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GAME THEORY AND PRESCRIPTIVE ANALYTICS FOR

NAVAL WARGAMING BATTLE MANAGEMENT AIDS

by

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To achieve and maintain decision and mission superiority, the Navy has prioritized research in computational technologies and data analytic methods for automating and improving battle management and decision-making. This project studied novel automated techniques using a multidisciplinary systems analysis approach and developed conceptual designs for automated wargaming systems to support tactical decisions and operational planning. The research approach revealed three different applications for automated wargaming: (1) to support table-top wargames as an automated white cell for adjudication or as a red team cognitive agent, (2) to support operational mission planners as a non-real-time course of action (COA) engine, and (3) to support the tactical warfighter as a real-time COA engine that considers second, third, and nth order effects as it evaluates and recommends possible tactical COAs. The study found that automated wargaming battle management systems (leveraging game theory, prescriptive analytics, predictive analytics, artificial intelligence, etc.) are needed to support enhanced situational awareness, reasoning and problem-solving, faster decision timelines, and the identification and evaluation of tactical and operational COAs. The study recommends further research into the use of automated wargaming systems, the emerging field of course of action engineering, and the applications of these novel techniques to support table-top wargaming, operational planning, and tactical decision-making.

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ABSTRACT

To achieve and maintain decision and mission superiority, the Navy has prioritized research in computational technologies and data analytic methods for automating and improving battle management and decision-making. This project studied novel automated techniques using a multidisciplinary systems analysis approach and developed conceptual designs for automated wargaming systems to support tactical decisions and operational planning. The research approach revealed three different applications for automated wargaming: (1) to support table-top wargames as an automated white cell for adjudication or as a red team cognitive agent, (2) to support operational mission planners as a non-real-time course of action (COA) engine, and (3) to support the tactical warfighter as a real-time COA engine that considers second, third, and nth order effects as it evaluates and recommends possible tactical COAs. The study found that automated wargaming battle management systems (leveraging game theory, prescriptive analytics, predictive analytics, artificial intelligence, etc.) are needed to support enhanced situational awareness, reasoning and problem-solving, faster decision timelines, and the identification and evaluation of tactical and operational COAs. The study recommends further research into the use of automated wargaming systems, the emerging field of course of action engineering, and the applications of these novel techniques to support table-top wargaming, operational planning, and tactical decision-making.

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I. INTRODUCTION

A. PROJECT STATEMENT

Game theory and prescriptive analytics offer two potential game changing capabilities for naval mission and decision superiority. Tactical operations can take a significant leap in progress with the aid of a real-time automated wargaming battle management aid that predicts the success of different course of action (COA) options and considers possible second and third order effects. This future capability would accompany current development inf the use of artificial intelligence (AI) to improve battlespace knowledge and offer a decision aid to tactical warfighters.

B. RESEARCH OBJECTIVES

The primary research objective was to develop and evaluate a conceptual design for a real-time wargaming capability that can be used operationally as a tactical battle management aid. Additional research objectives were to:

- Study the operational need for a real-time naval wargaming battle management aid,
- Develop requirements and a conceptual design for a real-time naval wargaming battle management aid, and
- Identify and evaluate data analytic methods including game theory and prescriptive analytics for application to real-time wargaming battle management aid capabilities.

C. RESEARCH APPROACH

The NPS research team, consisting of NPS researchers and NPS graduate students, applied a systems analysis approach to the project. The team began with a literature review of (1) automated advanced data analytics methods, (2) analytic capabilities that have been developed by the Navy and the Department of Defense (DoD), and (3) naval wargaming applications. The team identified three types of automated wargaming systems that could be developed for the Navy: (1) systems to support table-top wargames, (2) systems to support operational planning, and (3) systems to support real-time tactical decisions. The research team focused on the second two types of automated wargaming capabilities. The research team then applied a systems analysis approach to each of these types—starting with needs analysis, then developing requirements, and then synthesizing conceptual designs. Finally, the team studied each of the conceptual designs using operational analysis – to study how these future conceptual automated wargaming systems could enhance the wargaming needs in each of the applications.

D. REPORT ORGANIZATION

This report is organized into five chapters. Chapter 1 introduces the study, Chapter 2 contains the literature review, Chapters 3 and 4 present the system analyses of the two types of automated wargaming systems, and Chapter 5 concludes the study.

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II. LITERATURE REVIEW

A. GAME THEORY

Game theory is the study of mathematical models of strategic interactions among rational agents. Game theory provides tools for analyzing situations in which players make decisions that are independent. This independence causes each player to consider the other player's possible decisions, or strategies, in formulating strategy. Game theory includes strategic thinking in which players make decisions by viewing various perspectives and by looking at the viewpoint of other participant players; also, by analyzing their actions and reactions in particular situations. A practical implication of game theory lies in explaining events and situations that occurred in the past to determine different actions players may take in the future. Game theory can be a powerful medium for forecasting or predicting the output of interactions between different participants or competitors in which reaction of one depends on the action of others. The foundational work of John Von Neumann (Von Neumann and Morgenstern 1944) and John Nash (Nash 1950 and Nash 1951) have led to the important recognition that the identification of optimal strategy in the context of complex interactions (games) between two or more parties (players) can lead to a predictable outcome or payoff (Ho et al. 2022).

