scenario (threat timeline), the level of automation for making kill chain decisions, and the risk associated with automation level. The team’s AI-AMD architectural models and kill chain analytical framework as presented in this chapter support the team’s M&S analysis presented in Chapter IV.

A. AI-AMD ARCHITECTURE

To support future AI-AMD program developments, the team pursued an MBSE approach for defining the overall architecture. Major contributors to AMD mission success are external to the AI-AMD decision aid; these include BLUFOR sensors, air defense weaponry, and the network. The AI-AMD decision aid is a system within the larger AMD SoS context, as described in Figure 17. The derived models for describing the desired SoS capabilities ensure the resulting system will meet stakeholder needs. Using Innoslate to ensure concordance throughout MBSE development, the team produced operational viewpoints (OV) and systems viewpoints (SV). These DODAF views are depicted in the following sub-chapters.

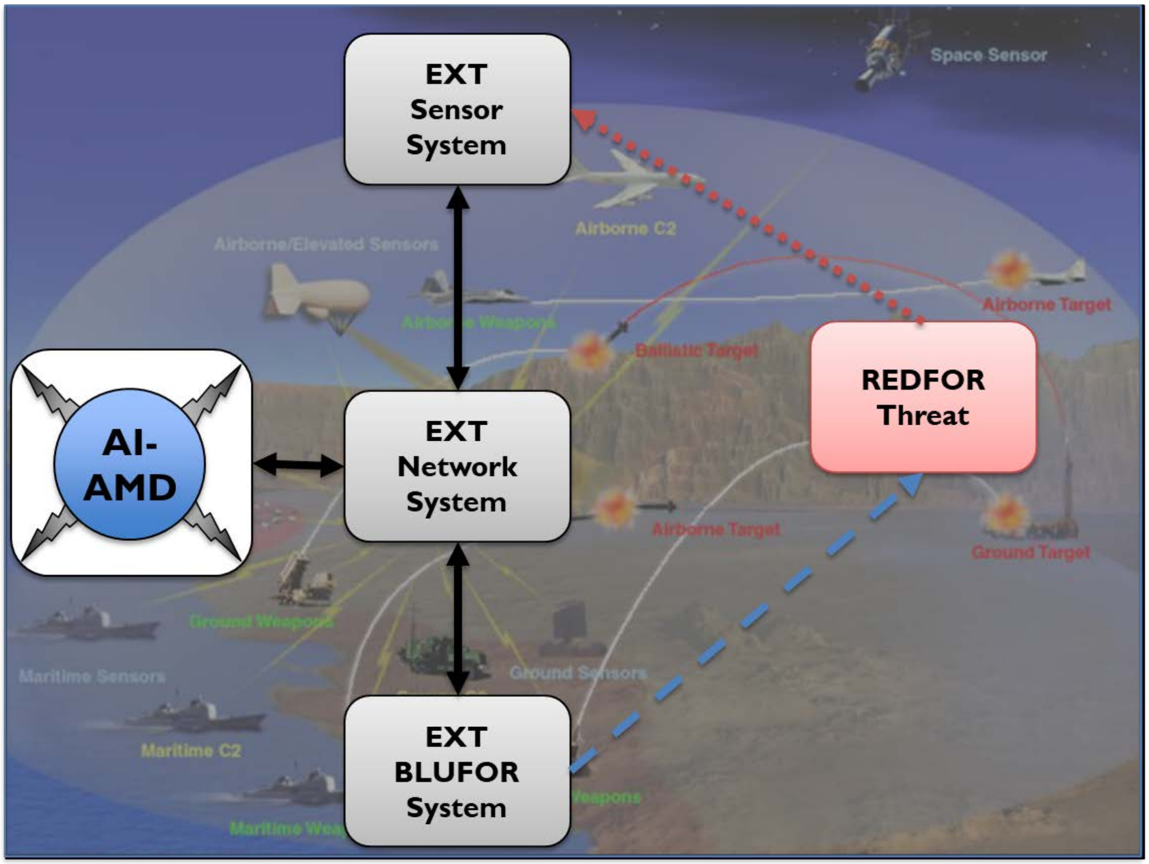


Figure 17. AI-AMD Context Diagram. Adapted from Skidmore (2012, 3).

1. Operational Viewpoint

To begin the architectural framework process, the team generated the OV. This conceptualizes the operational need, decomposes the need into actions, and illustrates communication exchanges and relationships. The OVs used for this project are shown in Table 8.

Table 8. DODAF OVs. Source: DODAF v2.02, DOD (2020).

Model	Description
OV-1: High-Level Operational Concept Diagram	The high-level graphical/textual description of the operational concept
OV-6c: Event-Trace Description	One of three models used to describe operational activity. It traces actions in a scenario or sequence
OV-5a: Operational Activity Decomposition Tree	The capabilities and operational activities organized in a hierarchal structure
OV-5b: Operational Activity Model	The context of capabilities and operational activities with their relationships among activities, inputs, and outputs
OV-5b/6c: Action Diagram	Combination diagram illustrating operational activities (including inputs & outputs) within a scenario or sequence of events

a. OV-1: High-Level Concept

The OV-1 is a visualization of the AI-AMD CONOPS within the mission context, illustrating the basic premise of the operational need. From this, stakeholders can share a vision of the system and begin deriving capabilities. The OV-1 depicting the AI-AMD decision aid (as part of a larger SoS including sensors, weapons, and network) was originally presented in Figure 6 to define the scope of this project. What is shown is a range of possibilities in the AI-AMD mission: multiple threat types, various air defense (AD) assets, numerous sensor capabilities, and a network to support the sharing of information. The OODA process is overlaid over the AMD mission. Whether human only, AI only, or AI-human team, the OODA process is used independent of scenario. However, the level of automation will drive time savings associated with the engagement timeline.

b. OV-6c: Operational Scenarios

From the concept depicted in the OV-1, the team selected an AMD scenario, and defined the sequence of actions that each agent performs during this scenario. The scenario is intended to include the planned sequence of events in addition to variations that capture other actions that may need to be performed. For the AMD mission, the typical scenario includes an incoming threat (hostile aircraft, drone, or missile), followed by its detection by BLUFOR sensors and a BLUFOR weapon engagement response. The team focused on a single AMD threat, but notes that more complex AMD scenarios for future consideration include multiple threats, failed engagements, and system or network failures.

The team developed an OV-6c (an Event Trace Description) to capture the AMD operational scenario. This OV-6c operational scenario is presented in Figure 18. It illustrates the AMD scenario based on JP 3-60 Joint Targeting. The purpose of the event trace is to depict the agents (AI-AMD decision aid, blue forces, red threat, sensors, and network) in the AMD scenario and their actions as they occur. It is a useful visual timeline to gain stakeholder agreement with the modeled scenario.

The engagement starts with the red threat launching an attack against BLUFOR assets. The BLUFOR are unaware of the threat until the BLUFOR sensors detect the incoming missile and provide the sensor detection data through the network to the AI-AMD decision aid. The AI-AMD decision aid then requests further information from the BLUFOR sensors through the network and the sensors send their updated detection information back to the AI-AMD decision aid. At this point, the AI-AMD confirms a valid detection and requests the BLUFOR sensors update the target track. The AI-AMD must determine available BLUFOR assets and ensure that there are no BLUFOR friendly forces within the area of operations and requests status and location of known forces. Once the AI-AMD can de-conflict the area, orders are issued and passed through the network along with fire command to the BLUFOR defeat mechanism. The BLUFOR then engage the threat, followed by an assessment of the engagement. If the red threat has not been defeated, the AI-AMD can re-issue an attack command, and the BLUFOR engages again. The OV-6c demonstrates the importance of the network as it is the only direct connection that the AI-AMD has with the BLUFOR.

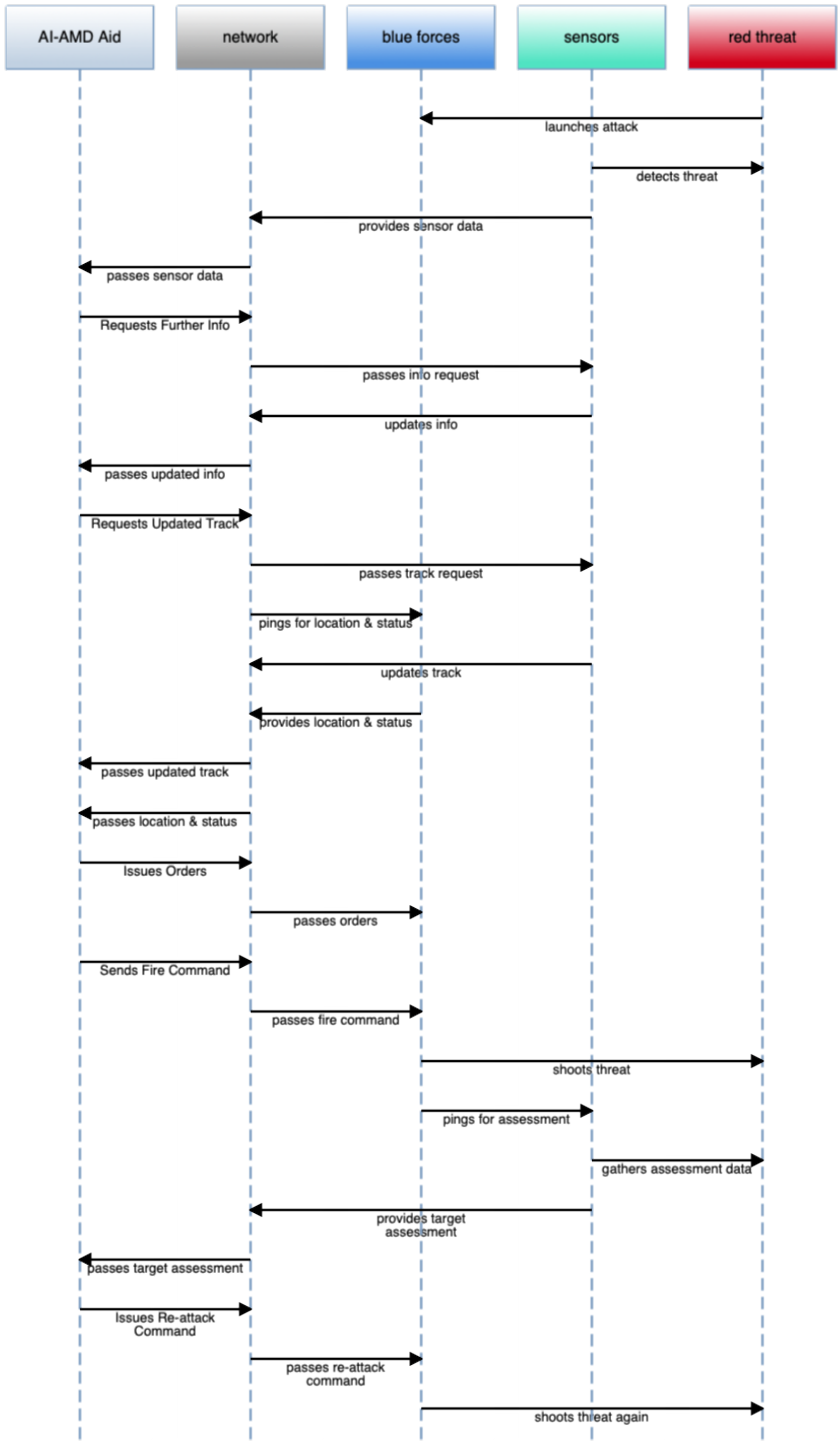


Figure 18. OV-6c: AI-AMD Event Trace for Single Engagement

c. *OV-5a: Operational Activity Decomposition Tree*

The operational activities of the AI-enabled AMD system are allocated to higher level functions from the JP 3-60 find, fix, track, target, engage, assess (F2T2EA) process. The team selected 17 critical functions of the JP 3-60 process for the AI-AMD system that encompass the main tasks of the F2T2EA kill chain; these 17 functions can be found in Table 9. The team developed an activity decomposition tree or OV-5a that depicts the operational scenario from the OV-6c sequence diagram in a hierarchical function diagram format. The OV-5a is depicted in both Figure 19 (the internal capabilities decomposition) and Figure 20 (the external system decomposition). Subsequent sections will further define how these functions were selected using a mapping of the JP 3-60 to OV-5b/6c action diagram, which can be found in Chapter III Section A.1.e.

Table 9. F2T2EA Functions

OODA	F2T2EA	Functions
Observe	Find	Collects Data
		Initial Detection
		Identifies Emerging Target
	Fix	Request Further Information
		Classifies Target
		Locates Target
		Validates Detection
Orient	Track	Update Target Track
		Validates Target
		Assess Blue Proximity
Decide	Target	Nominate Engagement Options
		Prioritize Target
		Select Attack Option
Act	Engage	Issue Orders
		Attack Target
	Assess	Assess Status of Target
		Authorize Re-attack

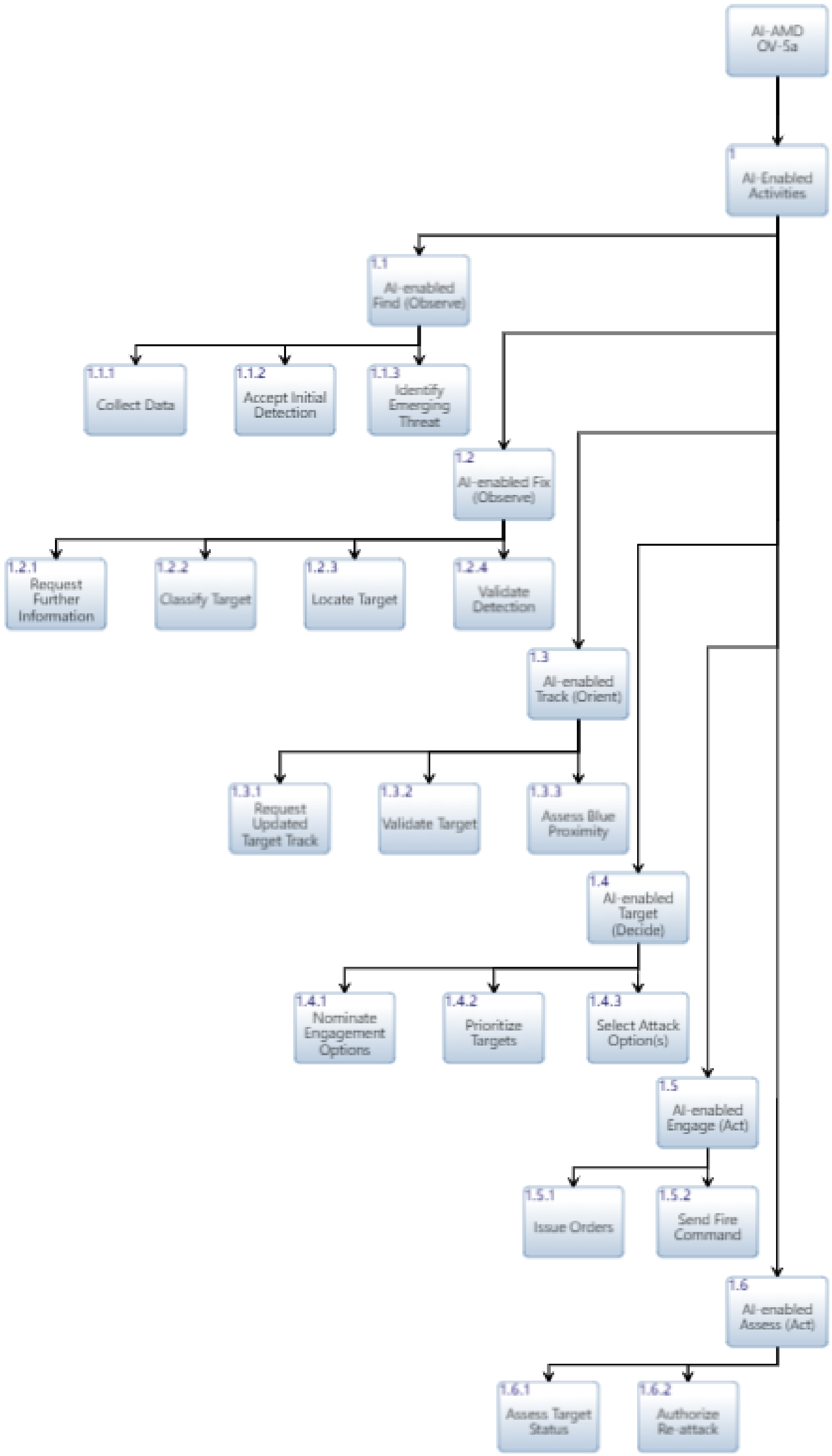


Figure 19. OV-5a: AI-AMD Operational Activity Decomposition—Internal Capabilities

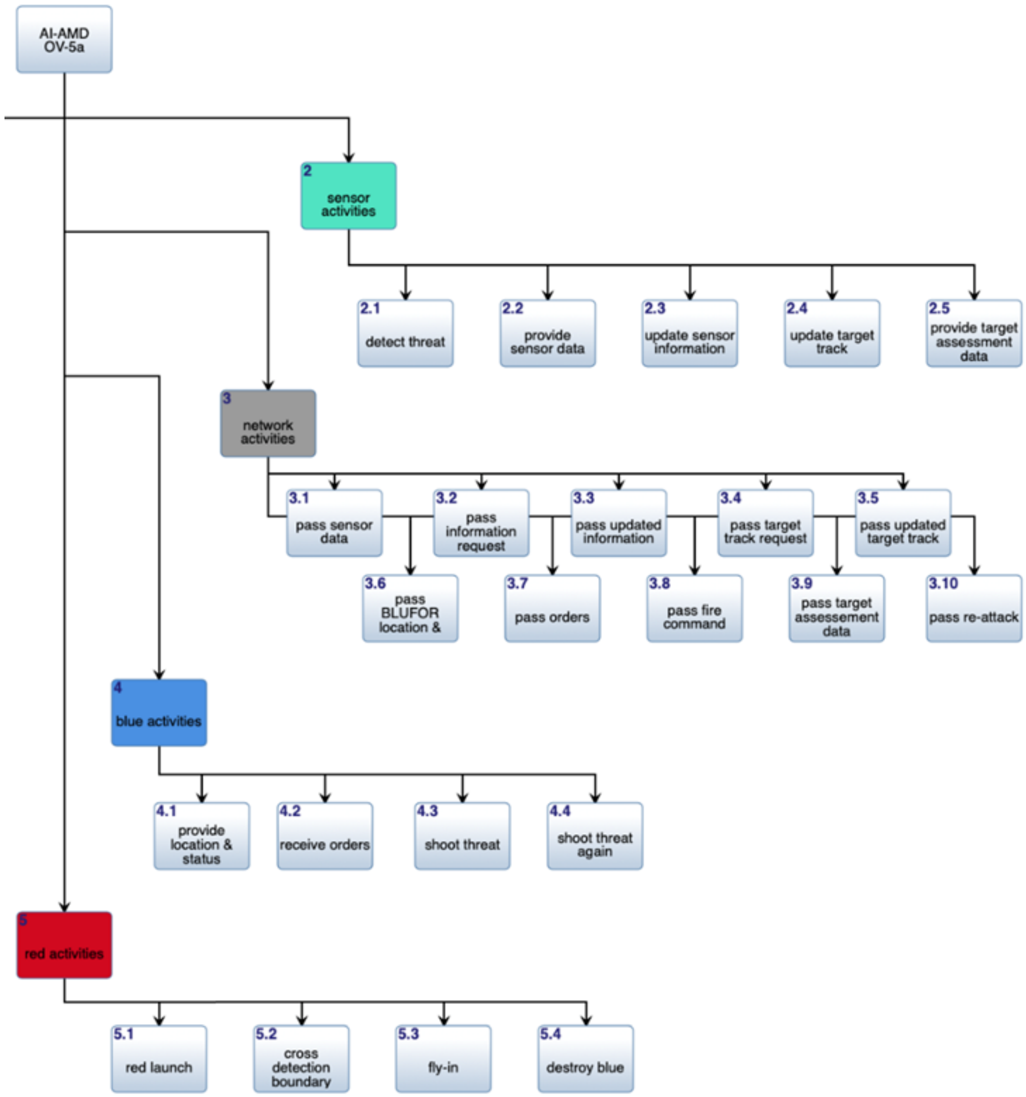


Figure 20. OV-5a: AI-AMD Operational Activity Decomposition—External Systems

F2T2EA functions are labeled to identify their relationship to the OODA loop (see the six primary activities in Figure 19. The find and fix steps were allocated to the observe phase, the track step was allocated to the orient phase, the target step was allocated to the decide phase, and the engage and assess steps were allocated to the act phase. The OV-5a captures the external agents of the SoS (i.e., BLUFOR sensors, weapons, and network) as well as the REDFOR threat (see the four external agents depicted in Figure 20. In total, each of the 17 steps or functions identified for the AI, human, or AI-human team have been decomposed using the F2T2EA to OODA loop mapping. Stakeholders should review the JP 3-60 related functions to determine their level of agreement with the intended mission set for AMD operations. This would also be an opportunity to identify potential mission overlap and/or competing resource constraints.

d. OV-5b: Operational Activity Model

The OV-5b activity model builds upon the relationship defined in the OV-5a to bring in the ICOM that are required to support each action. The top-level activities of the AI-AMD decision aid and external agents are shown in Figure 21. Also defined are the input and outputs of each action, the controls that trigger or limit functionality, and the mechanisms that enable the function. At this phase of the AI-AMD life cycle, only generic mechanisms were assigned to the actions; with continued maturity, specified systems, subsystems, or assemblies will be developed to perform the operational activities. It is important to note this view demonstrates how the AI-AMD system communicates with other SoS elements only via the network. Furthermore, it can be clearly seen how critical the network is for each of the SoS elements; it is the central hub for all operational activities. Greater detail can be seen at the next level of decomposition in Figure 22.