It has been noted that game theory can provide a rigorous mathematical framework for the evaluation and optimization of numerous military scenarios relative to predefined criteria (Ho et al. 2022). This study builds on this idea with the application of game theory as a real-time decision aid or planning aid to lead to decision superiority under time pressure.

Game theory can be used as an approach to model military decision-making scenarios (Merrick et. al. 2016). Behavioral game theory can model human decision making and the role of machine decision-making in warfare scenarios. Game theory can be used to describe strategic interactions and their likely outcomes. The application of game-theoretic approaches can capture the nature of warfare between an attacker and a defender. It can be used to perform tactical analysis of the options available in response to a threat. The games can be analyzed to establish equilibrium points and suggest beneficial strategies for players.

1. Traditional Game Theory

a. Risk Neutrality Assumption

Game-theoretic approaches generally assume players as risk neutral, implying that agents always choose the action that maximizes their expected payoffs; whereas the rationality assumption implies that the relationship between the utility of agent preferences over the choice is linear. This method incorporates risk preferences in models of agent decisions.

b. Cooperative and Non-cooperative Games

Cooperative games, also referred to as coalitional games, consist of players forming coalitions or collaborative groups; whose payoff within the game relies on collective behavior and strategies. Non-cooperative games are based on the self-interest of the individual players. In non-cooperative games, cooperation between players may arise, but only because the cooperation is seen as the best strategy to maximize each individual player's payoffs.

c. Simultaneous or Sequential Games

Game theory can be used in one of two ways: (1) simultaneous games in which players go ahead with moves or actions simultaneously, irrespective of looking for information related to the moves or actions chosen by other players; or (2) sequential games which include the dependencies of the players moves or actions on the previous action's results or another player's choice.

d. Discrete or Continuous Games

Continuous or differential games are modeled over a continuous time frame. Each state variable evolves continuously over time according to a differential equation. In such games, iterative rounds of decision making are much too discrete to model the continuous movements and computations of each player, so differential models can be used. Conversely, discrete games are modeled in discrete states.

e. Non-Zero-Sum Games or Zero-Sum Games

Zero-sum games are a class of competitive games where the total of the payoffs of all players is zero. In a two-player game, one player's loss in the payoff is equal to another player's gain in the payoff (Ho et al 2022).

f. Perfect or Imperfect Information Games

In a perfect information game, the players are aware of the full history of the previous actions of all other players as well as the initial state of the game. In imperfect information games, the players do not have full access to all of this information.

2. Behavioral Game Theory

Traditional game theory assumes that players are rational. However, in military operations, decision makers may not adhere to these assumptions. This has led to an increasing recognition that it is necessary to model players in greater detail, considering their behavioral characteristics including intent, objectives, strategies, and motives. Behavioral game theory is a recent approach that focuses on bounding the rationality assumption. This method takes into account the subjective rationality of individuals as a result of their intrinsic motivations, modeled as innate preferences for certain kinds of incentives. Players with different motives can perceive game payoffs differently and can therefore result in different play strategies and different equilibriums. Additionally, there can be multiple levels of players and therefore different motivations at different levels.

3. Evolutionary Games

Evolutionary games are based on population dynamics and provide a convenient framework to study competitive interactions in a dynamic setting. Different versions of evolutionary games exist including spatial games that study the dynamics on graphs. Evolutionary games are often modeled as iterative games where a population of players play the same game iteratively in a well-mixed or spatially distributed environment.

4. Quantum Game Theory

An emerging field called quantum game theory introduces superposed initial states, quantum entanglement of initial states, and superposition of strategies (Khan et al 2018, Iqbal and Toor 2002). Figure 1 illustrates a quantum game as compared with a classical game. It indicates a greater payoff for each individual player in the quantum game because of taking into account player entanglement into player strategies.

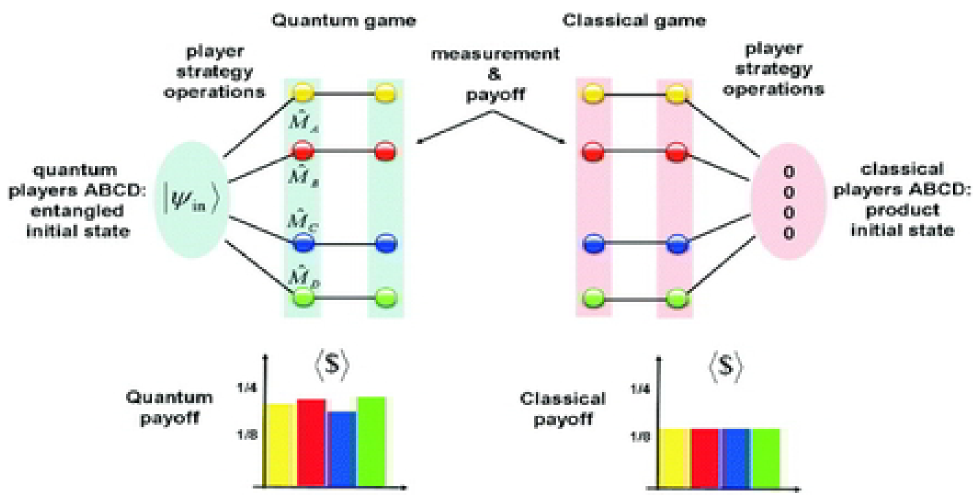

Figure 1. Quantum game vs. classical game

Quantum game theory can be used to modeled in a quantum domain where the linear superposition of actions is allowed (Hidalgo 2008). This allows for the modeling of the conflicting or cooperative behavior of players from the point of view of quantum mechanical interactions. This, in turn, enables the observation of entanglement between players, the definition of "socioeconomical temperature" in a system, the "collective welfare principle", and the analysis of the game through quantum information theory and from a global perspective (Hidalgo 2008). Figure 2 compares characteristics of quantum mechanics and game theory.

Quantum Mechanics	Game Theory
n system members	n players
Quantum States	Strategies
Density Operator	Relative Frequencies Vector
Von Neumann Equation	Replicator Dynamics
Von Neumann Entropy	Shannon Entropy
System Equilibrium	Payoff
Maximum Entropy	Maximum Payoff

Figure 2. Similarities between quantum mechanics and game theory (Hidalgo 2008)

Figure 3 shows an analogy between the quantum statistical mechanics representation of an entities' state with an evolutionary game theory representation of a player's strategy.

Quantum Statistical Mechanics	Evolutionary Game Theory
n system members	n population members
Each member in the state $\lvert\Psi_k\rangle$	Each member plays strategy s_i
$\lvert\Psi_k\rangle$ with $p_k \rightarrow \rho_{ij}$	$s_i \rightarrow x_i$
$\rho, \sum_i \rho_{ii} = 1$	$X, \sum_i x_i = 1$
$i\hbar \frac{d\rho}{dt} = \left[\hat{H}, \rho\right]$	$\frac{dX}{dt} = [\Lambda, X]$
$S = -Tr\{\rho \ln \rho\}$	$H = -\sum_i x_i \ln x_i$

Figure 3. Quantum statistics mechanics and evolutionary game theory (Hidalgo 2008)

5. Game Theory Application Example

A recent study used game theory to model strategies for protecting the privacy of biomedical data against adversary attacks (Wan et al. 2021). The study modeled the situation using a two-player Stackelberg game of perfect information and used the model to assess the risk associated with different data sharing strategies. The model represented adversary multistage attacks. The study assessed the model and developed risk mitigation strategies by explicitly modeling and quantifying privacy-utility tradeoff in the context of the adversary multistage attacks. The game theoretic model revealed the optimal sharing strategy to data subjects. Figure 4 illustrates the multistage privacy attack and its game theoretic protection. (A) A system-wide perspective of a multistage re-identification attack and its protection. Person-specific data records of a subject are accessible to an adversary through three databases: a targeted genomic database (D), a genetic genealogy database (DG), and a public identified database (DI). The adversary re-identifies a genomic record by inferring surnames in stage I and linking it to a public record in stage II. The data subject selects a sharing strategy based on a game model only when sharing data in D. (B) A masking game represented in the extensive form. In a masking game, the data subject moves first, and the adversary moves next. Each terminal node is associated with both players' payoffs. Sj is an m-dimensional vector of 0 and 1 values, representing the jth concrete action of the data subject. More denotation details are in the main text. The opt-in game is a special variation of the masking game in which the data subject only has those two strategies.