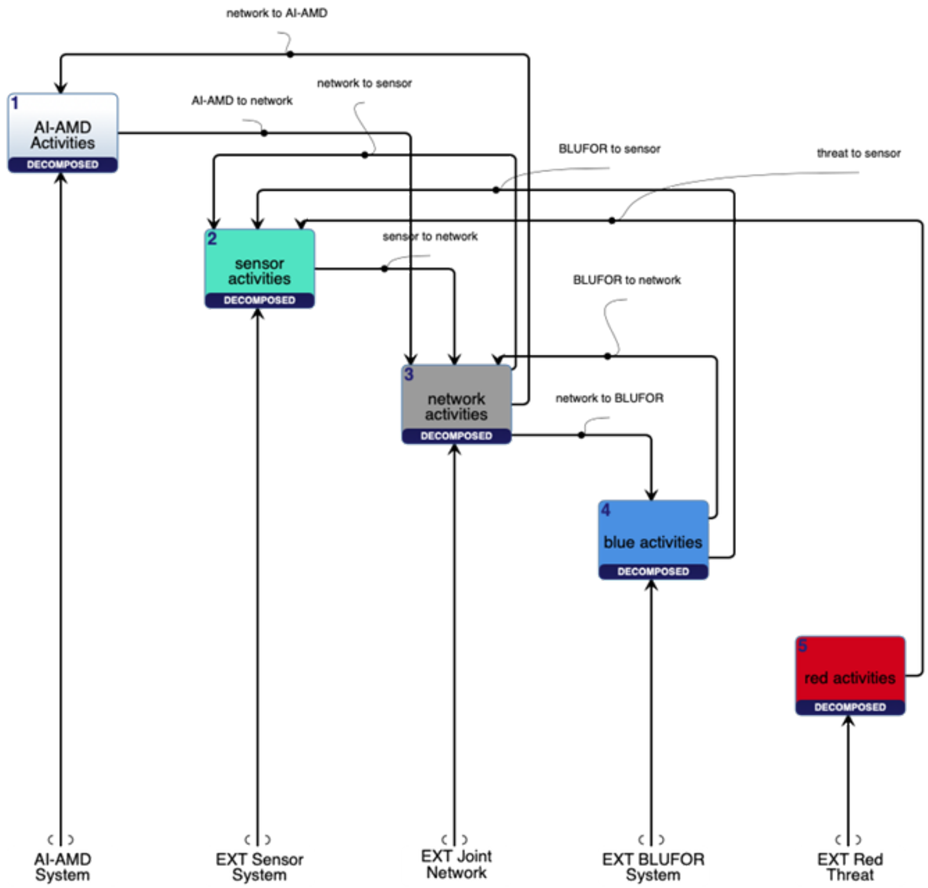


Figure 21. OV-5b: AI-AMD Operational Model

The operational activities of the AI-AMD decision aid were further defined on the OV-5b depicted in Figure 22. The same ICOM processes were maintained in the model through concordance. Here, the team focused on the AI-AMD system and its detailed connections to external systems. Again, the system was seen to be completely dependent on the network to send and receive data for informing decisions and issuing engagement commands. Concordance ensured the identified mechanisms performing these activities are the same at both high-level and low-level decomposition.

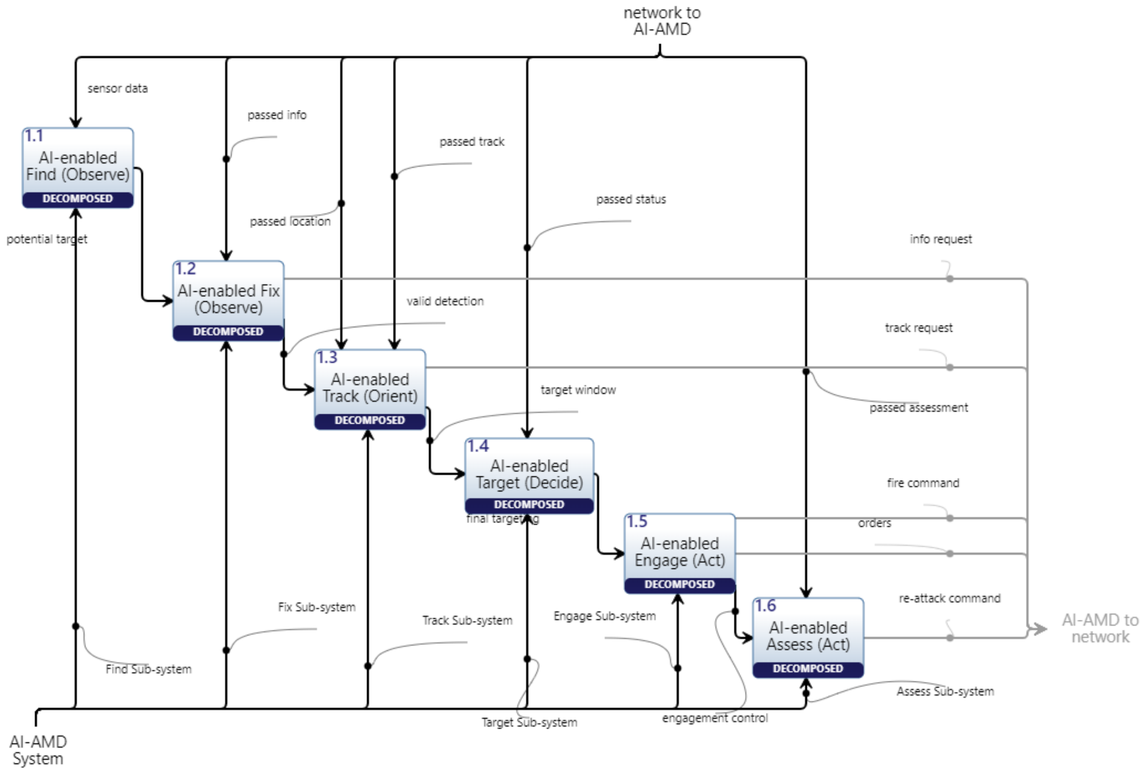


Figure 22. OV-5b: Decomposed AI-AMD Operational Activity Model

e. OV-5b/6c: Action Diagram

The OV-5b/6c integrates the operational activity model and the event trace diagram into a combined action diagram displaying the input/output (I/O) of the activity model and the sequence of events to demonstrate the relationships for a particular scenario. The OV-5b/6c served as the primary simulation tool for the team. Using the Innoslate MBSE tool, stochastic distributions for function durations were added to each step to turn the OV-5b/6c into a discrete event simulation. The simulation and analysis are captured in Chapter IV.

Figure 23 shows the AI-AMD top-level activities alongside the external agents. Exchanges of energy, matter, and information are triggers (depicted as green boxes) or controls for enabling actions such as sensor data or requests for information. Outputs of AI-AMD decision aid activities pass as inputs (gray boxes) into each F2T2EA step. Subsequent figures focus on each slice of the action diagram; there are many loops within the F2T2EA where external information is gathered and the decision aid is updated.

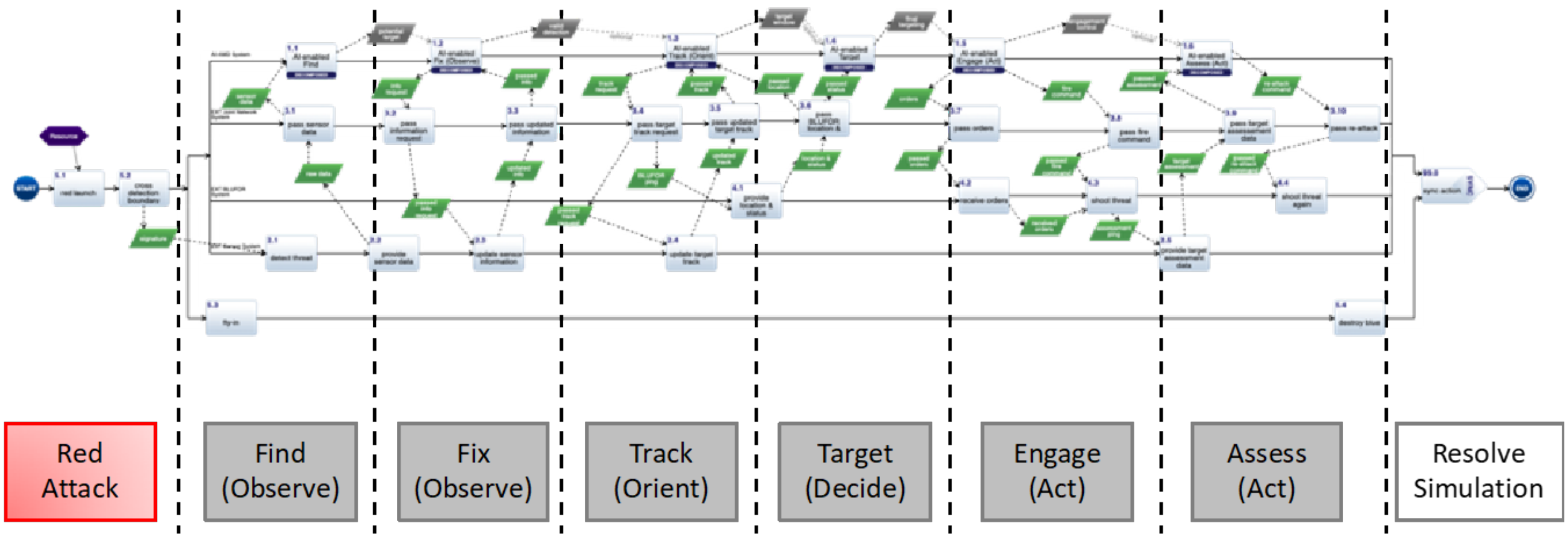


Figure 23. OV-5b/6c: AI-AMD Action Diagram

Starting on the left side of the OV-5b/6c in Figure 23, Figure 24 focuses on the initial engagement and the find step. The action diagram is initiated when the REDFOR launches an attack. The BLUFOR are unable to detect the threat until the threat crosses a detection boundary where the BLUFOR sensors are able to detect the threat that is triggered by a "signature" detection. Depicted on the graphic with a red circle, is the fly-in of the red threat. This was added to the OV-5b/6c to track the fly-in time of the REDFOR against the BLUFOR to assess success in defeating the threat. The simulation also contains a "resource" which was added to allow the Innoslate model to run the discrete event simulation. Once the REDFOR crosses the detection boundary, the model moves through four parallel systems: the AI-AMD system at the top, the external joint network system below that, the external BLUFOR system (defeat mechanism) below that, and the external sensor system (detection mechanism) below that. The find step starts when the BLUFOR sensors detect the threat and provide the sensor data to the network as annotated by the "raw data" trigger. The network then passes that data to the AI-AMD system which identifies a "potential target" output into the next step, fix.

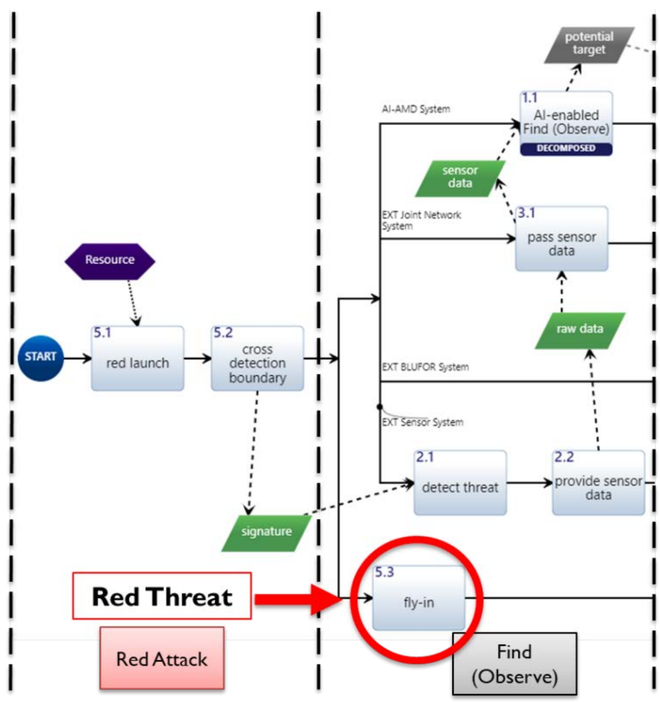


Figure 24. OV-5b/6c: Red Attack and Find (Observe)

The next OV-5b/6c action diagram is for the fix step found in Figure 25. The fix step starts when the “potential target” trigger from the previous find step enters the AI-AMD decision aid. The decision aid then requests more information through the network using an “info request” trigger to the sensors using a “passed info” trigger. The sensors then update their information and pass that to the network through an “updated info” trigger. Once the network successfully passes the information to the AI-AMD decision add through a “passed info” trigger, a “valid detection” output to the next step, track, is made. The fix step is a loop where the AI-AMD system is continuously updating the decision aid based on sensor data.

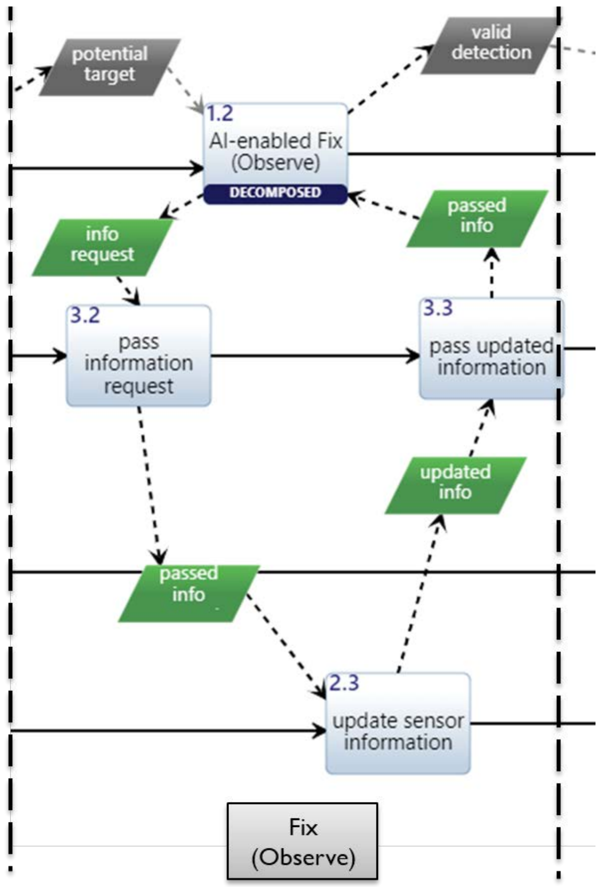


Figure 25. OV-5b/6c: Fix (Observe)

The next step in the F2T2EA kill chain is the track step found in Figure 26. The track step performs two key functions: to update sensor detection tracks and to determine BLUFOR defeat capabilities based on the target track. The track step is initiated when a "valid detection" trigger is sent to the AI-AMD decision aid. The decision aid then sends a "track request" through the network. The network then sends the "passed track" request to the sensors and also sends a "BLUFOR ping" to the BLUFOR assets to determine location and status of available assets. The sensors then send an "updated track" to the network, and the network sends the "passed track" to the AI-AMD system. There are several feedback loops between the track and target steps that feed information back into the AI-AMD decision aid for sensor detection tracks and BLUFOR location data. Location data from the target step using the trigger "passed location" is used by the track step to update the "target window." The "target window" is then outputted from the track step into the next step, target.

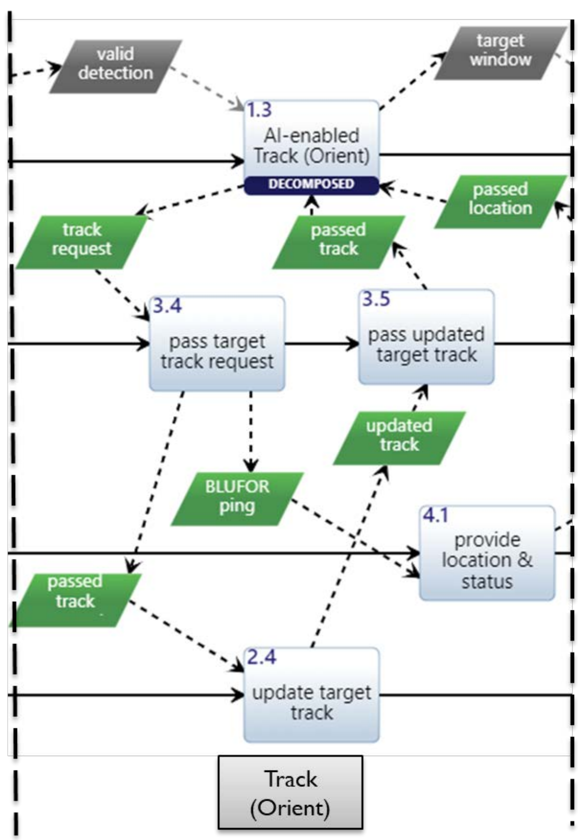


Figure 26. OV-5b/6c: Track (Orient)

The next step is the target step found in Figure 27. The target step is initiated when the AI-AMD system takes in the “target window” from the track step. The AI-AMD decision aid accepts the BLUFOR location and status from the network using the trigger “passed status” which is sent from the BLUFOR assets using the trigger “location & status.” This information is then used by the AI-AMD system to generate COAs, select an engagement, and send a “final targeting” trigger to the next step, engage.

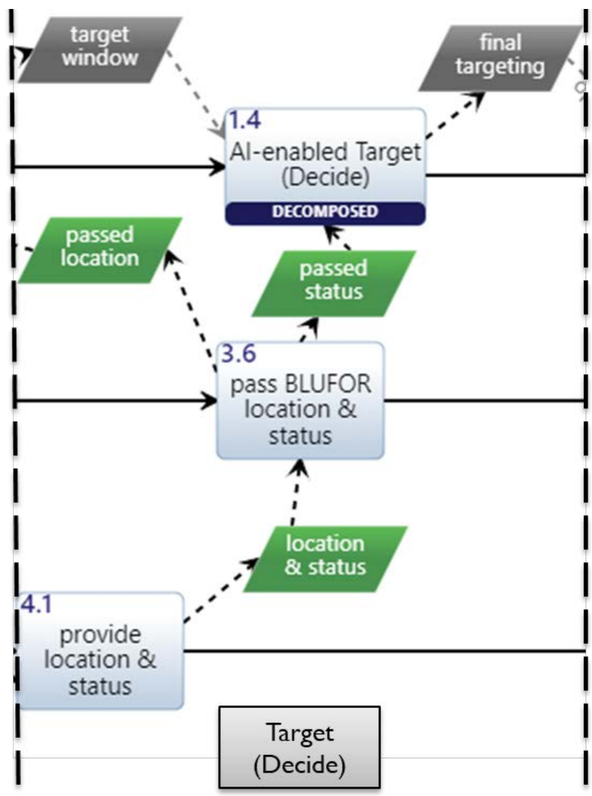


Figure 27. OV-5b/6c: Target (Decide)

The next step in the kill chain is the engage step found in Figure 28. The engage step includes issuing of the orders and sending the fire command to the BLUFOR systems. The engage step initiates when the “final targeting” trigger from the target step is passed into the AI-AMD. The AI-AMD system then issues the orders and the fire command to the network using the triggers “orders” and “fire command,” respectively. The orders are then sent to the BLUFOR assets using the trigger “passed orders” and once the fire command is received by the BLUFOR using the trigger “passed fire command,” the BLUFOR shoots the threat. An output of the AI-AMD decision aid called “engagement control” is then sent to the next step, assess.

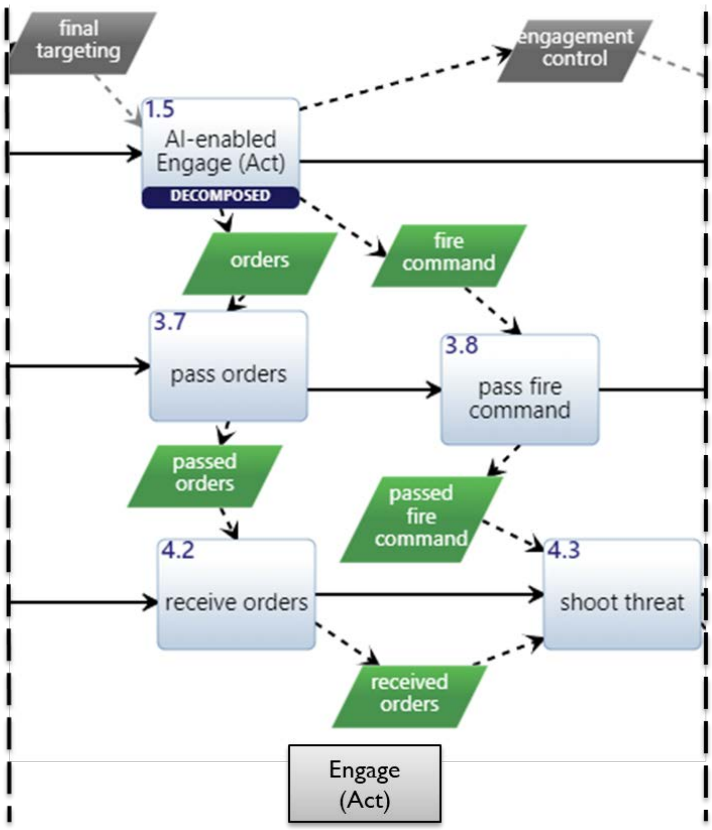


Figure 28. OV-5b/6c: Engage (Act)

The final step in the kill chain is the assess step found in Figure 29. The assess step starts when the “engagement control” trigger from the engage step is passed into the AI-AMD system. The assess step makes a target assessment using data from the sensors and if the threat is not defeated, authorizes re-attack. Data from the BLUFOR sensors is sent to the network using the trigger “target assessment,” which is then sent to the AI-AMD using the trigger “passed assessment.” The AI-AMD system then authorizes a re-attack by using the trigger “re-attack command,” which is then sent to the BLUFOR defeat mechanisms to shoot the threat again. The simulation resolves with a sync of the parallel actions to determine if the BLUFOR was able to defeat the REDFOR fly-in within the engagement timeline; in other words, if BLUFOR completes all operational activities before REDFOR completes fly-in and destroys blue, the SoS achieved mission success.

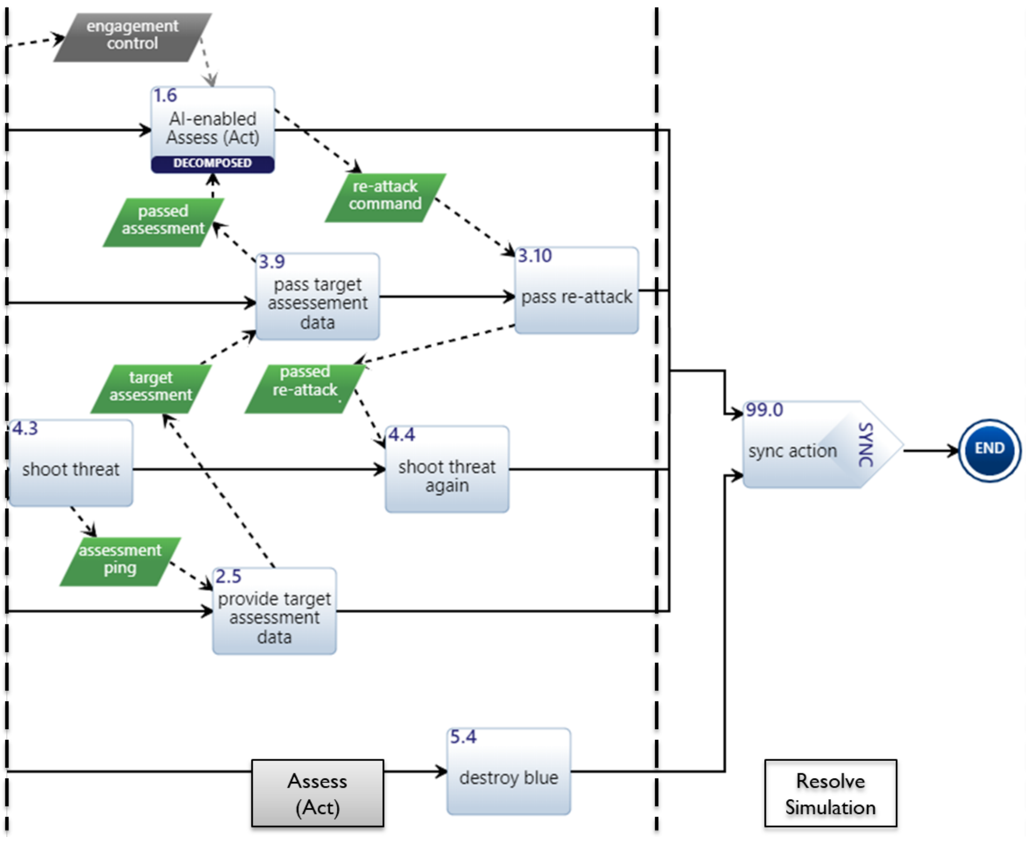


Figure 29. OV-5b/6c: Assess (Act) and Resolve Simulation

f. *JP 3-60 to OV-5b/6c Mapping*

Leveraging the high level OV-5b/6c for the AI-AMD system in the previous section, the team then decomposed each of the F2T2EA AI-enabled decision aid actions into lower level actions. In order to do so, a review of the JP 3-60 targeting doctrine flow charts was reviewed to assess the applicability to the AMD mission. Figure 30 shows the find step JP 3-60 to OV-5b/6c mapping. The team simplified the find step into three serialized actions; collect data, accept initial detection, and identify emerging threat. The "sensor data" trigger is used as an input to the collect data step and the find step concludes by outputting a "potential target" trigger to the next step, fix.

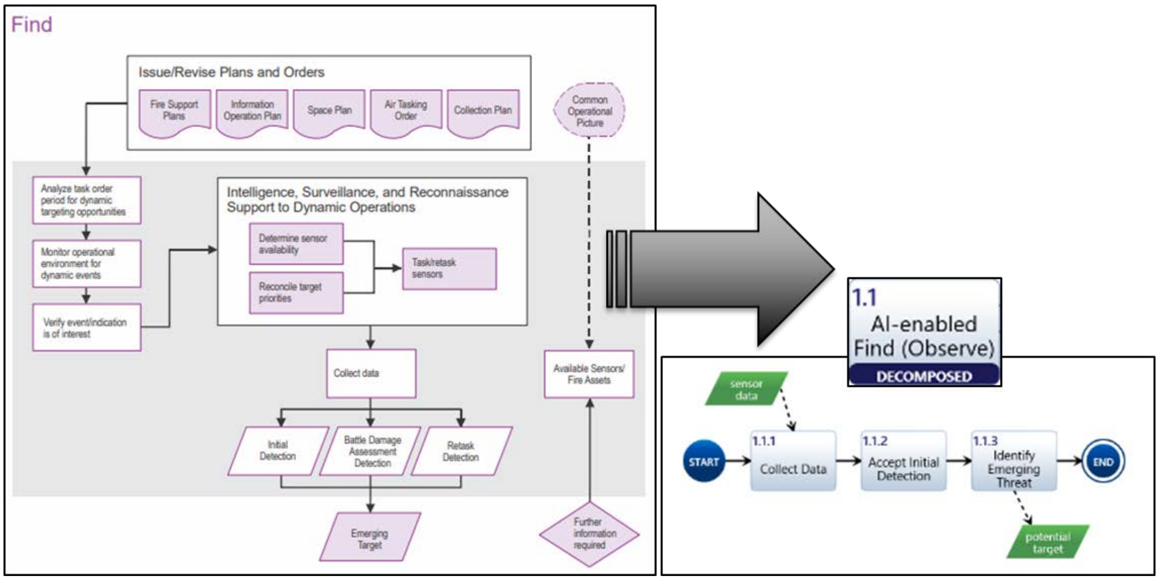


Figure 30. OV-5b/6c: Mapping the Find Step. JP 3-60 (left). Innoslate Model (right). Adapted from Joint Chiefs of Staff (2018, Figure II-11).

Mapping the fix step from JP 3-60 to the model can be found in Figure 31. The fix step was simplified to four actions; request further information, classify target, locate target, and validate detection. The classify target and locate target actions are done in parallel. Several triggers exist in the model including accepting the AI-AMD "potential target" from the find step and the "passed info" from the sensors which is used to both classify and locate the target. The step concludes with an output of "valid detection" which is used by the AI-AMD system in the next step, track.

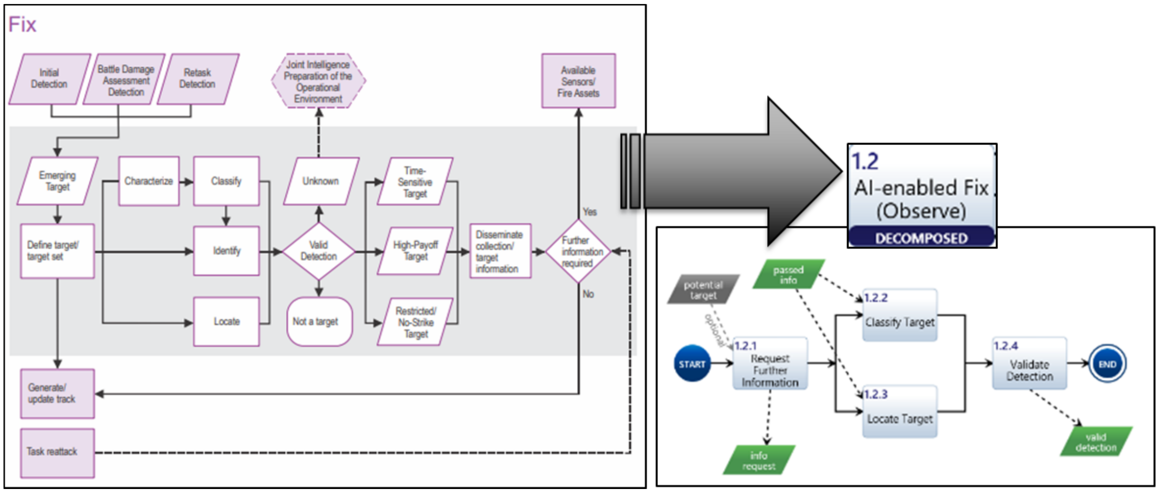


Figure 31. OV-5b/6c: Mapping the Fix Step. JP 3-60 (left). Innoslate Model (right). Adapted from Joint Chiefs of Staff (2018, Figure II-13).

The track step JP 3-60 to OV-5b/6c actions can be found in Figure 32. This step was simplified to include three actions; request updated target track, validate target, and assess blue proximity. The validate target and assess blue proximity are conducted in parallel. The simulation starts with the “valid detection” output from the fix step. Once the valid detection is received, the AI-AMD sends a “track request” trigger to the sensors. The “passed track” is then used in the validate target action and the “passed location” is used to assess blue proximity. The AI-AMD uses the BLUFOR proximity and the valid target to determine the time and location required to respond as annotated by the “target window” output.

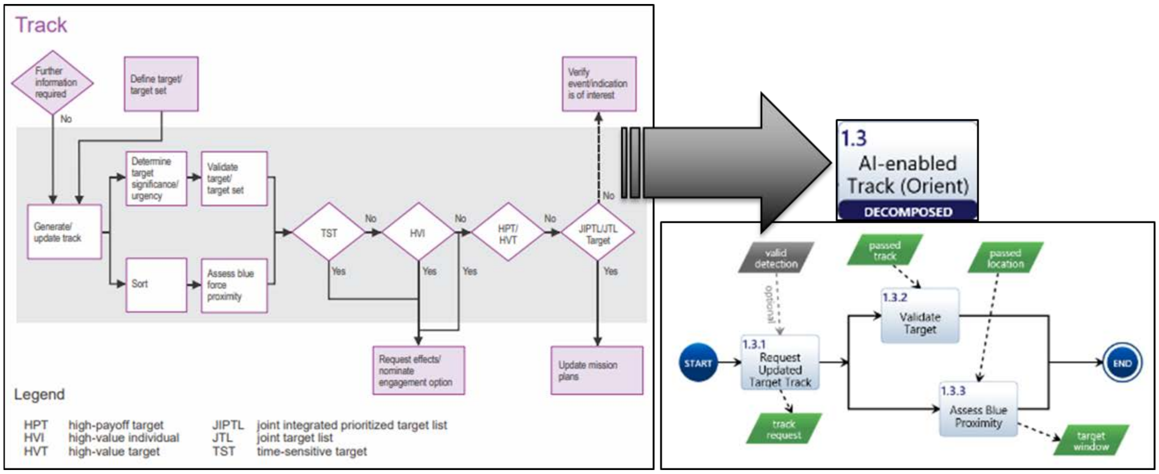


Figure 32. OV-5b/6c: Mapping the Track Step. JP 3-60 (left). Innoslate Model (right). Adapted from Joint Chiefs of Staff (2018, Figure II-14).

Mapping the target step to the OV-5b/6c can be found in Figure 33. The target step is simplified to contain three actions: nominate engagement options, prioritize targets, and select attack option(s). These three actions are executed in series. The simulation starts with the "target window" from the track step. Nomination of engagement options is triggered by "passed status" from the BLUFOR defeat mechanisms. The step concludes with a "final targeting" output passed to the next step, engage.

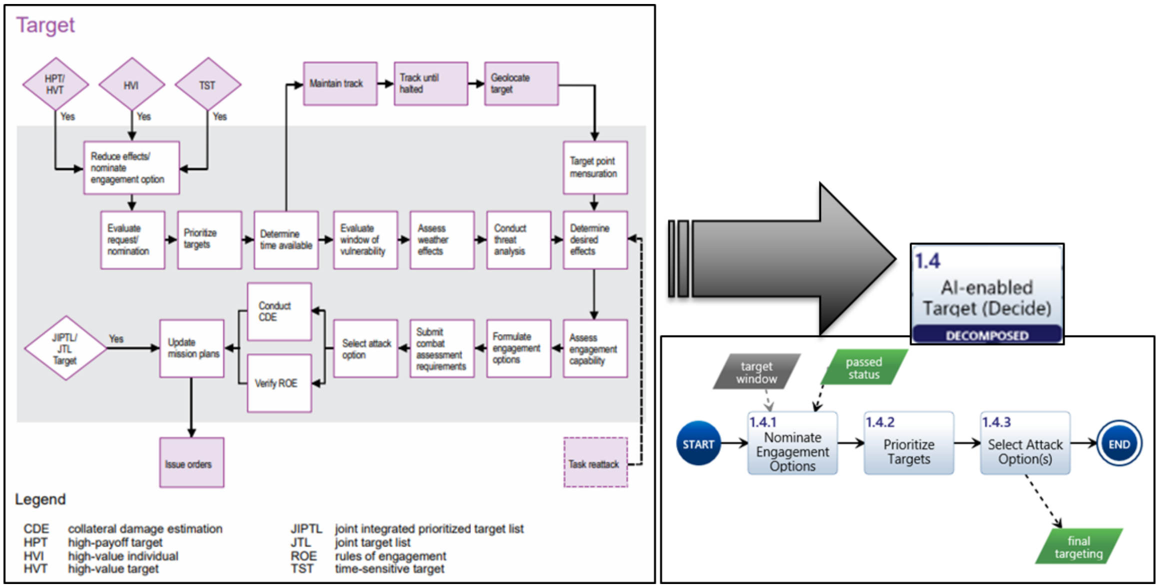


Figure 33. OV-5b/6c: Mapping the Target Step. JP 3-60 (left). Innoslate Model (right). Adapted from Joint Chiefs of Staff (2018, Figure II-15).

The engage step JP 3-60 to OV-5b/6c can be found in Figure 34. The engage step has two actions that are conducted in series; issue orders and send fire command. The step initiates using the “final targeting” trigger from the previous step, target. The issues are passed to the BLUFOR systems using the “orders trigger.” The AI-AMD then send the “fire command” to the BLUFOR systems which execute the engagement. The simulation concludes with an “engagement control” trigger that will be passed into the final step in the kill chain, assess.

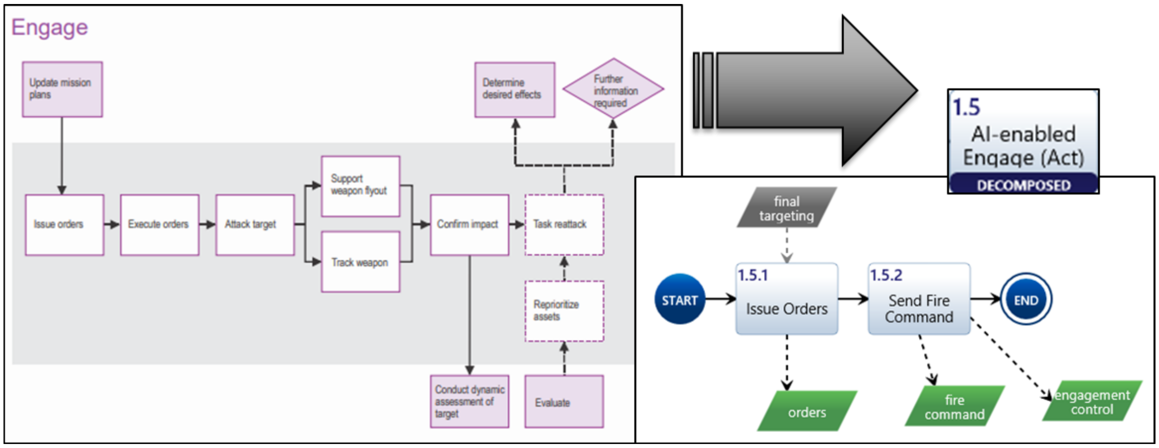


Figure 34. OV-5b/6c: Mapping the Engage Step. JP 3-60 (left). Innoslate Model (right). Adapted from Joint Chiefs of Staff (2018, Figure II-16).

JP 3-60 does not contain a flow chart process for the assessment phase. The actions for the assessment step were derived from reviewing the publication and assessing which key actions were best represented within the step. JP 3-60 states:

> During the assess step, initial assessment of the physical or functional status of the target takes place. For attacks in the physical environment, the assessment confirms impact of the weapon on the target and makes an initial estimate of the damage. For nonlethal weapons, the initial assessment attempts to detect changes in functionality indicating a successful engagement. (Joint Chiefs of Staff 2013, II-30)

From this information, the assess step was simplified to include two actions that occur in series; assess target status and authorize re-attack. The step starts with the AI-AMD system receiving the "engagement control" trigger from the engage step. The "passed assessment" trigger is then received from the BLUFOR sensors via the network. If the REDFOR is not defeated, a re-attack is authorized, and the AI-AMD decision aid sends the "re-attack command" to the BLUFOR to initiate a follow-on engagement. The assess step concludes AI-AMD activities within the OV-5b/6c action diagram.

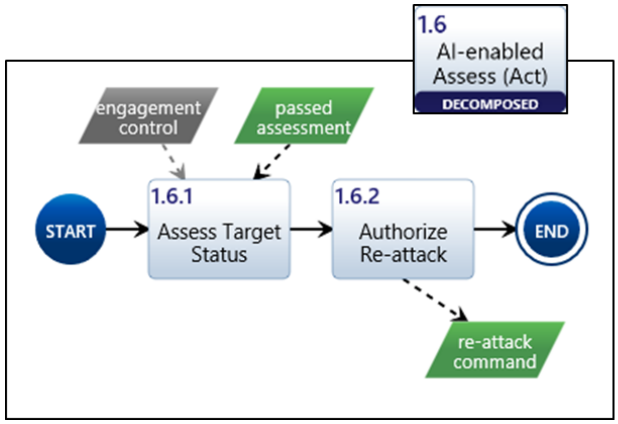


Figure 35. Mapping the Assess Step

2. System Architecture Viewpoint

The system architecture view defines the system's design. The system's view identifies the interfaces, interconnections, and relationships in a SoS construct. The team identified two key SVs to model which are the SV-1 system interface description and the SV-3 systems-systems matrix. A description of these views can be found in Table 10. The team used the SV-1 and the SV-3 to describe the relationships between the AI-AMD internal components and its external systems.

Table 10. DODAF SVs Source: DODAF v2.02, DOD (2020).