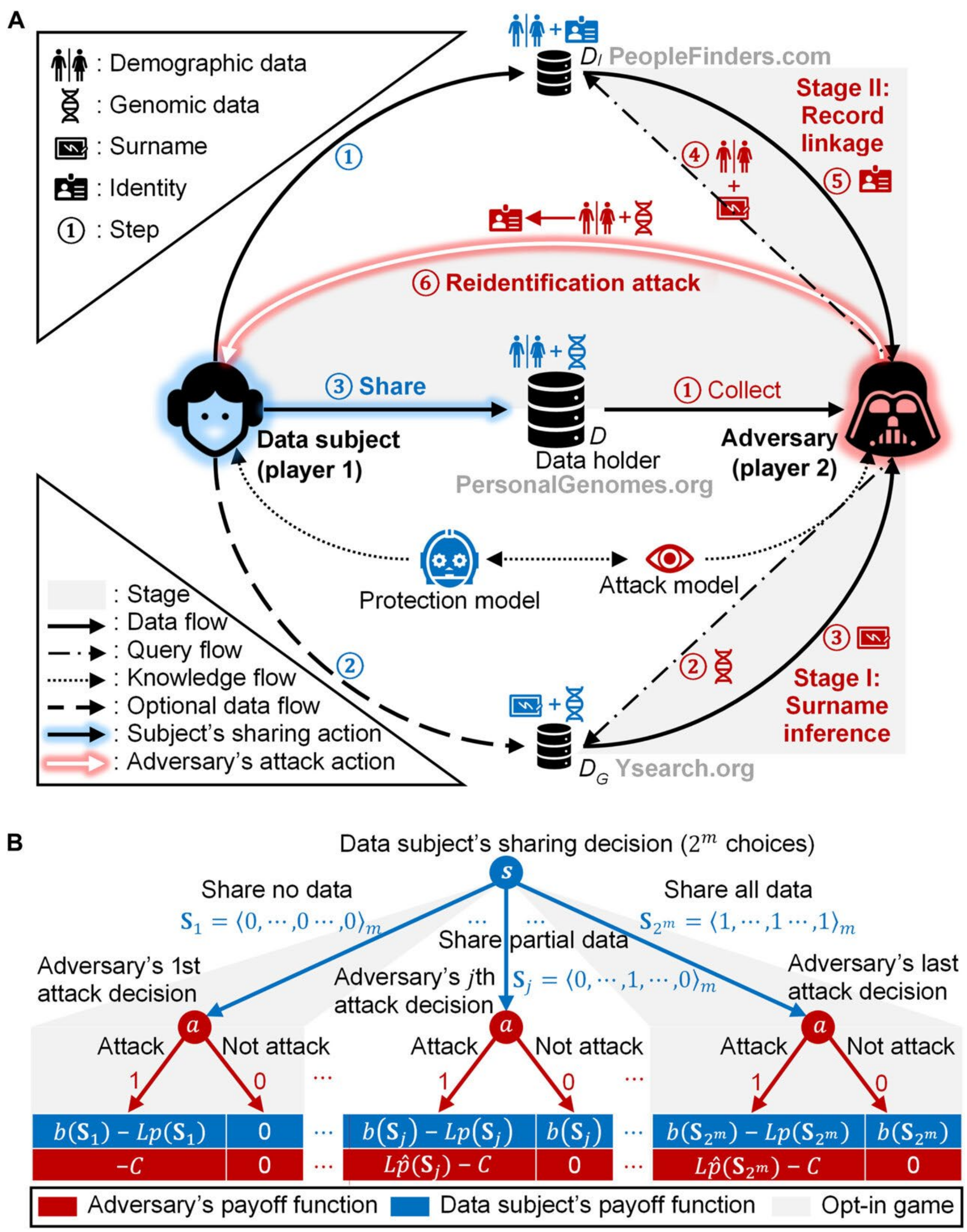

Figure 4. Game Theory Model for a Multistage Privacy Attack (Wan et al. 2021)

The model for this multistage privacy attack game is a good example of how military games can be represented and how game play and strategies can be described and analyzed quantitatively.

B. PRESCRIPTIVE ANALYTICS

In a nutshell, prescriptive analytics is the process of using data to determine an optimal course of action (COA). The process considers relevant factors and yield recommendations for next steps. Prescriptive analytics is a valuable data-driven decision-making approach.

1. Types of Explorative Analytics

Explorative data analytics can be divided into three categories based on the type of question being asked. The three types are:

1. **Descriptive Analytics** – answering the questions: What has happened?", "Why did it happen?", and also, "What is happening now?"
2. **Predictive Analytics** – answering the questions: "What might happen?", and "What is the likelihood of possible future outcomes?"
3. **Prescriptive Analytics** – answering the questions: "What should I do?", and "Why should I do it?"

Descriptive analytics explore data concerning a situation to describe what has happened in the past and what is happening currently. In a military scenario, descriptive analytics are used to build situational knowledge—identifying what is known about blue forces and red forces and the operational environment. This knowledge may include the existence, type, location, and intent of blue and red forces as well as information about the geography, civilian structures, defended areas, and the weather.

Predictive analytics explore data to estimate what might happen in the future and how likely different possible future outcomes are to occur. In a military scenario, predictive analytics could be used to perform threat assessments using information that is known (or speculated) about the locations of adversary forces and assets and their possible intent. Additionally, predictive analytics could be used to assess blue force vulnerabilities—based on how vulnerable specific blue forces and their assets are as well as the vulnerability of possible blue force COAs. Predictive analytics can be further categorized according to the methods shown in Table 1.

Table 1. Types of Predictive Analytic Methods

Predictive Analytic Method	Description
Predictive Modeling	Modeling what might happen next
Root Cause Analysis	Causal analysis to determine why something happened
Data Mining	Identifying correlated data
Forecasting	Determining what will happen if existing trends continue
Monte-Carlo Simulation	Exploring what could happen next
Pattern Identification and Alerts	Identifying when an action needs to occur

Prescriptive analytics explore future COAs—identifying possible COAs and evaluating the possible first-, second-, third-, and nth-order effects of COAs. Prescriptive analytics simulates future scenarios to explore possible options and make recommendations on which COA to perform based on many factors. In the military realm, prescriptive analytics can identify possible blue force COAs and evaluate their possible effects on the red force and explore how the red force might react.

A model that shows the different types of exploratory analytics and their relationships is shown in Figure 5. In this figure, the analytics are shown sequentially building on each other and developing a continuum of hindsight, insight, and foresight to take information and make assessments and develop recommended actions based in optimization. The x-axis indicates that the difficulty level in the analytic process increases as the analytics shift from descriptive to diagnostic to predictive to prescriptive. The y-axis shows that the value increases accordingly. The figure also introduces a fourth type of analytic method: diagnostic analytics. Some analytic taxonomies lump diagnostic analytics and descriptive analytics together. Diagnostic analytics can be distinguished from descriptive as a form of advanced analytics that diagnoses a situation based on examining data to explore why something happened. Diagnostic analytics includes techniques such as drill-down, data discover, data mining, and correlations.

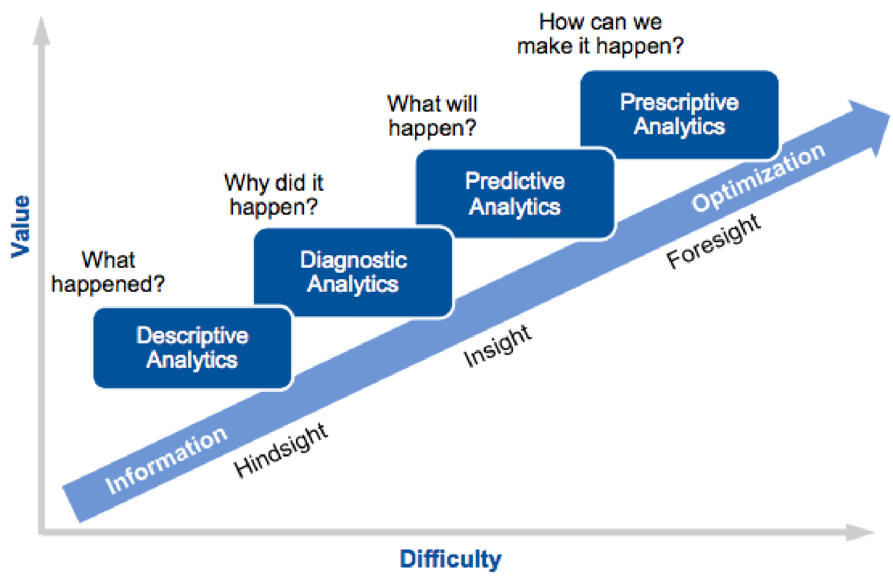

Figure 5. Hindsight, insight, and foresight (Garner 2012)

Figure 6 illustrates the range of prescriptive analytics starting with predictions, moving to decision, and finally studying the effects of decisions. This perspective aligns with the NPS research team's study into "COA engineering." COA engineering is a term the team coined this year to describe the process of identifying and generating possible military COAs, evaluating them based on their feasibility and predicted success based on forecasting and possible effects, and then acting the COAs with real military systems, forces, tactics, and actions.

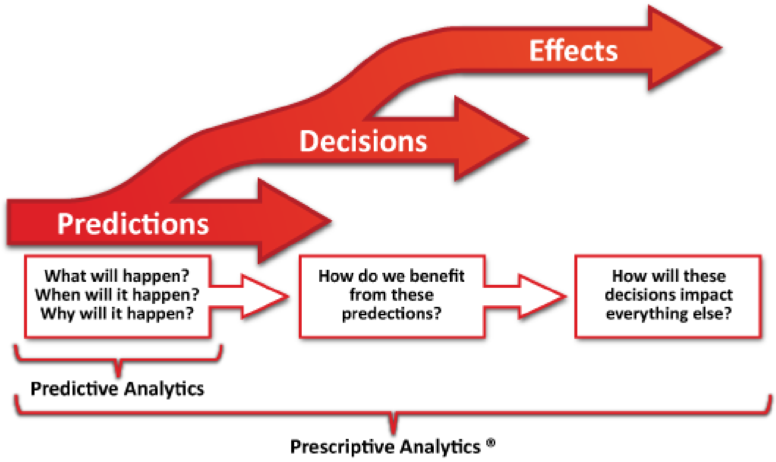

Figure 6. Prescriptive Analytics (Modaniel 204)

Figure 7 is another illustration of the different types of explorative analytics. This diagram introduces cognitive analytics, as yet another category of analytics. Cognitive analytics apply human-like (yet automated) intelligence to certain tasks, bringing together a number of intelligent methods including semantics, AI, deep learning, and machine learning. Cognitive analytics can include understanding the context and meaning of a situation, recognizing objects in an image, and revealing patterns and connections.