Model	Description
SV-1 Systems Interface Description	The identification of systems, system items, and their interconnections
SV-3 Systems-Systems Matrix	The relationships among systems in a given Architectural Description. It can be designed to show relationships of interest

a. SV-1: Systems Interface Description

The SV-1 brings together the mechanisms listed in the OV-5b and provides interfaces to create the basic system and sub-system architecture. The systems and sub-systems are presented along with the interfaces between the sub-systems in order to establish conduits between the systems. The SV-1 becomes the base architecture to begin more detailed design of the system in the next phase of the life cycle as hardware and software configuration items and sub-assemblies become more defined. A high level of dependence on the network is observed in the SoS view illustrated in Figure 36. The internal connections are anticipated to be serial as depicted in Figure 37. AI-AMD stakeholders should work with external system stakeholders (particularly the network) to ensure effective SoS communications. Future life cycle development should determine the impact of failures with this sub-system series arrangement. With this current arrangement, reliability will determine AI-AMD operations since a failure early in the system prevents downstream activities.

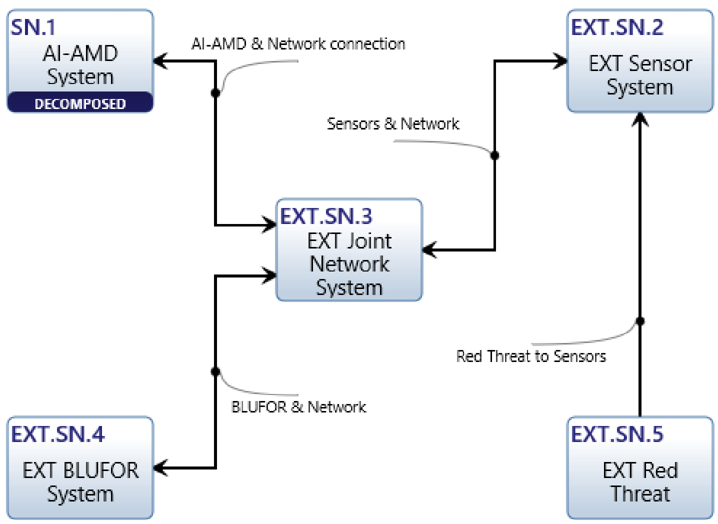


Figure 36. AI-AMD SoS Interface Diagram

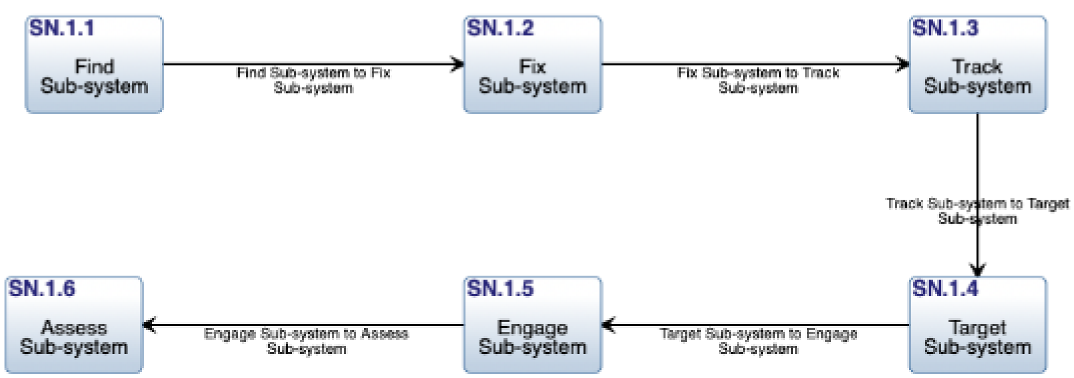


Figure 37. AI-AMD System Internal Interface Diagram

b. *SV-3: Systems-Systems Matrix*

After the SV-1 was generated to show the connections between the subsystems, the SV-3 was created to define the exchanges between assets. Figure 38 presents the relationship between the AI-AMD system and external elements of the SoS. This N^2 diagram depicts connections and directionality of systems' interfaces. Concordance ensures the mechanisms identified earlier in the OV-5b and SV-1 are the same as shown here in the matrix view. Once again, the AI-AMD system interfaces with four external agents. The strong dependency on the network can be seen again, as the network provides the critical conduit of information to and from the AI-AMD decision aid. As the AI-AMD system life cycle develops, stakeholders should revisit the SoS interfaces. Additional decomposition at the sub-system level may be helpful as technologies mature.

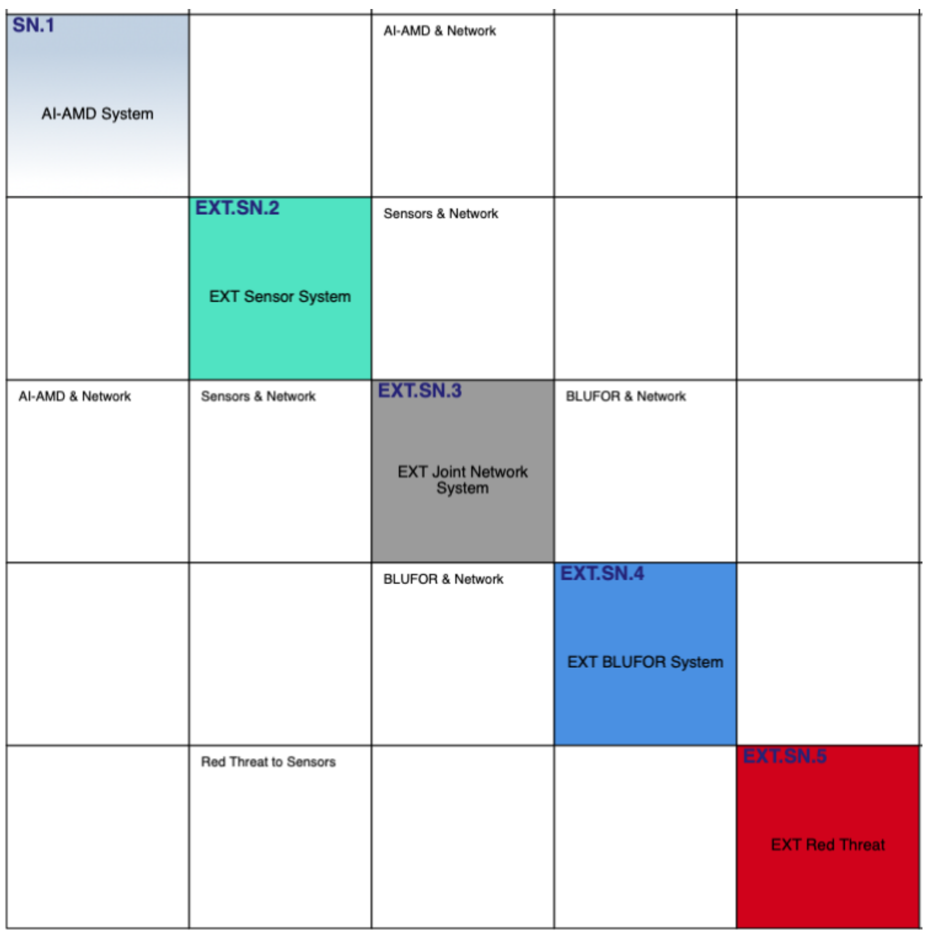


Figure 38. AI-AMD Systems-Systems Matrix

B. AI-AMD KILL CHAIN ANALYTICAL FRAMEWORK

This section presents the team's findings regarding the AI-AMD mission timeline and the resultant representative scenarios. The team explored response times available given several notional REDFOR AMD threats and BLUFOR assets. These scenario timelines were decomposed and allocated to determine needed AI-AMD capabilities at the operational activity level (i.e., the amount of time it would take for the BLUFOR to implement the kill chain functions to defend against AMD threats). The team reviewed open source data to gather this information but acknowledges that there are potentially many other threats and BLUFOR assets available.

This section also contains a description of the AI-AMD kill chain analytical framework that was developed by the team. The team studied AMD kill chain functions and identified 17 functions that require decisions. The team studied the application of AI and higher levels of automation for each of the 17 kill chain functions with a focus on the potential for improving the AMD timeline. The team developed a method for analyzing the risk associated with automating kill chain functions.

1. Red Force Threats

AMD is composed of various threats derived from many of the U.S. adversaries looking to undermine U.S. interests abroad. The team reviewed open source threat data available to derive the threat timeline. Though the scope of the adversarial threat list can come from numerous different opponents and modalities, the project focused on three main countries that possess the greatest risk as a near peer threat to the U.S. national security interests which are China, Russia, and Iran. As near peers have continuously closed the gap between U.S. military superiority, the ability for the AI to neutralize threats in a timely manner has become extremely imperative. Therefore, the project focuses on the air missile threats that can result in an engagement timeline ranging from a few minutes to a few hours. It is assumed that airborne threats such as fixed wing aircrafts, and rotary aircrafts will be neutralized by BLUFOR using fixed wing aircrafts with long range capabilities. Therefore, enemy air missile and unmanned aerial vehicle (UAV) threats were the main focus of study in this project. One will quickly see that the air missile threat is far more demanding than the UAV threat due to the velocity of the missile and associated time to respond.

In Table 11, the open source missile threats from China, Russia, and Iran are selected as the focus of research for the project. These threats provide the data required to successfully run the model to determine the capabilities of the AI. By dividing the operational range in kilometers by the velocity in kilometers per minute, the associated timeline of the red threat from launch to impact can be calculated. The range in time for a threat such as the WZ-8 drone is 72.89 minutes whereas the threat for a short-range 3M-54 Kalibr missile is only 3.11 minutes. It is also important to note the variations in speed of the potential threats. Hypersonic missiles such as the DF-17 capable of traveling 2,500 km in 12.15 minutes poses a significant threat and the need for the decision aid to mitigate the threat in a short period of time.

Table 11. Red Force Threats

Red Force	Operational Range (km)	Velocity (kpm)	Time (minutes)
DF-21D Hypersonic (China)[a]	12,000	205.80	58.31
DF-17 Hypersonic (China)[b]	2,500	205.80	12.15
WZ-8 Drone (China)[c]	6,000	82.32	72.89
P-270 Moskit (Russia)[d]	250	61.75	4.05
BrahMos-11 (Russia)[e]	600	144.07	4.16
3M-54 Kalibr (Russia)[f]	50	16.08	3.11
Khaliij Fars (Iran)[g]	300	61.73	4.86
Shahed-129 Drone (Iran)[h]	170	2.92	58.29

[a]Source: Webb (2017); [b]Source: Missile Defense Project (2020); [c]Source: Chan (2020); [d]Source: Missile Defense Advocacy Alliance [MDAA] (2018a); [e]Source: MDAA (2018b); [f]Source: MDAA (2017); [g]Source: Roblin (2019); [h]Source: Military Factory (2019).

2. Blue Force Detection Sensors

Using a similar approach to the REDFOR threat, an open source review of available BLUFOR detection sensors was conducted. During AMD operations, the timeline to respond to the threat starts with the initial detection. As depicted by the OV-1 diagram in Figure 6, the AI capability must support MDO leveraging sensors and systems on land, sea, air, and space through a joint network. As such, it is important to delineate the BLUFOR detection capabilities specific to each branch. Each of the BLUFOR detection assets as depicted in Table 12 is based on the current military hardware from an open source review that is fielded by the U.S. Navy/Marine Corps, U.S. Army, and Missile Defense Agency.

Table 12. Blue Force Detection Capabilities

Blue Force Detection Assets		**Detection Range (Km)**
Navy	Aegis Weapon System (AWS) / AN/SPY-1 Radar[a]	310
Army	Sentinel Radar[b]	75
	AN/TPQ-53 (replacement for AN/TPQ-36)[c]	20
	AN/TPQ-50 Light-weight Counter Mortar Radar (LCMR)[d]	10
	Patriot System[e]	100
	Terminal High Altitude Area Defense (THAAD)[f]	1000
Missile Defense Agency	Upgraded Early Warning Radars (UEWR)[g]	4828
	Cobra Dane Radar[h]	3218
	Sea-based X-band Radar[i]	4023

[a]Source: MDAA (2018d); [b]Source: USA (n.d.c); [c]Source: USA (n.d.b); [d]Source: USA (n.d.a); [e]Source: Army Technology (n.d.a); [f]Source: MDAA (2019); [g]Source: MDA (2016a); [h]Source: MDA (2016b); [i]Source: MDA (2016c).

3. Blue Force Kinetic Capabilities

The DOD has various kinetic and directed energy weapons that are configured to support the AMD mission. The blue force missile capabilities provide the AI with courses of action to neutralize oncoming enemy air threats. Using a similar approach to red threat data and blue force detection sensors, an open source material review of Navy, Marine, and Army defeat assets was conducted. Using the velocity of the blue force kinetic asset and the range, a timeline to defeat the red threat can be calculated. Table 13 depicts the standard missile capabilities of each branch that was selected for this project.

Table 13. Blue Force Defeat Assets

Blue Force Defeat Assets		Maximum Effective Range (km)	Velocity (kpm)
Navy	Standard Missile (SM) 2[a]	167	72.02
	SM 3[b]	2,500	270.00
	Phalanx Close-in Weapons System (CIWS) / M-61A1 Gatling Gun[c]	5.48	66.77
Marines	Tomahawk Missile[d]	1,600	14.67
Army	Stinger Systems[e]	8	41.17
	MM-104F Patriot system (PAC 3)[f]	20	83.33
	THAAD[g]	200	168.00

[a]Source: Berger (2016); [b]Source: Johnson-Freese and Savelsberg (2013); [c]Source: MDAA (2018c); [d]Source: USN (2018); [e]Source: Army Technology (n.d.b); [f]Source: Defense World (2018).

4. AMD Timeline

Leveraging the data in the previous sections for REDFOR threats, BLUFOR detection sensors, and BLUFOR kinetic capabilities, the data was organized to determine the various timelines and scenarios. The data was then binned into clusters and performance outliers could be identified. Figure 39 is a summary of the calculated timelines.

		Red Threat:	DF-21D (China)	DF-17 Hypersonic (China)	WZ-8 Drone (China)	P-270 Moskit (Russia)	BrahMos-11 (Russia)	3M-54 Kalibr (Russia)	Khaliij Fars (Iran)	Shahed-129 Drone (Iran)
		Maximum Operational Range (km)	2000	2500	6000	250	600	50	300	170
		Velocity (kpm)	205.80	205.80	82.32	61.75	144.07	16.08	61.73	2.92
		Time to engage at Maximum Operational Range (minutes)	9.72	12.15	72.89	4.05	4.16	3.11	4.86	58.29
Blue Force Detection Assets		Detection Range (Km)	Time to Respond to Red Threat (minutes)							
Navy	Aegis Weapon System (AWS) / AN/SPY-1 Radar	310	1.5	1.5	3.8	4.0	2.2	3.1	4.9	58.3
Army	Sentinel Radar	75	0.4	0.4	0.9	1.2	0.5	3.1	1.2	25.7
	AN/TPQ-53 (replacement for AN/TPQ-36)	20	0.1	0.1	0.2	0.3	0.1	1.2	0.3	6.9
	AN/TPQ-50 Light-weight Counter Mortar Radar (LCMR)	10	0.0	0.0	0.1	0.2	0.1	0.6	0.2	3.4
	Patriot system	100	0.5	0.5	1.2	1.6	0.7	3.1	1.6	34.3
	Terminal High Altitude Area Defense (THAAD)	1000	4.9	4.9	12.1	4.0	4.2	3.1	4.9	58.3
Missile Defense Agency	Upgraded Early Warning Radars (UEWR)	4828	9.7	12.1	58.7	4.0	4.2	3.1	4.9	58.3
	Cobra Dane radar	3218	9.7	12.1	39.1	4.0	4.2	3.1	4.9	58.3
	Sea-based X-band radar	4023	9.7	12.1	48.9	4.0	4.2	3.1	4.9	58.3

Quartile	1	2	3	4
Color				
Value	0.68	3.27	5.36	58.65

Figure 39. Threat Timelines

The top rows of Figure 39 depict the various red threats, operational ranges, velocities, and timelines based on the maximum range of the threat which was previously shown in Table 11. From there, each BLUFOR detection capability as previously referenced in Table 12 was used to determine the associated time to respond against each of the red threats. The logic behind the timeline was calculated by comparing the maximum BLUFOR detection range to the maximum red threat operational range. Since the AI-AMD system cannot process the data until a detection is made, the timeline started at the maximum detection range of the BLUFOR detection asset. However, if the red threat maximum operational range was less than the BLUFOR detection range, then the timeline was initiated at the red threat maximum operational range. Using the statistics package in Microsoft Excel, the associated timings were separated into quartiles as depicted in the legend.

Further analysis of the data revealed several scenarios where the timeline was too low to respond to the threat. The Army's AN/TPQ-53 and AN/TPQ-50 sensors with a 20 km and 10 km detection range, respectively, resulted in timelines well below one minute to respond to the threat. As a result, both of these BLUFOR assets were eliminated from consideration as a viable option. To characterize the needed capability trade space, three scenarios were selected from the data. A "low-stress" scenario using an MDA UEWR detection against a WZ-8 Drone resulting in a 58.7-minute timeline, a "moderate-stress" scenario using an MDA UEWR detection against a DF-21D resulting in a 9.72-minute timeline, and a "high-stress" scenario using a Navy AWS detection against a DF-17 hypersonic missile threat resulting in a 1.5-minute scenario. Figure 40 depicts the filtering of the data and the scenarios selected are indicated with dotted circles.

			DF-21D (China)	DF-17 Hypersonic (China)	WZ-8 Drone (China)	P-270 Moskit (Russia)	BrahMos-11 (Russia)	3M-54 Kalibr (Russia)	Khaliij Fars (Iran)	Shahed-129 Drone (Iran)
	Red Threat:									
	Maximum Operational Range (km)		2000	2500	6000	250	600	50	300	170
	Velocity (kpm)		205.80	205.80	82.32	61.75	144.07	16.08	61.73	2.92
	Time to engage at Maximum Operational Range (minutes)		9.72	12.15	72.89	4.05	4.16	3.11	4.86	58.29
	Blue Force Detection Assets	**Detection Range (Km)**	**Time to Respond to Red Threat (minutes)**							
Navy	Aegis Weapon System (AWS) / AN/SPY-1 Radar	310	1.5	1.5	3.8	4.0	2.2	3.1	4.9	58.3
Army	Sentinel Radar	75	0.4	0.4	0.9	1.2	0.5	3.1	1.2	25.7
	AN/TPQ-53 (replacement for AN/TPQ-36)	20	0.1	0.1	0.2	0.3	0.1	1.2	0.3	6.9
	AN/TPQ-50 Light-weight Counter Mortar Radar (LCMR)	10	0.0	0.0	0.1	0.2	0.1	0.6	0.2	3.4
	Patriot system	100	0.5	0.5	1.2	1.6	0.7	3.1	1.6	34.3
	Terminal High Altitude Area Defense (THAAD)	1000	4.9	4.9	12.1	4.0	4.2	3.1	4.9	58.3
Missile Defense Agency	Upgraded Early Warning Radars (UEWR)	4828	9.7	12.1	58.7	4.0	4.2	3.1	4.9	58.3
	Cobra Dane radar	3218	9.7	12.1	39.1	4.0	4.2	3.1	4.9	58.3
	Sea-based X-band radar	4023	9.7	12.1	48.9	4.0	4.2	3.1	4.9	58.3

Figure 40. Filtering the Threat Timelines

The team used these timelines to benchmark the AI-AMD performance to represent a human making all decisions with no assistance from the computer versus a fully automated computer decision. With established “low-stress” and “high-stress” scenario timelines, levels of automation for each of the 17 steps in the F2T2EA targeting process were determined by inspection. The low-stress scenario was used to represent the human making all decisions, level of automation 1. The high-stress scenario depicted in the previous section was used to represent the fully autonomous computer decisions, level of automation 10. The benchmarked timelines were then decomposed to each AI-AMD operational activity (i.e., equally distributed across the 17 steps). A graphic can be seen in Figure 41; this spreadsheet model illustrates one approach of aggregating the expected value of operational activity times into a simple total AI-AMD capability. However, the AI-AMD capability timelines are unforgiving; if one activity runs long, the other activities must either react faster or fail to defend the scenario.