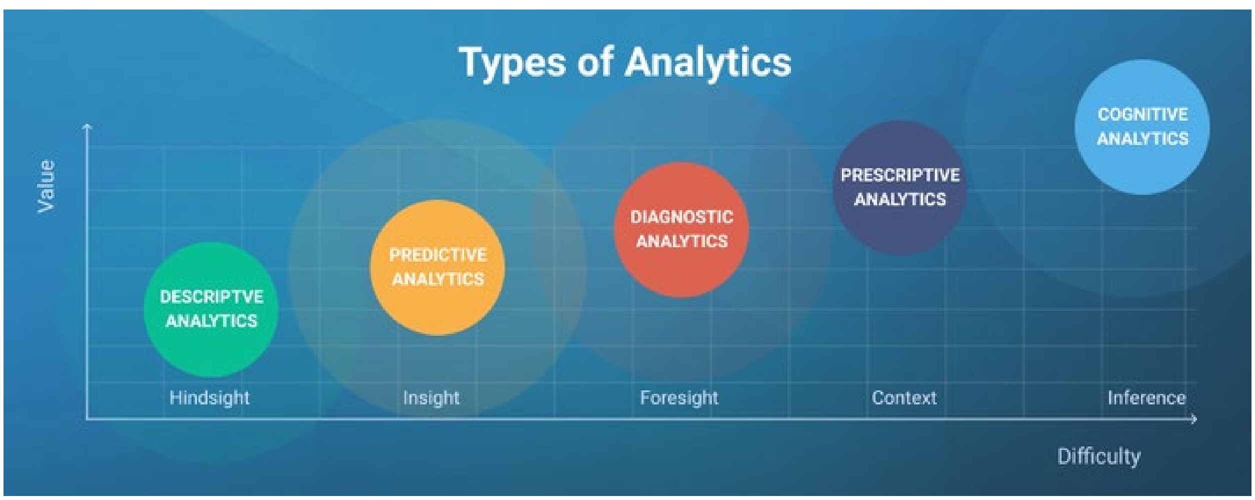

Figure 7. Types of Explorative Analytics (Soulpage 2020)

2. Prescriptive Analytics Methods

Common methods used for descriptive and predictive analytics include data mining, machine learning, artificial intelligence, and simulation (den Hertog & Postek 2016, Habeeb et al. 2018, Larose & Larose 2015). Comparatively, prescriptive analytics is less mature (Gartner 2017). However, it is viewed as the next step towards increasing data analytics maturity and leading to optimized decision making (Lepenioti et al 2020). Prescriptive analytics aims at suggesting (prescribing) the best decision options in order to take advantage of the predicted future utilizing large amounts of data (Siksnys & Pedersen 2016). It incorporates the output of predictive analytics and uses AI, optimization algorithms, and expert systems in a probabilistic context in order to provide adaptive, automated, constrained, time-dependent, and optimal decisions (Lepenioti et al 2020, Basu 2013, Engel, Etzion, & Feldman 2012, Gartner 2017).

Bertsimas and Kallus (2020) introduce a new mathematical framework that combines ideas from machine learning and operations research to prescribe optimal decisions. Their proposed framework is based on data-driven optimization that includes observations of associated auxiliary quantities. It is meant to be applied to conditional stochastic optimization problems with imperfect observations and unknowns. The framework introduces a coefficient of prescriptiveness, P, to measure the prescriptive content of the data.

3. Scientific Disciplines Related to Prescriptive Analytics

Figure 8 shows eight different disciplines that contribute to prescriptive analytics. These include traditional analytic method from applied statistics, signal processing and image processing. They include AI methods: machine learning, computer vision, and natural language processing. Another method is metaheuristics which is a computer science and mathematical optimization method involving higher-level procedures to find, generate, or select a heuristic that may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or limited computation capacity. Finally, prescriptive analytics also draws upon operations research to apply these methods to particular operations.

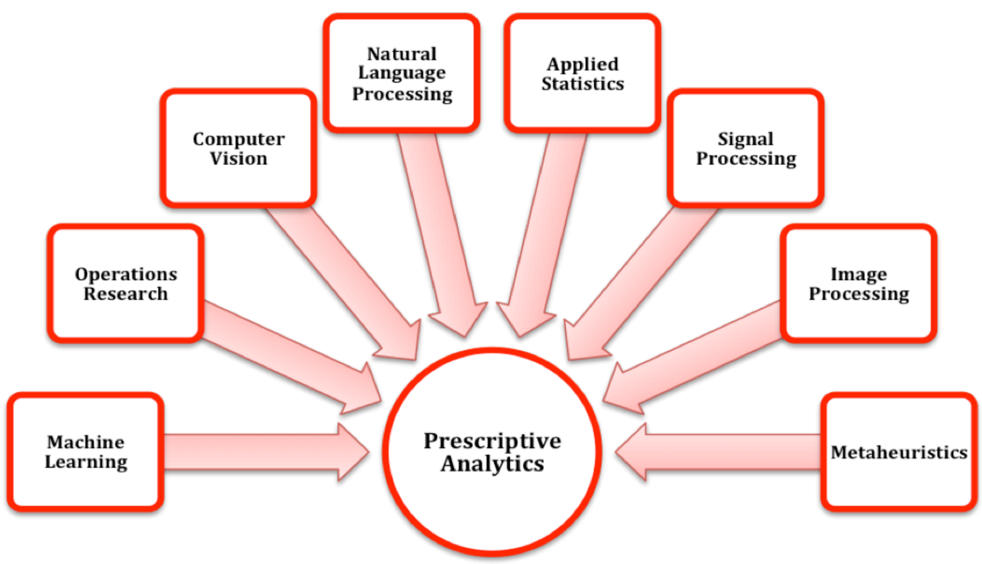

Figure 8. Scientific disciplines related to prescriptive analytics (Modaniel 2015)

4. Concept for Tactical Decision Aid using Explorative Analytics

In 2019, the NPS research team studied the use of predictive analytics for naval decision-making. This study produced a conceptual design for an automated decision aid that could use explorative analytics as a COA engine to identify possible blue force COAs and predict their effects on the red force; and then identify possible red force responses and predict their second order effects on the blue force (Johnson 2020). The concept was based on the desire to "wargame" nth order effects and counter effects using an automated intelligent system. Figure 9 illustrates the conceptual design of this capability.

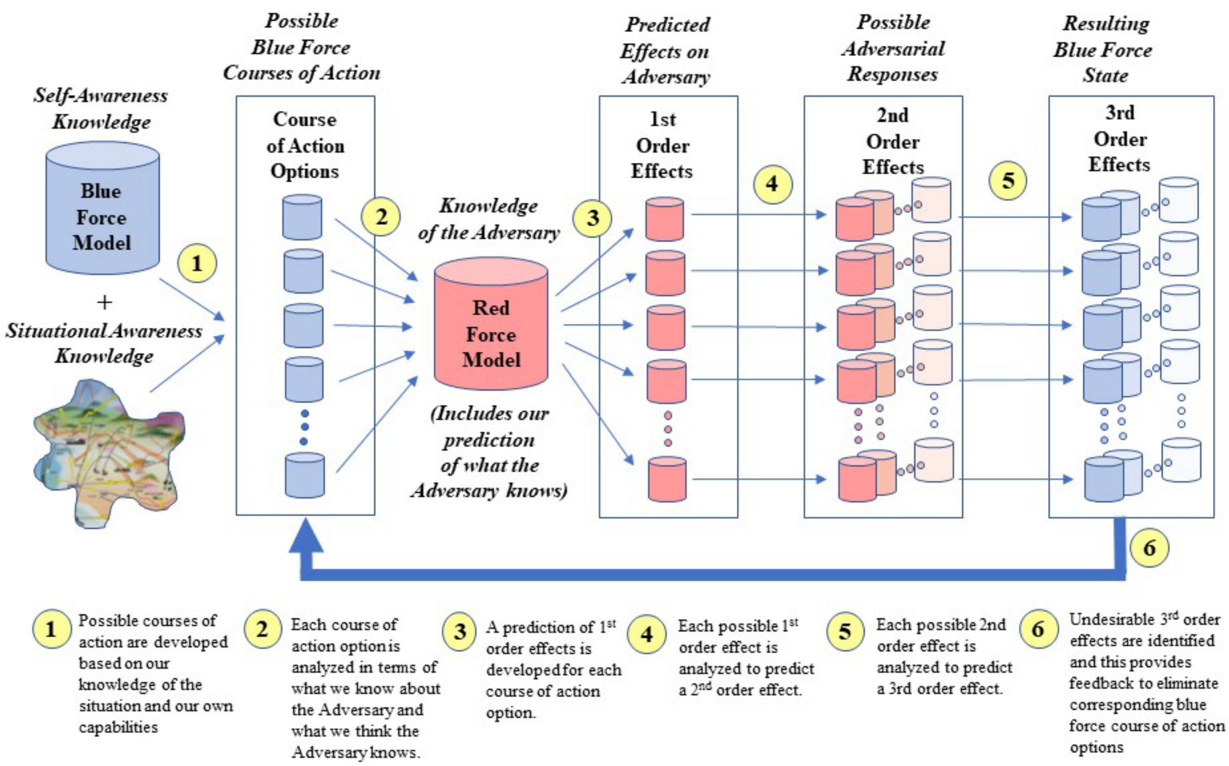

Figure 9. Conceptual design of a tactical explorative analytics capability (Johnson 2020)

The study produced a context diagram shown in Figure 10 that identifies some of the major features of a future automated tactical decision aid that imports data to discover knowledge about a military operation and determine COAs to support multi-mission resource allocation

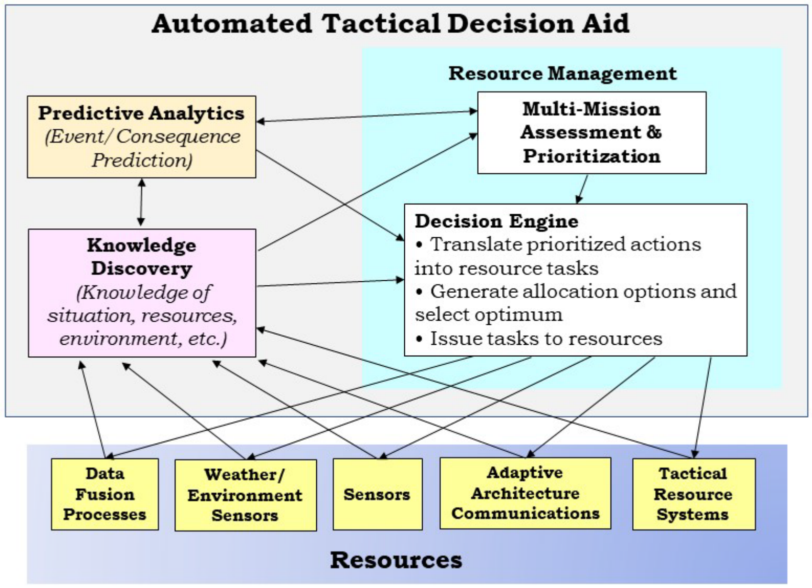

Figure 10. Automated predictive tactical decision aid concept (Johnson 2020)

The study also identified the need for the automated computer system to develop three internal models: one of the blue forces, one of the red forces, and one to represent the operational situation. These internal models are illustrated in Figure 11.