			Low Stress Scenario			High Stress Scenario		
			Threat Timeline:	58.65	min	Threat Timeline:	1.51	min
OODA	F2T2EA	Action	Automation	Utility	Activity Time	Automation	Utility	Activity Time
Observe	Find	Collects Data	1	0%	3.45	10	100%	0.09
		Initial Detection	1	0%	3.45	10	100%	0.09
		Identifies Emerging Target	1	0%	3.45	10	100%	0.09
	Fix	Request Futher Information	1	0%	3.45	10	100%	0.09
		Classifies Target	1	0%	3.45	10	100%	0.09
		Locates Target	1	0%	3.45	10	100%	0.09
		Validates Detection	1	0%	3.45	10	100%	0.09
Orient	Track	Update Target Track	1	0%	3.45	10	100%	0.09
		Validates Target	1	0%	3.45	10	100%	0.09
		Assess Blue Proximity	1	0%	3.45	10	100%	0.09
Decide	Target	Nominate Engagement Options	1	0%	3.45	10	100%	0.09
		Prioritize Target	1	0%	3.45	10	100%	0.09
		Select Attack Option	1	0%	3.45	10	100%	0.09
Act	Engage	Issue Orders	1	0%	3.45	10	100%	0.09
		Attack Target	1	0%	3.45	10	100%	0.09
	Assess	Assess Status of Target	1	0%	3.45	10	100%	0.09
		Authorize Reattack	1	0%	3.45	10	100%	0.09

Time taken: 58.65 min

Time taken: 1.51 min

Figure 41. Benchmarking AI-AMD Performance

5. Decision Risk

For other timelines, such as the "moderate-stress" scenario, decision risk informs an appropriate level or automation for each of the steps using the DOD Risk Issues and Opportunities Guide (DOD 2017) as well as the National Aeronautics and Space Administration (NASA) Guidelines for Risk Management (NASA 2017). The risk matrix used for the analysis can be found in Figure 42. Using the risk matrix, risk likelihood and consequence determinations were correlated to a risk value which the team used to quantitatively provide an assessment of risk.

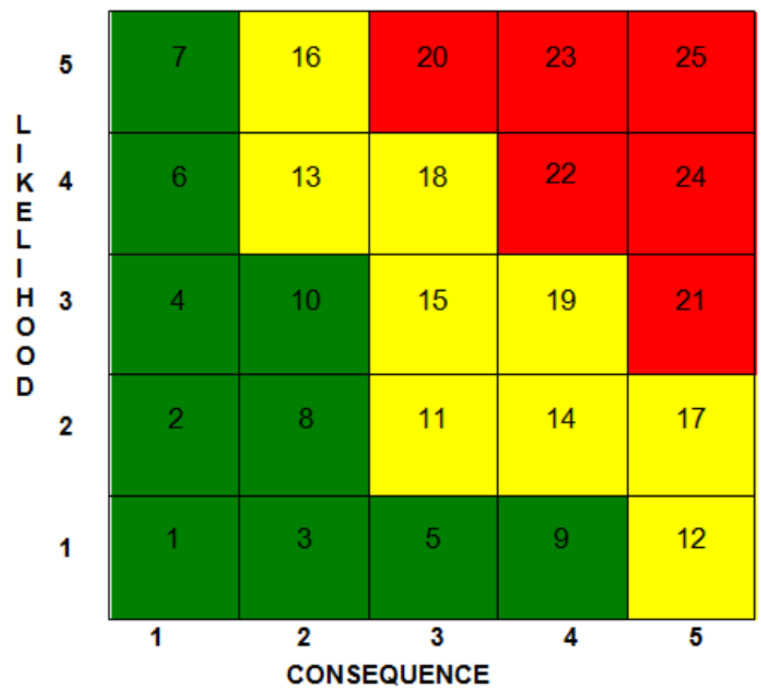


Figure 42. Risk Matrix Source: NASA (2017, Figure 4–5)

The risk assessment for each of the 17 steps in the F2T2EA process were binned into four categories; low, moderate-low, moderate, and high. An associated risk value was used to make the risk assessment determination. Leveraging Parasuraman's levels of automation depicted in Table 3, the risk assessment was correlated to an appropriate level of automation for each individual step. The risk assessment criteria can be found in Table 14.

Table 14. Risk Assessment Criteria

Color	Risk Assessment	Risk Value	Level of Automation
Green	Low	< 6	10
Green	Moderate-Low	< 12	7
Yellow	Moderate	< 20	5
Red	High	< 26	3

Each step in the F2T2EA kill-chain used by the team was then assigned a likelihood/consequence risk rating, associated risk value, and level of automation. A summary of the risk ratings using the DOD risk cube can be found in Figure 43; the complete description and rationale can be found in Table 15.

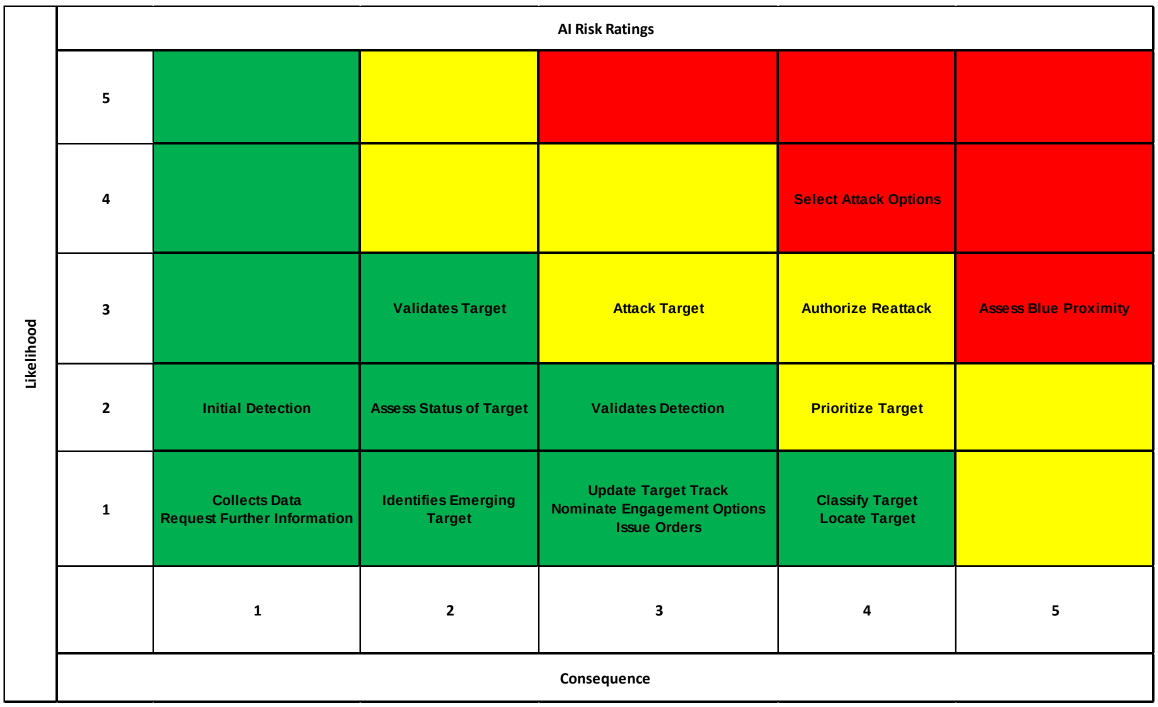


Figure 43. F2T2EA Risk Summary

Table 15. Risk Assessment and Rationale

OODA	F2T2EA	Action	Risk Rating	Risk Assessment	Risk Value	Level of Automation	Risk Rationale
Observe	Find	Collects Data	1-1	Low	1	10	Sensors collecting data can be fully autonomouse at litte to no risk to the user. Sensor data collection is assumped to be various sensor modalities searching the field of view for potential threats. As a result, full automation level 10 is recommend and a 1-1 rating has been assigned since the likihood and consequence of autonomouse data collection having an adver affect on operation is very low.
		Initial Detection	2-1	Low	2	10	Initial detection is assumed to refer to the point at which autonomous data collection detects an emerging tarted. This step is assumed to be low risk to the user. As a result, full automation level 10 is recommended and a 2-1 rating has been assigned since the liklihood of a false detection may be higher, but the consequence is considered to be low due to the various follow-on steps in the kill chain.
		Identifies Emerging Target	1-2	Low	3	10	Identifying emerging targets is assumed to mean sensor detections that are starting to form a pattern or demonstrate ill-intent. As a result, full automation level 10 is recommended and a rating of 1-3 is assigned because the liklihood of a blue force sensor with a high probability of detection, falsely identifying a threat is low, but the consequence is a medium. There are many other steps in the kill chain through the fix and track phase that further burn down the risk of fully automating this step.
	Fix	Request Futher Information	1-1	Low	1	10	The request for further information phase is assumed to be the command and control station requesting more information from the sensors on the emerging threat. As a result, full automation is recommended and a rating of 1-1 has been assigned since the liklihood and consequence associate with this informaiton is low.
		Classifies Target	1-4	Moderate-Low	8	7	The classify targeting step is assumed to be the passing of the emerging threat through a threat classification library. This classification of the threat is rated as a 1-4 because the risk of falsely classifying the threat could have a significant consequence. As a result, level of automation 7 is suggested, which represents the AI automatically classifying the threat and then informing the operator of the classification.
		Locates Target	1-4	Moderate-Low	8	7	Similar to classification of the target, incorrectly locating the target could have catestrophic results when it comes to position, navigation, and timing. As a result, level of automation 7 is suggested, which represents the AI automatically locating and then informing the operator of the location and a rating of 1-4 has been assigned.
		Validates Detection	2-3	Moderate-Low	11	7	Validating detection step is the checks and balances between finding the emerging target and determining that the target is a threat. It uses the initial detection, further information, classification, and location to validate the threat. As a result, level 7 automation is suggested which represents the AI automatically validating the threat and informing the operator of the validation.
Orient	Track	Update Target Track	1-3	Low	5	10	Updating the target track is assumed to have passed the prior gates established and the sensors are simply providing updated information on the threat as new detections and locations are established. As a result, a full automation level 10 is recommend and a risk rating of 1-2 has been assigned.
		Validates Target	1-4	Moderate-Low	8	7	The validate target step is assumed to represent the target tracks and validated detections corresponding to a threat against blue forces. Since this step results in a high degree of follow-on tasks where false alarms should be extremely minimal, an automation of level 7 and a risk rating of 1-4 has been established. This corresponds to the AI automatically validating and the operating being informed of the validated target.
		Assess Blue Proximity	3-5	High	21	3	Assessing blue proximity for a potential engagement against the threat is a high risk operation. Miscalcuation or misinformation will have catastrophic results to blue forces. As a result, this step is considered to be high risk, a level of automation of 3 establishd, and a risk rating of 3-5. This corresponds to the AI providing COAs, but the operator making the decision.
Decide	Target	Nominate Engagement Options	1-3	Low	5	10	The nomination of engagement options is assumed to be low risk because the step is purely nominating engagement options not executing the options. It is assumed that the operator would want this step to be as quick as possible to reduce the timeline. As a result, this step is considered to be low risk with recommended full level of automation of level 10 and a risk rating of 1-3.
		Prioritize Target	2-4	Moderate	14	5	The prioritization of the target is a critical step in the kill chain where the operator should select the prioritization that the AI presents. As a result, automation level 5 is recommend at a risk rating of 2-3
		Select Attack Option	4-4	High	22	3	Selecting the attack options is a critical step in the kill chain where the operator should make the decision based on the COAs that the AI provides. As a result, a level of automation of 3 is recommended and a risk rating of 4-4 has been established.
Act	Engage	Issue Orders	1-3	Low	5	10	The issuing of the orders is assumed to be a medium-low risk because the operator has already selected the attack options and all of the previous steps in the kill chain. As a result, a level of automation of 7 is recommended corresponding to the AI issuing the orders and informing the operator and a risk rating of 1-3.
		Attack Target	3-3	Moderate	15	5	Attacking the target is considered to be a medium risk where the operator should be informed of the COA and select the attack. As a result, a level of automation of 5 is recommended and a risk rating of 3-3 has been established.
	Assess	Assess Status of Target	2-2	Moderate-Low	7	7	Assessing the status of the target by the AI is considered to be a medium-low risk because the assessment from the AI does not result in action. It is assumed that the AI would inform the operator of the status and the operator would determine a COA. As a result, a level of automation of 7 is recommended and a risk rating of 2-2 has been established.
		Authorize Reattack	3-4	Moderate	19	5	Reauthorizing the attack will require the operator to select the attack option. As a result, the level of automation is recommended to be 5 where the operator selects the AI COA and a risk rating of 3-4.

The team then used an automation action selection utility curve to perform quantitative analysis on the AI time savings associated with the level of automation. The descriptive levels described by Parasuraman were translated into a numeric utility curve as depicted in as depicted in Figure 44. Again referencing the levels of automation, the team observed low automation / AI utilization for levels 1, 2, and 3. Similarly, the team observed high levels of automation / AI utilization for levels 8, 9, and 10. A linear change in automation / AI utilization was assumed from levels 3 to 8. Additionally, it is observed the utility curve describes the trend in AI-enabled time savings associated with each level of automation. The higher the level of automation, the higher the time savings. It is recommended that the utility curve be reviewed with the stakeholders to fully capture the utility of automation.

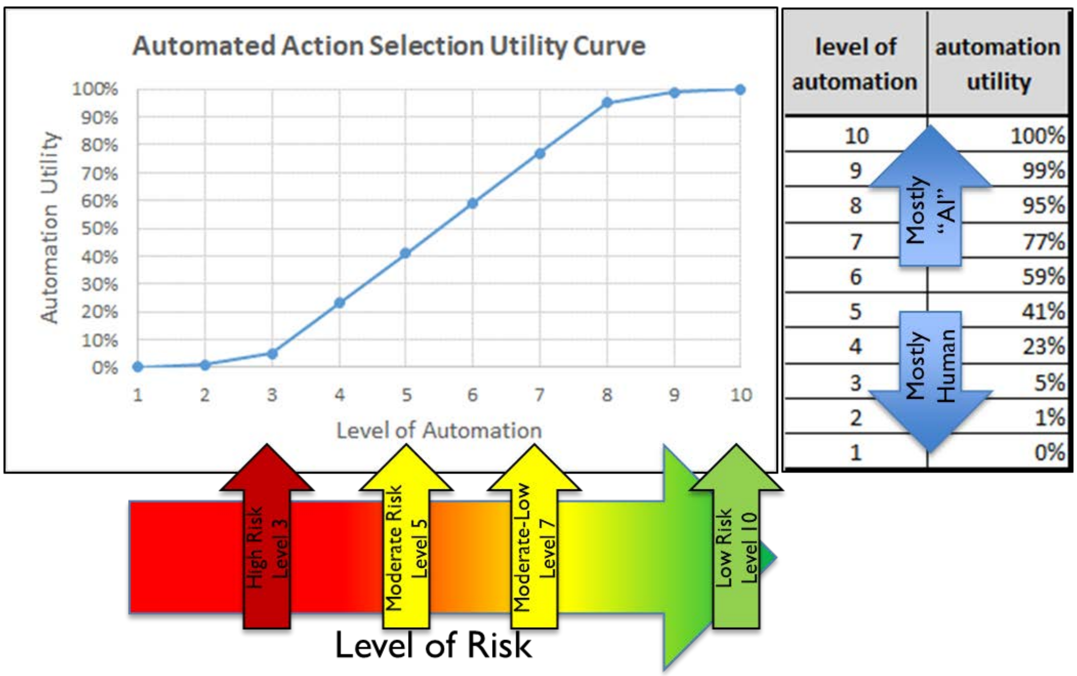


Figure 44. Utility Curve

The risk assessment was used to set the initial conditions for the levels of automation as depicted in Table 15. The allocated operational activity times from the benchmarked scenarios were used to transform the utility curve into timing estimates. For example, level of automation 1 was set to 3.43 minutes, level of automation 10 was set to 0.09 minutes, and expected values for intermediate levels followed shape of the utility curve (e.g., level of automation 7 was found to be 0.86 minutes). Using the risk informed levels of automation and the utility curve, the team was able to estimate resulting timelines for AI-AMD capabilities. Unfortunately, as seen in Figure 45, the levels of automation selected on the basis of risk were not successful in responding within the moderate-stress scenario timeline and increased automation is required. This is of importance because it means that a higher risk tolerance is likely needed to adequately respond to the threat. Chapter IV describes how the team analyzed this using modeling and simulation for the low-stress, high-stress, and moderate-stress scenarios at the determined higher levels of automation.

	unsuccessful Moderate Stress Scenario				Moderate Stress Scenario		
		Threat Timeline:	9.72	min	Threat Timeline:	9.72	min
Action	**Risk Rating**	**Automation**	**Utility**	**Activity Time**	**Automation**	**Utility**	**Activity Time**
Collects Data	Low	10	100%	0.09	10	100%	0.09
Initial Detection	Low	10	100%	0.09	10	100%	0.09
Identifies Emerging Target	Low	10	100%	0.09	10	100%	0.09
Request Futher Information	Low	10	100%	0.09	10	100%	0.09
Classifies Target	Moderate-Low	7	77%	0.86	7	77%	0.86
Locates Target	Moderate-Low	7	77%	0.86	7	77%	0.86
Validates Detection	Moderate-Low	7	77%	0.86	7	77%	0.86
Update Target Track	Low	10	100%	0.09	10	100%	0.09
Validates Target	Moderate-Low	7	77%	0.86	7	77%	0.86
Assess Blue Proximity	High	3	5%	3.28	7	77%	0.86
Nominate Engagement Options	Low	10	100%	0.09	10	100%	0.09
Prioritize Target	Moderate	5	41%	2.07	8	95%	0.26
Select Attack Option	High	3	5%	3.28	6	59%	1.47
Issue Orders	Low	10	100%	0.09	10	100%	0.09
Attack Target	Moderate	5	41%	2.07	6	59%	1.47
Assess Status of Target	Moderate-Low	7	77%	0.86	10	100%	0.09
Authorize Reattack	Moderate	5	41%	2.07	7	77%	0.86
				Time taken: 17.71 min			Time taken: 9.07 min

Figure 45. Determining AI-AMD Operational Capabilities

IV. ANALYSIS AND AI APPLICATIONS

This chapter presents the capabilities of the AI-AMD system as characterized by analysis of M&S results. The Innoslate MBSE tool facilitated the execution of the team's analyses of scenarios previously described. The team performed a design of experiments (DOE) to gain insight into the breadth of possible AI-AMD capabilities and to identify which grouping of operation activities had the strongest influence on the AI-AMD timing outcome. The team also conducted a sensitivity analysis to explore the impact of alternative underlying representative distributions (baseline, symmetric variable spread, and highly skewed). The findings of the M&S analysis were documented and interpreted by the team.

This chapter also contains the team's identified AI techniques with application to the AI-AMD system. The team documented the relationships of the AI-AMD system, the operational activities, risks, and uncertainties associated with these techniques. The team discussed implications of these techniques to increasing levels of automation. An acknowledgement of differences between current and future AI methods was provided. The team's M&S analyses and AI applications presented in this chapter support the team's conclusions and suggestions for future work presented in Chapter V.

A. MODELING AND SIMULATION

Modeling and simulation is an effective method for visualizing and analyzing conceptual designs. The team modeled the AI-AMD system architecture described in Chapter III and used the kill chain analytical framework's derived timing to simulate the kill chain with AI-AMD low, moderate, and high levels of automation. The team analyzed data produced in the simulations to draw conclusions on AI-AMD conceptual design capabilities.

1. Purpose

Creating a simulation served two purposes. The first purpose was to demonstrate a gain in efficiency and time reduction, with the introduction of AI-AMD increased automation into the kill chain. This was accomplished by comparing human versus AI-enabled performance in the low-stress and moderate- to high-stress scenarios. The second purpose was to create a tool that future stakeholders can adjust to reflect their specific scenario data to further define requirements of AI-AMD development.

a. Scenarios

The OV-5b/6c action diagram showed the potential for automated processes and decisions to accelerate the kill chain. The M&S analysis was based on a single threat engagement. Three scenarios were created from quartiles of Figure 40. A low-stress scenario was selected to be the human only scenario, where current capabilities were assumed to successfully complete the kill chain. The second scenario was a moderate-stress scenario. Here, a faster threat launched from a closer position dictated a shorter time for the SoS to respond. Lastly, a high-stress scenario was simulated using the fastest open source threat. During this scenario, the time to respond was significantly shorter than the response time for the low- or moderate-stress scenarios.

b. Tools

The team used several modeling and simulation tools to analyze AI-AMD capabilities. The team used Innoslate (from Spec Innovation) to create the DODAF views and to maintain concordance between the views using the Life Cycle Modeling Language (LML). In addition to supporting the team's creation of the views created in Chapter III, the team used Innoslate's discrete modeling capabilities. The team used Innoslate to assign time durations to the OV-5b/6c Action Diagram and used this model to run simple sequences. Innoslate's MBSE environment facilitated time savings that was leveraged elsewhere in the project (e.g., preparing for IPRs, constructing the DOE, and conducting sensitivity analysis). The team used the statistical analysis tool Minitab to support the teams' DOE. The team used Excel to build a meta-model for refining the OV-5b/6c initial timing, for executing the sensitivity analysis, and for creating many report graphics.

c. Assumptions and Constraints

In order to keep the project unclassified, many assumptions were made to constrain the simulations. Although uncertainty exists in the probability of detection and the probability of kill for AMD missions, the team assigned 100% for both probabilities and held these values constant for all threat scenarios in order to compare different AI-AMD levels of automation. Although real AMD threats vary in their abilities to maneuver (i.e., drones and hypersonic missiles have vastly different kinematics), the model assumed that threats followed a linear inbound path with constant speed. Network latency was assumed to be 250 milliseconds for each message crossing the network (send and receive). Similarly, BLUFOR engagement reaction time was assumed to be 1 second (i.e., the weapon system fires against the threat within 1 second after receiving orders). In aggregate, the model assumed that BLUFOR external systems contributed approximately 0.10 minutes of total delay. Lastly, with no data indicating otherwise, the model applied a single utility curve to all steps in the kill chain.

d. Capabilities

The team used Excel to create a meta-model to evaluate timing and sequencing before investing heavily in the action diagram. The meta-model also provided a means of comparison for the initial results for error checking and to determine acceptability. The team used Innoslate to model the architecture and run single discrete event simulations, as well as Monte Carlo simulations to test the sequencing and performance of the model. The team acknowledged Innoslate's inability to run multiple engagements and simulate failed engagements. The team recommends future analysis to study multiple concurrent engagements to explore how AMD missions may benefit from an AI-AMD approach.

2. Model Description

The model was based on the description presented in Chapter III Section A.1.e: information was collected from the various sensors, passed back and forth from AI-AMD across the network, and orders were sent to the air defense (AD) assets to engage. The model ran the inbound threat timing in parallel with these BLUFOR activities to see if a defeat occurred first. This model and sequence remained the same for the three scenarios. The timing of the various AI-AMD steps (actions) were adjusted in each scenario. The model's decision timing was derived from Figure 23, as described in Chapter III. Network latency and sensor timing were assumed to be 250 milliseconds, and AD weapon engagements were assumed to occur within 1 second. Timing was applied to each operational activity the BLUFOR systems in the model including both internal (17 decision steps) and external (19 BLUFOR actions and 4 threat actions). To allow for variation about the most likely value, the model used triangular distributions with ±10% for maximum and minimum values. Initially, the team tested each scenario as a discrete event simulation to check model functionality, sequencing, and confirm event timing. Next, the team performed a Monte Carlo simulation of 1,000 runs. The team used Innoslate's timing tree map and bar chart to display the results and extracted additional data to determine the quantity of replications where the AI-AMD SoS was successful against the threat.

a. Low-Stress Scenario

The low-stress scenario represented the AMD decision timing for human-only decision-making "without" AI (level of automation 1). The team selected the Chinese WZ-8 drone as the threat and the UEWR as the BLUFOR detection sensor to derive a most likely inbound threat timing of 58.65 minutes. The model allocated this time allotment equally among each of the AI-AMD 17 decision steps, allowing 3.45 minutes per decision.

b. Moderate-Stress Scenario

The moderate-stress scenario represented an AI assisted AI-AMD system in which the levels of automation were informed by the risk assessment and meta-model results described in Chapter III Section B.5. The model kept the human decision-maker in the AMD decision loop, but AI-AMD automated many of the lower risk decisions such as detection and status updates. High risk actions such as selecting the COA for engagement required human input. For this scenario, the team selected the Chinese DF-21D hypersonic missile as the threat and the UEWR as the BLUFOR detection sensor to derive a most likely inbound threat timing of 9.72 minutes. The model allocated this time allotment to each of the AI-AMD 17 decision steps as determined from the utility curve (potential time savings as a function of planned level of automation) described in Chapter III Section B. Therefore, the timing of the individual steps varied according to the team's kill chain analytical framework.

c. High-Stress Scenario

The high-stress scenario represented a fully automated AI-AMD “with” AI; therefore, the model implemented level 10 automation for each of the 17 kill chain steps. In other words, this scenario removed the human as a decision-maker in the AMD kill chain. The team selected the Chinese DF-17 hypersonic missile as the high-speed threat and a medium range sensor for the BLUFOR detection. This produced a most likely inbound threat timing of 1.51 minutes. The model allocated this time allotment equally among each of the AI-AMD 17 kill chain decision steps, allowing 0.09 minutes per task.

B. DESIGN OF EXPERIMENTS

The team initially described the system operational activities at the highest level as an “OODA loop” (observe, orient, decide, and act). By leveraging the Joint targeting doctrine of JP 3-60, these high-level activities were decomposed into the middle tier of F2T2EA (find, fix, track, target, engage, and assess). Recall also, the further decomposition to the lowest level herein, a simplification of JP 3-60, as described in Chapter III. This project relied on time (as in time taken to sense, decide on the course of action, and respond to the red threat) to be the primary measure for characterizing the capabilities of the AMD mission. Operational activity timing, being the adjustable parameter considered in the model, varied throughout the 17 kill chain tasks; however, total AMD response time (in aggregate) was the determinate of mission success. The team conducted a DOE at the “OODA” level to assess the effects of AI-AMD timing input parameters on the overall mission.

1. DOE Analysis

The team selected Minitab statistical data analysis tool to perform the DOE and used Minitab’s built-in features for the full factorial approach including setup and analysis. Due to the complexity of a full-factorial analysis with 17 factors (2^{17} would be overwhelmingly cumbersome), the team decided to evaluate at the OODA level, with four factors (analysis of 2^4 elements is more presentable for decision makers). To characterize the effects of high-level operational activities, the team aggregated the decomposed high-stress scenario allocations of Figure 41 for resultant timing. The team conducted a two-level analysis with ±10% of the operational activity expected value set for high and low input parameters. Resultant estimates for the AI-AMD system timing DOE response are shown in Table 16.

Table 16. DOE Response Table

Run	Observe	Orient	Decide	Act		Timing
1	0.5582	0.2392	0.2392	0.3190		1.36
2	0.6823	0.2392	0.2392	0.3190		1.48
3	0.5582	0.2924	0.2392	0.3190		1.41
4	0.6823	0.2924	0.2392	0.3190		1.53
5	0.5582	0.2392	0.2924	0.3190		1.41
6	0.6823	0.2392	0.2924	0.3190		1.53
7	0.5582	0.2924	0.2924	0.3190		1.46
8	0.6823	0.2924	0.2924	0.3190		1.59
9	0.5582	0.2392	0.2392	0.3899		1.43
10	0.6823	0.2392	0.2392	0.3899		1.55
11	0.5582	0.2924	0.2392	0.3899		1.48
12	0.6823	0.2924	0.2392	0.3899		1.60
13	0.5582	0.2392	0.2924	0.3899		1.48
14	0.6823	0.2392	0.2924	0.3899		1.60
15	0.5582	0.2924	0.2924	0.3899		1.53
16	0.6823	0.2924	0.2924	0.3899		1.66

The unforgiving nature of the timeline dictated by the threat was observed from these DOE response measures. If one OODA element was over budget, it was difficult for AI-AMD to defeat the high stress, 1.51-minute timeline. The DOE was also interpreted with a Pareto effects chart and timing contour plot described in the follow subsections.

2. Pareto Effects Chart and Contour Plots

The team conducted a Pareto analysis with the DOE timing estimates. This gave the team insight into the operational activities generating the greatest effects on the output of the model. The OODA Pareto Chart is shown in Figure 46. The Pareto Chart showed that the "observe" step provoked the strongest effects on timing within the kill chain; therefore, it became a primary candidate for high levels of automation. This correlated well with the team's risk analysis in Chapter IV Section B, in which high levels of automation were assigned to low decision risk kill chain functions for expediting the targeting process. Based on the series design of the AI-AMD architecture, combinations of factors (at second order or higher) did not produce effects.

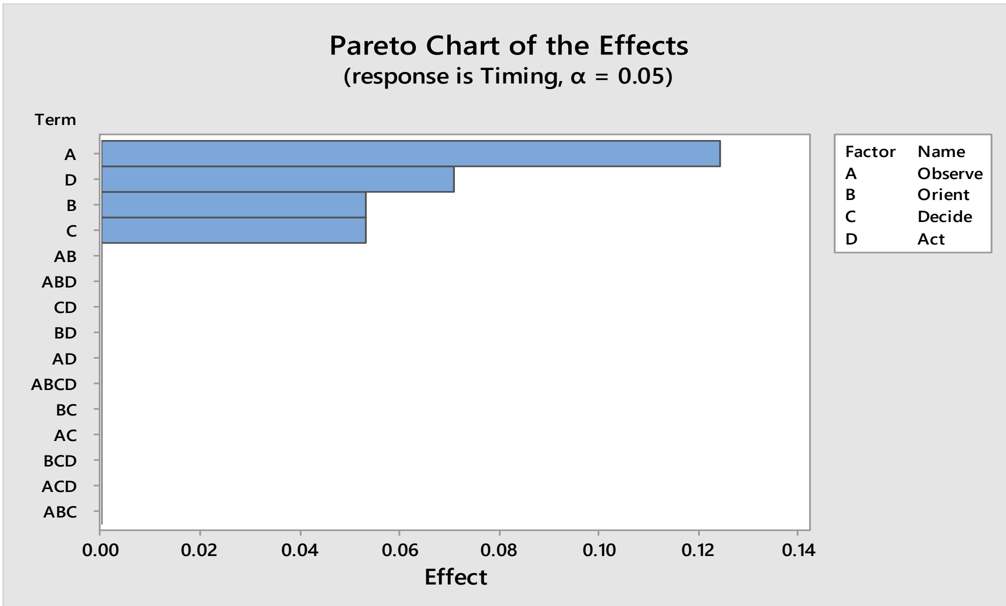


Figure 46. AI-AMD OODA Pareto Chart

The main effects plot for timing, in Figure 47, provided another view. The slope of the line of each Minitab plot indicated the strength of the relationship between resultant timing and the plotted factor. This figure compared the range of variations in AI-AMD timing to the ±10% expected value for each operational activity; "observe" was again seen to produce the strongest effect.

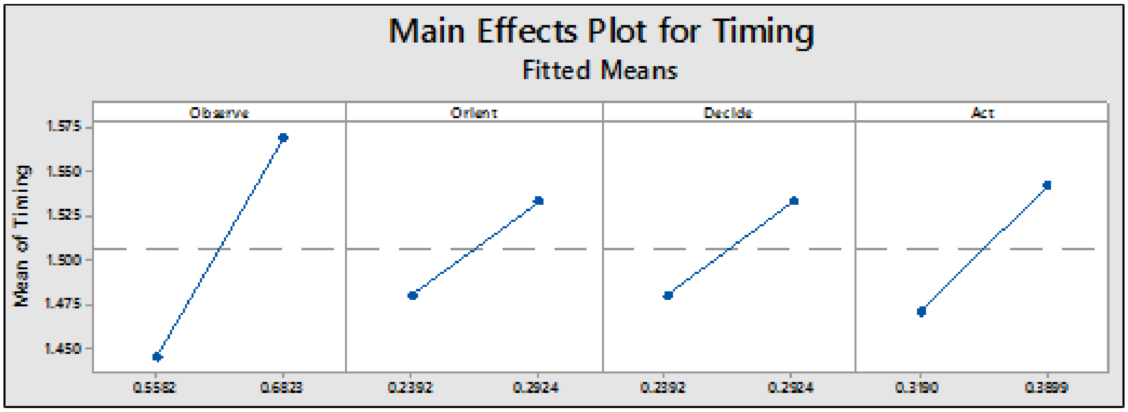


Figure 47. AI-AMD OODA Main Effects Plot for Timing

Minitab contour plots helped visualize the contributions of each operational activity to the overall timing. The impact of variability in each step contributed to the understanding of AI-AMD system performance. AI-AMD contour plots are shown in Figure 48. Recall, for the high-stress scenario, the threat dictated a timeline of 1.51 minutes. Performing the DOE generated a range of potential successful solutions (as illustrated by the two lightest shaded contours). Additionally, it was again noted that AI-AMD capability timelines were unforgiving; the contours indicated regions where if one activity ran long, the other activities were unable to compensate, and the BLUFOR failed to defend the scenario.

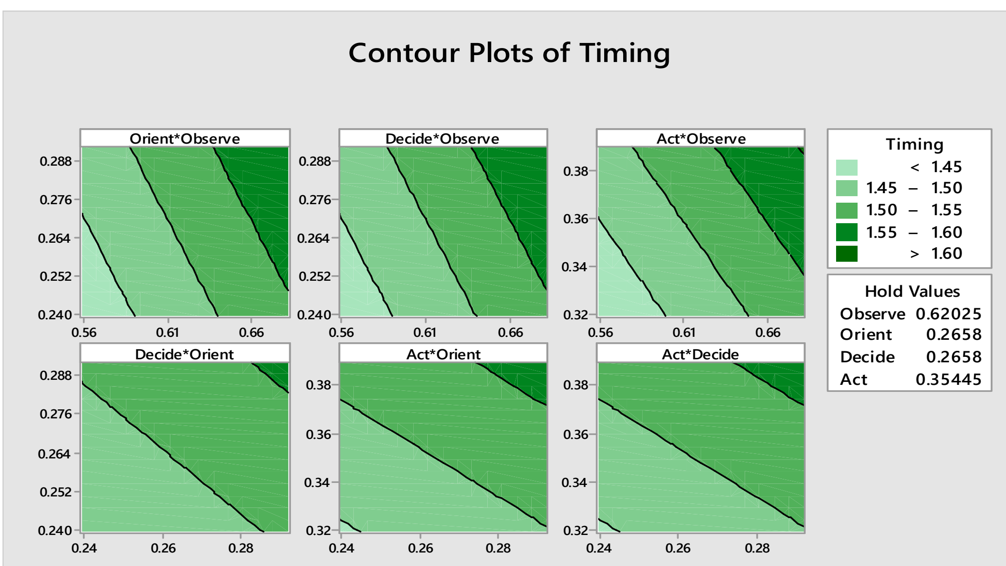


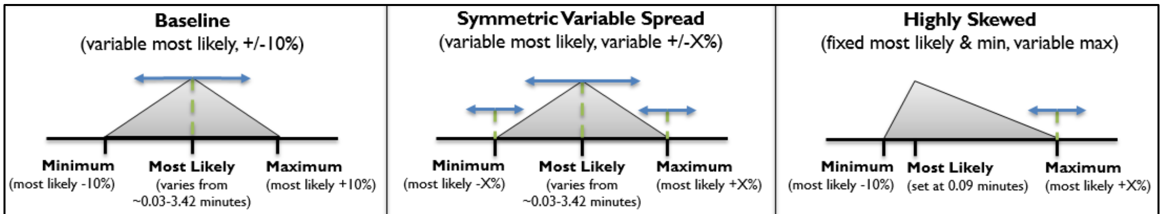
Figure 48. AI-AMD OODA Contour Plots

C. SENSITIVITY ANALYSIS

As stated previously, one objective of this project was to utilize M&S to compare the kill chain at low levels of automation (“without” AI) with high levels of automation (“with” AI). The general lack of openly available performance data limited the ability of the team to determine specific decision time estimates; however, the team was able to use top-down timeline decomposition to generate the needed benchmarking and assumptions. The operational activity timing distributions were estimated based on the assumption of a known functional form (triangular of most likely, ±10%). As described in Pledger’s PhD dissertation, when the shape of the underlying distributions is unknown, one must also consider alternative forms (Pledger 1970). Therefore, it is important to recognize that the operational capabilities demonstrated by the M&S may be sensitive to the choice of underlying probability distributions. The team utilized a numeric spreadsheet model to explore the resulting capability estimates for three distinct input distributions (alternative forms).

1. Numeric Estimation

The initial conditions for the spreadsheet model were selected to reflect the range of performance from the low- to high-stress scenarios. Recall the low-stress threat timeline (of 58.65 minutes) was decomposed to AI-AMD level of automation 1 operational activities (3.45 minutes each). Similarly, the high-stress threat timeline (of 1.51 minutes) was decomposed to AI-AMD level of automation 10 operational activities (0.09 minutes each). Boundaries for a representative triangular distribution were selected with the traditional engineering ± 10% rule of thumb. Figure 49 provides a visual guide for the three distinct input distributions explored for the sensitivity analysis: baseline, symmetric variable spread, and highly skewed.



Operational Activity Timing Distribution	min	most likely	max
best case	0.03	0.03	0.04
worst case	3.07	3.42	3.76
AI-enabled savings (*relative to* 3.45 min)			
best case	99.10%	99.00%	98.90%
worst case	10.90%	1.00%	-8.90%

Operational Activity Timing Distribution	min	most likely	max
best case	0.01	0.03	0.04
worst case	2.98	3.42	6.32
AI-enabled savings (*relative to* 3.45 min)			
best case	99.74%	99.00%	98.89%
worst case	13.76%	1.00%	-83.26%

Operational Activity Timing Distribution	min	most likely	max
best case	0.08	0.09	0.10
worst case	0.08	0.09	3.42
AI-enabled savings (*relative to* 3.45 min)			
best case	97.69%	97.43%	97.00%
worst case	97.69%	97.43%	1.00%

Figure 49. Sensitivity Analysis Distributions

The baseline triangular distribution assumed a range of most likely operational activities times varied from 0.03–3.42 minutes. Relative to the level of automation 1 case, this generated a most likely AI-enabled time savings from 1% to 99%, respectively. The symmetric variable spread triangular distribution also provided a broad range of most likely input values; however, instead of the fixed ± 10%, the boundaries were varied from 10% to 90%. As seen in Figure 49, the worst case represented an instance where there was no savings; AI-enabled time was actually increased by 83.26% over the level of automation 1 operational activities time of 3.45 minutes. As noted by Pledger, the underlying form of the distribution may not be known. The team explored this possibility with the highly skewed triangular distribution; the level of automation 10 operational activity time was fixed at a most likely of 0.09 minutes (with a 0.08-minute minimum, a 97.69% savings), but the maximum time varied from 0.10-3.42 minutes (AI-enabled savings from 97% down to 1%, respectively).

2. Results

The team used the numeric spreadsheet model to conduct a Monte Carlo experiment for the three sensitivity analysis distributions (with 1,000 replications each). The resulting capability estimates are depicted in Figure 50. As indicated by the sensitivity analysis, the overall AI-AMD capability was impacted by the shape of the underlying distributions representing the operational activities. The results of the baseline Monte Carlo indicated the AI-AMD system (under the conditions and assumptions represented during this project) would provide sufficient capability against the low-stress threat. As the threat level increased, the needed AI-enabled savings also increased. Against the high-stress threat, success was only observed at AI-enabled savings above approximately 97%. The results of the symmetric variable spread Monte Carlo were similar; however, a broad spread in variability was observed in the results. This was attributable to the wider variability in each of the AI-AMD operational activities during this set of replications. Because the skewed distribution held the operational activities at a most likely time of 0.09 minutes, this set of Monte Carlo replications predicted the best AI-AMD system performance. Note again, successful system capability against high-stress threats remained observable only at the highest levels of automation. As the AI-AMD system matures, it is recommended for stakeholders to consider data collection efforts for characterizing the timing attributes of each operational activity. Stakeholders should note that robust statistical representation of the system functions will improve understanding of future AI-AMD operations.

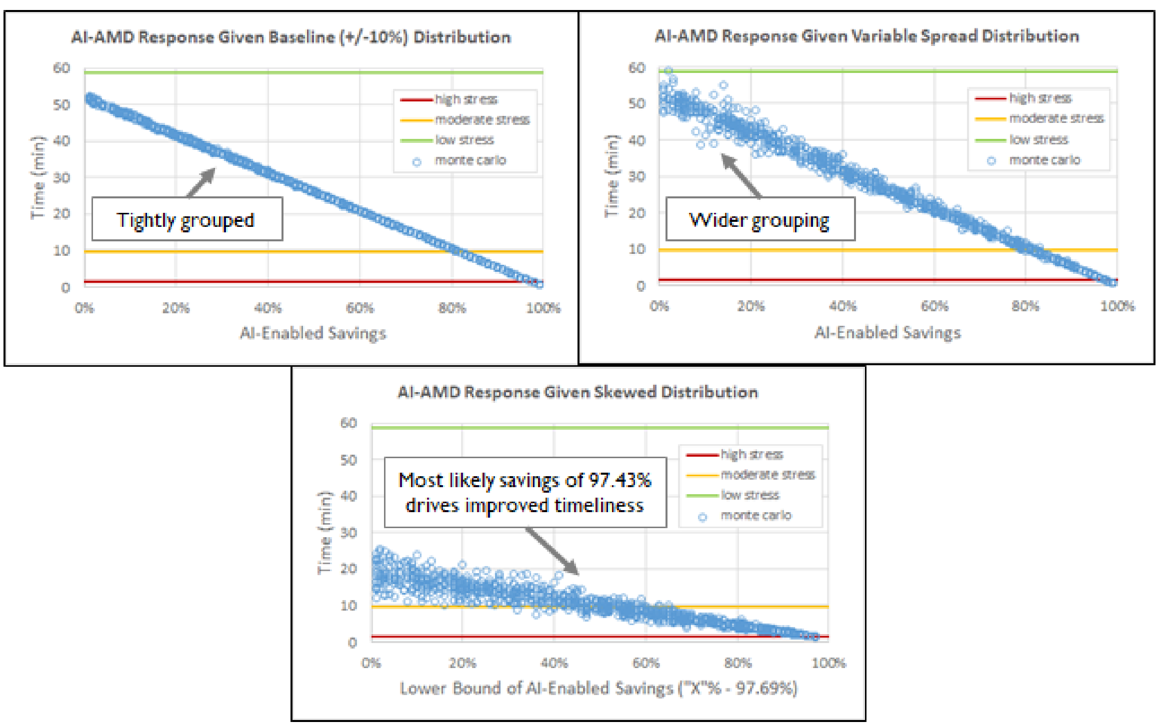


Figure 50. Sensitivity Analysis Capability Estimates

D. SIMULATION ANALYSIS

The primary goal of the M&S was to compare the kill chain at low levels of automation ("without" AI) through high levels of automation ("with" AI), and assess improvements based on time saved. From this M&S, the team described high level decision aid operational capabilities for AI-AMD and illustrated conceptual designs for AI-enabled decision superiority. A secondary goal was to ensure the model was a properly functioning design tool as a deliverable for the project. For each previously described scenario, the respective triangular distributions were input into the OV-5b/6c action diagram. The action diagram contained 17 decomposed AI-AMD actions (with 5 represented when allocated at higher level), 10 network actions, 5 sensor actions, 4 BLUFOR actions, and 4 threat actions. Only the 17 internal AI-AMD actions and threat "fly-in" action were varied between the scenarios as AI-AMD was not optimized to reduce the action timing of the external agents (e.g., network latency and sensor performance). The architecture (i.e., sequence and control) was also unchanged, as the information exchanged remained the same.

Innoslate produced a Gantt chart on the timing of each event for visualizing the results in sequence and gaining a sense of the duration of each action. From there a Monte Carlo simulation was produced and 1,000 iterations were performed. Innoslate produced a bar chart to show a distribution of the overall timing for the kill chain through the iterations. Lastly, an action report was produced with specific timing, in milliseconds, for each of the actions in each run.

1. Low-Stress Scenario: Human Decision Making

The low-stress scenario represented the human only decision timing "without" AI (level of automation 1). Early warning threat detection provided nearly an hour before the threat reached the target. Each decision node completed, and there was minimal external system latency; as a result, the Monte Carlo analysis indicated the human defeated the threat every time. Keep in mind, for this project the probability of detection and successful kill was held at 100%. Figure 51 shows a distribution of the overall timing of the engagement. Because the sequence was complete before the threat fly-in finishes, the threat timing was not produced. For this scenario the most likely fly-in timing was 58 minutes. As seen in Figure 51, the sequence was completed in less than 58 minutes in all cases.

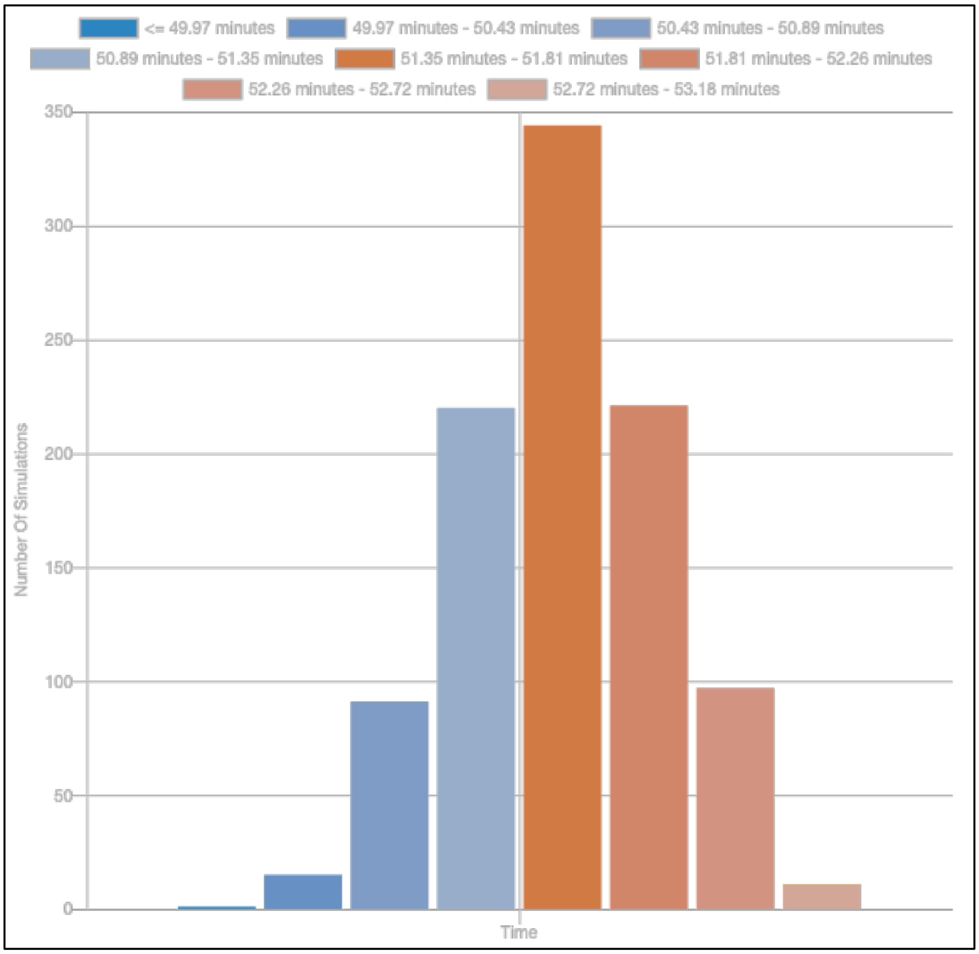


Figure 51. AI-AMD Low-Stress Monte Carlo Timing Bar Chart

2. Moderate-Stress Scenario 1: AI-AMD Assisted Decision Making

The moderate-stress scenario represented an AI assisted AI-AMD system in which the levels of automation were informed by the risk assessment and meta-model results from Chapter III Section B.5. It was similar to the low-stress model, but the AI-AMD timing distributions and threat “fly-in” times were adjusted; all other actions were unchanged. The meta-model predicted that levels of automation selected on the basis of risk alone would be insufficient to defeat the threat. Within the discrete even simulation, the team confirmed those levels of automation were not adequate for AI-AMD to successfully complete the engagement. Using the Gantt chart, Figure 52, the need to accept more risk at higher levels of automation was clear. After running the Monte Carlo, each of the 1,000 replications ended during the attack selection as the threat hit the target (a 0% success rate). The team revisited the performance table, Figure 45, to increase the level of automation of 6 of the 17 actions.

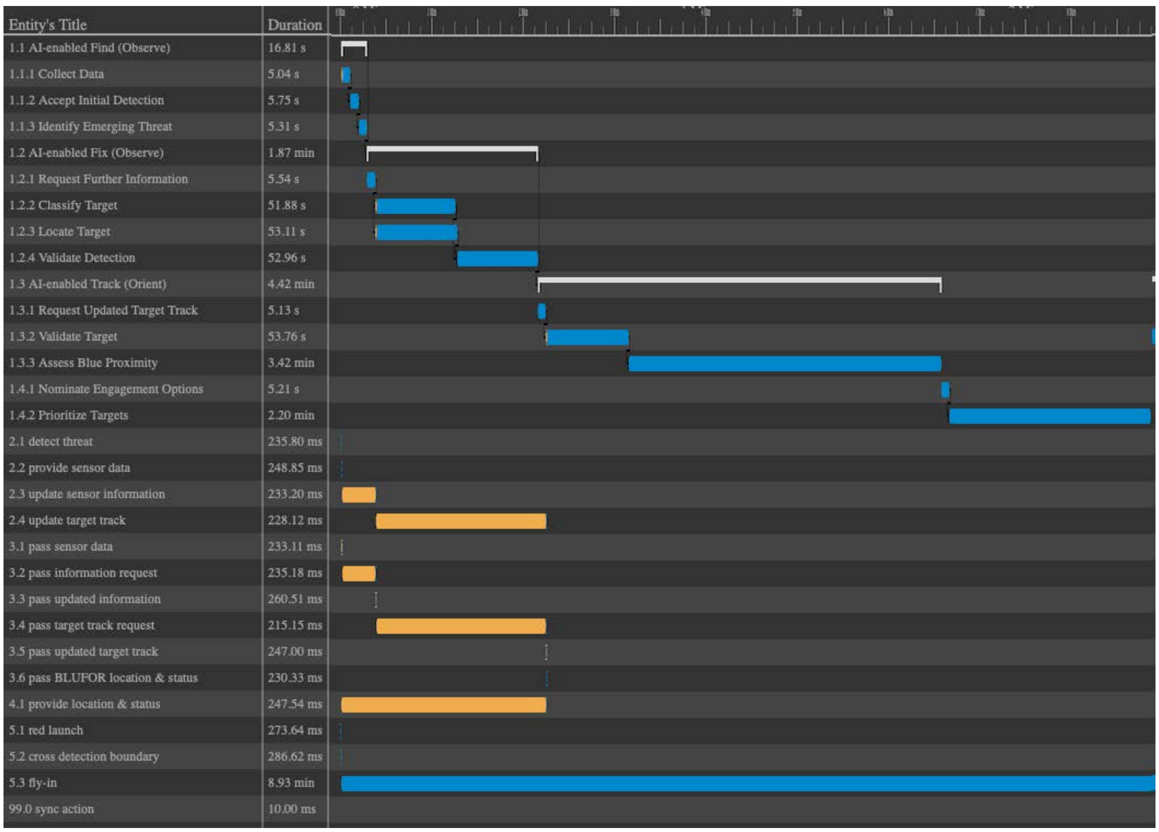


Figure 52. AI-AMD Moderate-Stress Gantt Chart

3. Moderate Stress Scenario 2: AI-AMD Assisted Decision Making

As listed in Figure 45, to defeat the moderate-stress threat, there was a needed increase in levels of automation associated with multiple operational activities (i.e., “assess blue proximity,” “prioritize target,” “select attack option,” “attack target,” “assess status of target,” and “authorize re-attack”). A range of adjustments were made, from lower levels of automation (level 3 to 7) up to higher levels of automation (level 6 to 10). Timing distributions were recreated and loaded into the model. The discrete simulation showed promise with AI-AMD completing the engagement. With these adjustments in level of automation, the AI-AMD SoS demonstrated a 100% success rate across all 1,000 Monte Carlo replications. Figure 53 is the overall timing distribution for the kill chain moderate-stress scenario. Again, because the AI-AMD SoS completed the engagement before the missile fly-in the threat timing was not captured (the threat was destroyed). Recall from Chapter III Section B.4, the moderate-stress threat most likely time was 9.7 minutes. As shown in the bar chart, AI-AMD completed all engagements in less time.

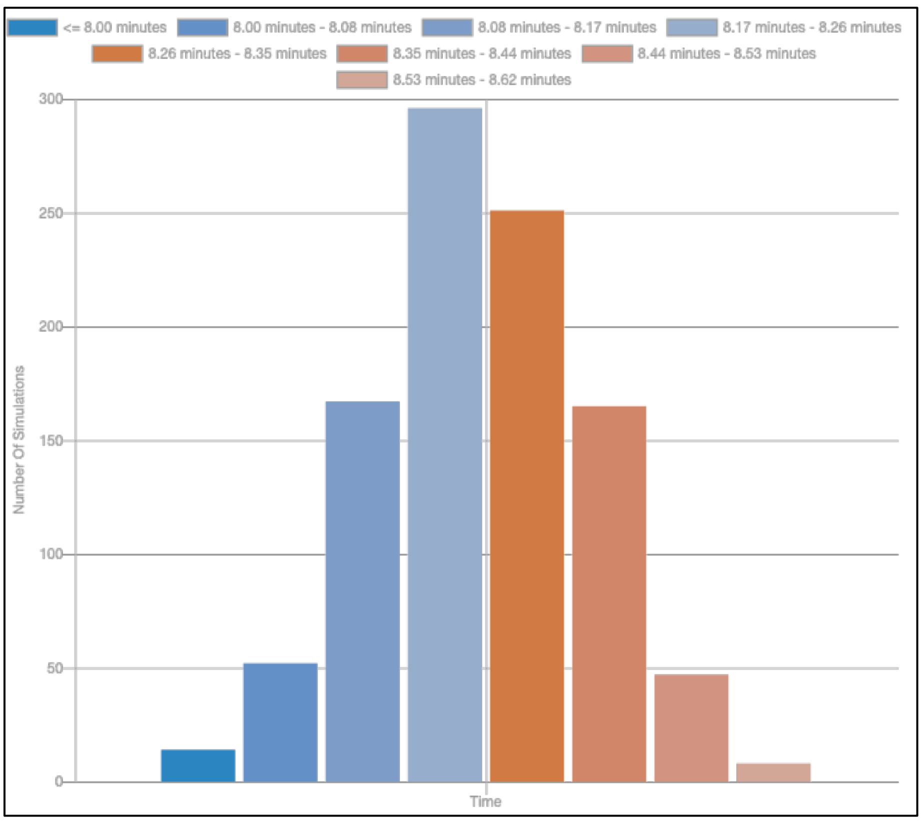


Figure 53. AI-AMD Moderate-Stress Monte Carlo Timing Bar Chart

4. High Stress Scenario: AI-AMD Fully Automated Decision Making

The high-stress scenario represented a fully automated AI-AMD "with" AI; level of automation 10 was implemented for each of the 17 decision steps. The high-speed threat against medium range detection produced a most likely inbound threat timing of 1.51 minutes, producing a very short engagement duration and therefore a small window to complete the targeting process. With AI-AMD at level of automation 10, the initial discrete event showed promise. Out of the 1,000 Monte Carlo replications, 165 runs resulted in the threat arriving before the engagement process could be complete; however, the AI-AMD SoS defeated the threat in 835 instances (an 83.5% success rate). The high-stress scenario bar chart is shown in Figure 54; it does not report the replications where AI-AMD failed to defeat the threat.

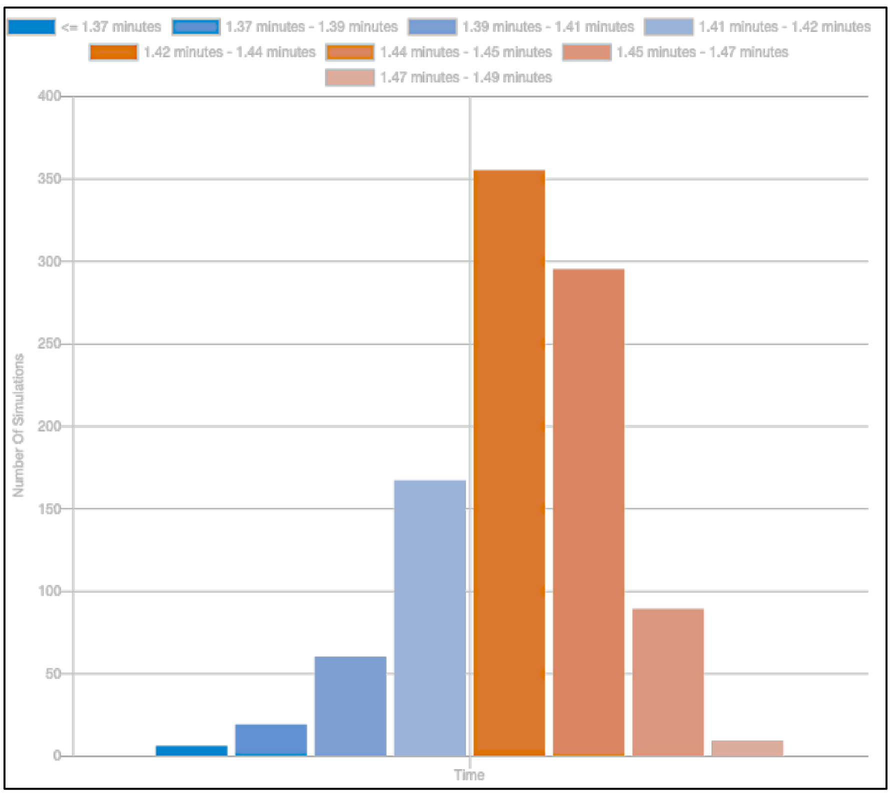


Figure 54. AI-AMD High-Stress Monte Carlo Timing Bar Chart

E. SIMULATION FINDINGS

Automating decisions through use of AI showed promise for reducing the kill chain timeline and opened current AD assets to a wider range of threats. The AI-AMD SoS was very successful in simulated engagements; however, this may be due to the open source data and project assumptions. For certain threats, the necessary levels of automation may exceed doctrinal risk limitations. Similarly, there may exist threats and engagement conditions that defeat even the highest levels of automation. Stakeholders are encouraged to consider the project methods and utility curve implementation for applicability during future program development; there may be upper limits imposed beyond the high-stress scenario where lengthier decisions were eclipsed by the faster threats.

In Chapter V, the team suggests obtaining specific threat performance, sensor capabilities, and decision timing to refine the model. The model allowed for adjustability for those refinements and functionality to further enhance the AI-AMD decision aid. Threat and sensor inputs can be changed to the particular threats being pursued along with AD engagement assets. The tree maps and Gantt charts helped create a visual on the actions with significant impact on timing. This can create focal points for ongoing system design to determine where the most gains can be found. Additional data should be gathered to characterize system performance distributions; the shape of the underlying distribution was observed to directly impact AI-AMD system capability. Overall, the MBSE representation of the AI-AMD SoS showed promise in assisting further development.

F. AI METHODS AND TECHNIQUES

Each of the AI-AMD kill chain steps is unique. Within decomposed context, the team reviewed each operational activity to understand the functions and uncertainty associated with the action. From that, a comparison was made with various algorithms and logic methods designed to replicate human cognitive behaviors and decisions. As observed in the literature review, various methods and algorithms have been designed for decision applications such as simple “go” versus “no go” situations, search engines, and games like chess. This section identifies existing and future AI methods and suggests applications within the AI-AMD kill chain.

1. Action Inputs / Outputs

In Chapter II, the team explored the F2T2EA process, sensors, and AI. Here, the team looked at combining techniques described in that section with the AI-AMD architecture. There were 17 actions identified in the OV-5a for a human or AI-enabled machine to conduct in during the AMD sequence. These steps are shown in Table 17 along with prescribed methodologies for performance of the actions.

Table 17. AI-Enabled Kill Chain Methods

Process	Action	Method of Automation/AI	Description
Find (Observe)	Collect Data	Data Management	Preprocessing and storing data
	Accept Initial Detection	Data Fusion/Fuzzy Reasoning	Fuse vague data to detect an anomaly
	Identify Emerging Threat	Case-based Reasoning	Retrieve similar cases
Fix (Observe)	Request Further Information	Event Procedure	Auto executes when triggered (emerged target)
	Classify Target	Decision Theory/Evidential Reasoning	Decide on target from data mining knowledge base
	Locate Target	Spatial Reasoning	Monitors the target in space and time
	Validate Detection	Predictive Analytics	Predicts trajectory of threat
Track (Orient)	Request Updated Target Track	Event Procedure	Auto execute request once detection is validated
	Validate Target	Target Coordinate Mensuration (TCM) Validation	Provide precision coordinates meeting requirements of AD system
	Assess Blue Proximity	Data Fusion/Forward Chaining	Combine location data with AD capabilities data
Target (Decide)	Nominate Engagement Options	Utility Theory/Predictive Analytics/Forward Chaining	Assesses utility (capability) and readiness
	Prioritize Targets	Decision Theory	Assesses both probability and utility of threat knowledge
	Select Attack Option(s)	Decision Theory	Assesses both probability and utility of COAs
Engage (Act)	Issue Orders	Event Procedure/Template Filling	Auto executes when triggered and auto-populate fields
	Send Fire Command	Event Procedure	Auto executes when triggered (attack order)
Assess (Act)	Assess Target Status	Predictive Analytics/Spatial Reasoning	Monitors and projects threat and AD asset
	Authorize Re-attack	Event Procedure	Auto executes when triggered (failed engagement)

The first step in defining the AI methods to automate decisions was to understand the inputs and outputs of each action. The JP 3-60 defines inputs for each of the activities and these inputs were reviewed in the creation of the OV-5b. From there, those capabilities were compared with the capabilities of the various methods of AI and expert systems to determine the most viable method to execute the task. Many algorithms based on various types of reasoning and theory have been developed to tackle specific tasks. Each built around the level of uncertainty from the known and unknown data presented. So, the second step was to look at the level of uncertainty for each action. This was closely tied to the level of risk assigned in Chapter III.

2. Action Uncertainty

Table 18 lists the 17 actions again, showing levels of uncertainty assessed for each step. Considerations for the knowns and unknowns are set around the type of data collected, the domain of operation, and the risk of the decision.

Table 18. AI-AMD Actions Level of Uncertainty

Action	Uncertainty	Knowns	Unknowns	Risk
Collect Data	Low	Operational Status	N/A	Low
Accept Initial Detection	Low	Target Data	N/A	Low
Identify Emerging Threat	Low	Target Data	N/A	Low
Request Further Information	Low	Emerging Threat Present	N/A	Low
Classify Target	Mild	Target Data Threat Data	Unavailable Non-Threat Data	Moderate-Low
Locate Target	Low	Target Data	N/A	Moderate-Low
Validate Detection	Low	Target Data		Moderate-Low
Request Updated Target Track	Low	Target Present	N/A	Low
Validate Target	Mild	Target Data, Threat Data	Unavailable Non-Threat Data	Moderate-Low
Assess Blue Proximity	Mild	Location, Capabilities	Readiness	High
Nominate Engagement Options	Low	Location, Capabilities	Readiness	Low
Prioritize Targets	Low	Target Data	Threat Success	Moderate
Select Attack Option(s)	Mild	Target Data Threat Data	Responsiveness	High
Issue Orders	Low	Form and Procedures	N/A	Low
Send Fire Command	Low	Threat	Success	Moderate
Assess Target Status	Low	Target Data	N/A	Moderate-Low
Authorize Re-attack	Low	Target Data Threat Data	Responsiveness	Moderate

3. Methods of Automation

The team compared the levels of uncertainty and I/O for the actions with methods from Table 18. Many actions were relatively simple; these were assigned high levels of automation, as shown in Chapter III. Actions such as collect data, initial detection, locate target, issue orders, and send fire command can be triggered by outputs of prior actions. The data collected can be assigned meta-data, organized, and stored for future retrieval. Orders can be auto-populated to expedite their creation.

Data fusion methods can be employed in instances where the sensor data is merged to create a COP of the target and battlespace. Forward chaining, fuzzy reasoning, and case-based reasoning can be used to compare changes in the dynamic environmental to locate and identify targets and air defense assets.

In an operational AMD scenario the first critical action is to identify and classify an emerging threat to ensure that it is indeed a threat. Here, an expert system can be employed to use decision theory with evidential reasoning to take the target data and compare the data with the knowledge based on threats. This can then be used to correlate a match. Faster threats like missiles will be easier to identify over slower moving aircraft which can be confused with commercial types. However, with faster threats comes shorter timelines to respond.

The second critical step in an AMD scenario is to understand the COP of AD assets and readiness. Sensor data can locate the assets and additional sensors can be employed to help assess readiness based on system operating statuses (e.g., round count). Data fusion and forward chaining can help create this picture.

After a COP is created on the AD assets, COAs must be developed and nominated. The knowledge based on each system's capabilities can be used as assets in utility theory to determine the best capability against the threat. Predictive analytics can look forward to assessing success rates based on the location and readiness of each asset compared to the incoming threat. From there, forward chaining can weigh the values of the COAs to nominate an engagement.

Finally, spatial reasoning can be used to continue to monitor the threat and AD engagement to assess success. If the BLUFOR systems fail to defeat the threat, the AI-AMD can initiate a re-attack, if time allows. Predictive analytics can be used again to predict a failed engagement to start the re-attack action sooner to increase the success rate.

4. Current versus Future AI-AMD

The methods described above focus on current capabilities in expert system type algorithms. Algorithms of this type would likely be manually produced initially, but could be developed by ML through training with field data. ML requires time and processing power to implement. A centralized AI system may not be feasible, potential compounding network traffic and latency issues can reduce the timing efficiencies gained.

A future iteration of AI-AMD, 10+ years down the road, might look different. When techniques in AI are refined, more readily available, and accepted for use on more complex tasks, higher levels of automation for AMD may be achieved. Future AI-AMD systems incorporating ML will likely require that the information it gathers be stored so it can refine its decision-making algorithms. Most likely sensors will continue to improve and increase in number in the future, providing an even more detailed and complete COP of the battlespace, providing more knowledge of both blue and red forces. This will increase a future AI-AMD system's awareness of the battlefield, with awareness being the highest form of AI (Blasch eta all, 2019). More sophisticated AD assets will be increasingly digitized so readiness can be better assessed logistically and operationally. AI-AMD may even suggest or command movement of AD for better coverage. The system may include in its recommended COAs, warning systems to abandon positions. As processing power continues to shrink in footprint and cost, more complex decision aids may be implemented to increase accuracy and reduce time in future iterations of an AI-AMD SoS.

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V. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

As current trends in naval warfare shift toward automated combat weapons systems, the U.S. Navy is focusing its strategies toward AI capabilities that reduce the time a warfighter needs to act decisively. This project represented the human-AI decision process (as informed by MCPP) through a decomposition of OODA and F2T2EA to the operational activity level. Increased levels of automation for operational activities within the kill-chain process were demonstrated to significantly reduce the timeline; which, if further developed and fielded, will provide Sailors and Marines a tactical advantage in air defense. Expediting the kill chain through use of expert system and AI has the ability to greatly shorten engagement times effectively expanding the battle space.

The AI-AMD architecture is designed to improve warfighting decisions by prioritizing threats and acting upon them with minimal input from human users. Therefore, the project objectives focused on understanding and evaluating the AMD kill chain to identify steps in the process that can be executed faster using AI-AMD, determining risks associated with AI-AMD levels of automation as applied to the various steps in the kill chain process, utilizing M&S to compare the kill chain at low levels of automation ("without" AI) through high levels of automation ("with" AI), assessing improvements based on time saved, developing high level decision aid operational capabilities from the M&S analysis for AI-AMD and conceptual designs for AI-enabled decision superiority, and identifying existing and future AI methods and apply them to the AI-AMD kill chain.

The conceptual architecture of the system was developed with a MBSE approach using the SE tool Innoslate. The DODAF architectural analysis combined BLUFOR air defense sensors, weaponry, and the Joint network to create a depiction of the AI-AMD SoS for neutralizing enemy threats. The results of an architectural analysis using a DOE, discrete event, and stochastic simulation showed an 83.5% success rate within high-stress scenarios (at level of automation 10—fully automated) while low-stress scenarios were shown in the model to be 100% successful (at level of automation 1—fully manual).

The team developed a kill chain analytical framework to understand and model the risks associated with the automation of kill chain functions. The risk assessments for each of the 17 steps in the targeting process were categorized into four categories; low, moderate-low, moderate, and high. Leveraging Parasuraman's levels of automation, a risk assessment was conducted for individual steps within the targeting process to determine an acceptable level of automation. The team developed and employed a utility curve to assist in determining the time savings for each level of automation. For example, AI-enabled greater time savings was associated with higher levels of automation.

A sensitivity analysis was conducted to explore the impact of alternative underlying representative distributions (baseline, symmetric variable spread, and highly skewed). While changes in distribution shape did impact result, in every case, success within the high-stress scenario only occurred with AI-enabled savings greater than 97%.

This project investigated how AI methods could apply to AMD decision making to increase levels of automation and reduce the execution time of a human-AI team (an AI-enabled decision aid). Each of 17 key decision points was analyzed to identify where AI-AMD could increase levels of automation and improve speed. The potential levels of automation were balanced against risks associated with each of the various steps. The developed conceptual architecture was exercised within M&S to evaluate the timeliness of decisions made within the AI-AMD system at low levels of automation ("without" AI) through high levels of automation ("with" AI). The resulting high-level capabilities of the AI-AMD conceptual architecture were documented with recommendations for stakeholder consideration as the system technologies mature. Several existing and future AI methods and their applications to the AI-AMD kill chain were also studied. The team recommends that future iterations of AI-AMD studies look at more complex situations with multiple threats and engagement across the entire battlefield.

B. CONTRIBUTIONS

The team successfully met the objectives of the project. Three key deliverables were created: a systems architecture for AI-AMD, an AI-AMD analysis methodology with tool set, and a list of preliminary AI kill chain enabling methods to execute a future AMD mission set. The project objectives defined in Chapter I focus on the methodology of applying AI methods to AMD decisions in order to reduce the human-AI execution time. Within the objectives, the goals were to identify the AMD kill chain with improved AI decision aids, assign various levels of automation to steps within the kill chain process, compare and contrast the human versus machine execution time using modeling and simulation, and develop decision aid operational capabilities that assist the human-machine decision-making skills to support a faster AMD operation. The following sections review the objectives and the work performed within the project.

1. Understand and Evaluate the AMD Kill Chain

The objective to understand and evaluate the AMD kill chain to identify steps in the process that can be improved using AI automated decision aids was successfully met through an extensive literature review of the AMD operation. Focusing on JP 3-60, the F2T2EA kill chain process was mapped to the OODA loop. As defined by the OV-5b/6c diagram in Figure 23, the six F2T2EA steps help identify the process that can be improved using AI automated decision aids. The team then decomposed the F2T2EA functions of joint targeting and chose steps in the process that more closely aligned to the AMD operation, which resulted in 17 critical actions. The team then used DODAF modeling operational and system views to create the architecture of the AI-AMD representative system. These architectures create the baseline for system design of AI-AMD and will help drive the automated decision aid design process.

2. Determine Levels of Automation within the Kill Chain

The objective to determine which levels of automation can be applied to the various steps in the kill chain process was met through a literature review on the various levels of automation and applying those levels of automation to the 17 steps in the kill chain. The levels of automation were derived using Parasuraman, Sheridan, and Wickens's (2000) research on the ten levels of automation. Level one being strictly human and level ten being strictly AI. These levels were then correlated to a risk assessment for each of the 17 steps in the kill chain. The acceptable level of risk determined the appropriate level of automation. For example, assessing blue force proximity is a critical action due to the necessity of ensuring friendly forces are not within range of the BLUFOR defeat mechanisms, which could result in catastrophic consequences. As a result, a low level of automation was assigned to this particular step. The same methodology was conducted throughout the kill chain to assign appropriate levels of automation.

3. Perform Modeling and Simulation to Compare Scenarios

The objective to utilize M&S to compare the kill chain "with" and "without" AI and assess improvements based on time saved, improvement of decisions, improvement of outcomes, and probability of defeating enemy threats was met through the use of the Innoslate model and DOE. A utility curve was derived to estimate time savings, and a DOE was constructed to assess the varying times of the input factors. Lastly, a model linked to the DODAF architectural views through concordance of Innoslate was created to run simulations. The simulations were used to compare human timing with AI assisted and AI performed automation. Using the REDFOR threats and BLUFOR kinetic capabilities, a utility curve was created to determine the capabilities of the AI in low- and high-stress scenarios. The low-stress scenarios required minimum automation while high-stress scenarios required maximum levels of automation to gain an efficiency when the kill chain is automated. The risk summary supplemented the utility curve in depicting the AI-enabled time savings associated with each level of automation.

4. Develop High-Level Capabilities from Modeling and Simulation

The objective to develop high-level decision aid operational capabilities from the M&S analysis for AI to support AMD and conceptual designs for AI-enabled decision superiority was met through the M&S of various scenarios within AMD. Focusing on the missile threat, the team chose a low-, moderate-, and high-stress scenario based upon open source data on REDFOR threats, BLUFOR detection sensors, and BLUFOR defeat mechanisms. The threat scenarios were used to determine capabilities of the AI-AMD system and requirements of the system in order to successfully defeat the threat. The team observed that human timing was not adequate to defeat higher-stress threats. Additionally, timing based upon the risk assessment was unsuccessful in defeating the moderate-stress missile threat without increases several levels of automation. In the event of high-stress scenarios, the AI-AMD must take full advantage of automation, regardless of risk factors, in order to be successful. AMD is a complex mission set and understanding that mission set is key to building the system architecture.

5. Identify AI Methods

The objective to identify existing and future AI methods that can be applied to the decision aid for application within the kill chain using the M&S results was met through an extensive literature review of current and future AI methods. Determining areas to automate is only a portion of the design process. The next phase is implementation and development of the AI to perform the necessary functions. The team examined many techniques in expert systems, automation, and AI to assess methods to perform the various decision steps in the kill chain. The team utilized the risk assessment along with evaluating task uncertainty to compare which techniques and methods were best suited to perform functions or make decisions. It is recommended that the AI methods identified be used to build the AI-AMD decision aid.

C. POTENTIAL BENEFITS

Automation has been used to replicate human behavior and functions for years. With the advent of AI, the potential to bring higher levels of automation to daily life has increased tremendously. The ability to consistently replicate cognitive processes to assist or take over decisions will be able to expedite processes. The ability to apply decision-making abilities to machines in the AMD domain will increase efficiency and effectiveness of the AMD mission. Decisions will no longer become human limited, but machine limited. Investing in ML processes can help mature decision-making algorithms as more data is ingested during the training process. Refined algorithms will increase accuracy, efficiency and effectiveness. Increases in automation should reduce manpower as well freeing operators up for other tasks and potentially reducing the number of men and women in harm’s way.

D. FUTURE WORK

Leveraging AI for AMD is a broad domain which required the team to use assumptions and constraints to set boundaries for the project. The team has taken a high-level approach, and additional work is required to improve the decision aid. Suggested future work includes using real-world data for human timing, further refining the AI-AMD utility curves for the AI-AMD time savings, capturing in-depth COA recommendations based on stakeholder input, considering logistics implications, modeling advanced threats and enemy tactics, techniques, and procedures (TTPs), and assessing external system impacts on the AI-AMD such as network latency and sensor detections.

1. AMD Human Decision-Making Timing

AMD requirements must be defined by the stakeholders upfront during the initial system development process. Additionally, the AI-AMD architectural model can be refined to reflect a more precise and accurate representation with real-world data. The efficiency and effectiveness of the model can greatly improve with real-time user data and accurate engagement times for missiles. A classified discussion can generate actual enemy missile engagement timelines, which can then be inputted into the model to further refine the system requirements. It is the team's recommendation that an in-depth discussion on AMD timelines without AI be conducted with the stakeholder in order to accurately reflect real world scenarios. The steps in the AMD kill-chain should be reviewed with the stakeholder in order to fully capture the human decision-making timeline without AI. The team simplified the kill-chain timeline in the JP 3-60 joint targeting publication to 17 critical functions. These functions will need to be vetted with AMD TTPs to ensure that all steps and associated engagement timelines are captured.

Furthermore, automating the kill chain will require an acceptable level of trust. The capabilities and limitations of the operator's ability to perform each task must be understood in order to promote trust in the AI decision aid. The Rasmussen Skill Rule Knowledge Framework can be used to determine the cognitive task analysis (CTA) and cognitive work analysis (CWA) for the F2T2EA human decision-making timeline in order to define which tasks in the kill chain could be automated (Paradis, Breton, Elm, and Potter

2002). Too much automation can result in an overreliance on the AI decision aid whereas not enough automation can result in an unsuccessful mission. Finding the acceptable balance between trust and level of automation is a critical step in defining the AI-AMD decision aid.

2. Refining Utility Curves and Risk Assessments

The team, absent of real world data, chose to represent the level of automation and associated time savings through a single utility curve as shown in Figure 44. This single utility curve applies to each of the 17 steps in the kill-chain. The team recognizes that this assumption is an oversimplification of the complex AMD operation. It is recommended that a utility curve is created for each of the steps in the AMD kill-chain that fully captures the timing and associated time savings of varying the automation for that particular step. In addition, it is recommended that a user defined risk assessment and risk rating be assigned to each of the kill-chain steps. The risk assessment will drive the acceptable level of automation and associated utility in automating that task.

3. Simulating Multiple Engagements

AI-AMD described in this project demonstrates that automated decision aids can increase the speed of the AMD mission and allow the user to decide faster. Future engagements may find AD systems engaging a multitude of incoming threats. Increasing the number of incoming enemy threats will add additional strain to the AI-AMD decision aid and COA recommendations. It is critical to understand the capabilities, limitations, and sensitivities of the system to understand its full scope. It is recommended that a user working group be conducted to capture scenarios and vignettes of the AMD operations where the AI-AMD decision aid system applies. More scenarios and greater detail will further improve the decision-making and AI/ML learning algorithms to account for as many potential scenarios as possible. Simulating the environment and collecting data on scenarios will further refine requirements of AI-AMD.

4. Refine Threat Models

To simplify the timing calculations as described in Chapter III, the team chose to model the inbound threat linearly by dividing the range by the speed in order to calculate a time component. The team recognizes that this is an over-simplification of the trajectory of both the REDFOR and BLUFOR missiles. The REDFOR threats identified in Table 11, the BLUFOR detection sensors in Table 12, and the BLUFOR defeat assets in Table 13 have a complex trajectory and physics that must be fully defined in order to capture the engagement timeline appropriately. Refining the model of the inboard threats will provide more accurate timing when applied to the AI-AMD models.

The threat environment should also be taken into consideration. Russell and Norvig (2015) describe multiple properties of the task environment to consider when working with various computational methods. Using these properties against the kill chain tasks will help determine optimal theories to apply to the decision aid. Table 19 shows the seven characteristics to consider for the task environment.

Table 19. Characteristic Considerations for the Task Environment. Adapted from Russel and Norvig (2015, Figure 2.6).

Characteristic	Values		Considerations
Observable	Fully Observable	Partially Observable	Sensors have access to complete state?
Agents	Single Agent	Multi-Agent	Number of agents involved?
Deterministic	Deterministic	Stochastic	Is the next state completely determined by the next agent action?
Episodic	Episodic	Sequential	Can the action effect all future states?
Static	Static	Dynamic	Can the environment change while the agent is deliberating?
Discrete	Discrete	Continuous	Is there a finite number of states?
Known	Known	Unknown	What are the unknowns?

5. Expanding the Target Set

AI-AMD replicated not only the AMD mission, but the JP 3-60 targeting process. This allows the AI-AMD to also defeat other target types represented within the JP 3-60 doctrine such as COAs when engaging time sensitive targets (TSTs), high value targets (HVTs), and high priority targets (HPTs). Similarly, monitoring the BLUFOR through programs such as Blue Force Tracker (BFT) will further refine the AI-AMD COA engine. Varying the types of engagements to not only type of potential target, but also classification of the target will create an increased complexity to the OV-5b/6c action diagram. However, this increased complexity will also allow for a higher fidelity of real-world representation, encompassing different engagements. Updating algorithms to detect other threat signatures as aided target recognition (AiTR) development continues, allows AI-AMD to expand its utility.

6. Applying AI-AMD at Additional Operational Levels

The targeting process and ability to generate COAs could be applied at various operational echelons. The team chose to focus on the Navy Task Force level for implementing the AI-AMD. However, AI-AMD could easily be applied at lower or at higher echelons. It is likely that the AI-AMD is a layered AI/ML approach with varying levels of AI at different echelons. Applying the AI-AMD to the strategic level can become an automated decision aid for senior leaders. It is recommended that the echelon application be reviewed to ensure that the AI-AMD is located within the appropriate level. If the AI-AMD is determined to be better suited as a layered approach, target handoff, coordination, and synchronization will become essential components for de-conflicting control

7. Logistics Applications

The team chose timing as a critical focus area of the project. However, there is also a logistical component to the decision aid that must be explored. Assessing items such as the quantity of BLUFOR assets, location of BLUFOR assets, logistical hubs, re-supply routes, cost of BLUFOR weapons, availability of assets in inventory, manufacturing capability of those assets, and funding available to restore stock are all potential logistical questions that could be used to generate the most informed decision. A thorough review of the AI-AMD sub-system components should be reviewed to ensure adequate availability and reliability is achieved along with appropriate level of redundancy. It is recommended that detailed logistics, reliability, availability, maintainability, supply chain, and manufacturability of BLUFOR assets be reviewed and applied to the AI-AMD decision aid.

8. Network Capability and Robustness

Current ML processes require a significant amount of computer power. If ML is utilized within the kill chain, the ML processing may not be capable of being collocated with the BLUFOR within the named area of interest (NAI). If the AI-AMD is separated from the BLUFOR NAI, it is assumed that this will increase network utilization and latency. The team assumed network timing based on the circumference of the Earth and the speed of light. Specific system position will determine specific timing for network communication. Having the timing association with network traffic will further refine the AI-AMD model and thereby AI-AMD network requirements.

AI-AMD is network centric, which means that the decision aid relies on external systems to perform its mission of sending and receiving data to the appropriate channels. The decision aid receives data to process for the decision, disseminates the data, and recommends a decision. Future design work will need to ensure a robust and secure network that can operate without a large amount of latency. A network study on the required sensitivity, bandwidth, redundancy, message traffic, protocols, and network infrastructure is recommended to fully capture the AI-AMD reliance on the external network. The external network will then drive the requirements for the AI-AMD and further define the timeline required to make a decision. Additionally, the network capability must have interoperability within joint services, multinational allied forces, and supporting MDO cross-platform operations. As the network capability is a key component of the decision aid model, future work is recommended to determine the integration required to incorporate the latest network hardware and software into the AI-AMD decision aid and integration required to incorporate the next generation of telecommunications and network infrastructure.

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