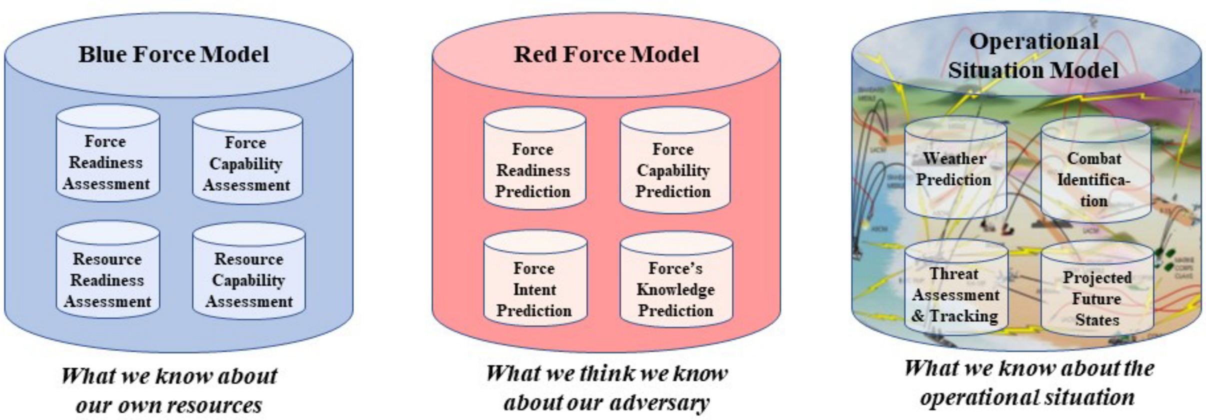

Figure 11. Internal models for an automated tactical decision aid (Johnson 2020)

C. DEPARTMENT OF DEFENSE MODELING SYSTEMS

Each of the Services (USN, USA, USAF, USMC) has funded and developed specific modeling and simulation capabilities to enable training that was deliberately focused on the tactical and operational levels of war. Within these levels of war, the service specific modeling and simulations have been utilized to mission plan, rehearse or train on established tactics, techniques, and procedures (TTPs), and experiment with the development of new doctrine or TTPs. These simulations employ physics-based modeling and data to adjudicate tactical and operational interactions of friendly and adversary platforms, munitions, sensors, emitters, and data links to produce a mathematical result of the interaction. The following subsections describe the capabilities and attributes of each of the Services modeling and simulation programs.

1. Joint Semi-Automated Forces (JSAF)

The current service level modeling and simulation programs began in the 1990s with a Defense Advanced Research Project Agency initiative called Synthetic Theater of War (STOW). STOW was an Advanced Capability Technology Demonstration (ACTD) that sought to develop "the next generation of computer-generated forces and distributed simulation: specifically, in areas of aggregation/de-aggregation, high vs. engineering fidelity, scalability (handling large numbers of distributed objects)," and protocol standards (Hardy 2001). In 1997, the STOW program transitioned a government owned joint distributed simulation product called Joint Semi-Automated Forces (JSAF). JSAF is a modeling and simulation system that has the capability to create constructive platforms (submarines, surface ships, fixed wing aircraft, and rotary wing aircraft) that Sailors and Marines can direct with its physics-based model database, while also having the ability to add virtual platforms (friendly and adversary) as well as live participants. Virtual platforms are entities that are overseen with a human trainer or automated from the modeling and simulation system using rules-based guidance to control the entity. Live entities are considered to be Sailors or Marines interacting with the simulation on their actual combat systems or on an approved (by Type Commander (TYCOM)) representative training system or simulator.

The USN and USMC uses JSAF as the primary modeling and simulation system for training and experimentation. Fleet training commands such as Afloat Training Group (ATG) and Tactical Training Group Pacific (TACTRAGRUPAC) use JSAF to enable platform / tactical training to multi-ship / Destroyer Squadron (DESRON) and Strike Group operational training. These Commands use JSAF to conduct Fleet Synthetic Trainings (FSTs) as certified training events / workups for the platform, staff, or Unit's readiness level. The JSAF modeling and simulation system meets the needs of these training commands because it has the characteristics to build a training scenario that meets the training objectives (tactical or operational) for the training audience. JSAF is able to incorporate live, virtual, and constructive (LVC) participants into one simulation that also has environmental models that represent ocean and atmospheric conditions. The combination of physics-based models with environmental models that are used in predictive tactical decision aids (TDAs) for sensor tools gives the USN and USMC a robust tool for tactical and operational training. Figure 12 depicts the JSAF schematic integrating environmental data into the simulation through Environmental Data Cube Support System (EDCSS) which uses data from the Oceanographic and Atmospheric Master Library (OAML), historical data from Naval Meteorology and Oceanography Command (CNMOC), and in-situational or current data from Fleet Numerical Meteorology (FNMOC).

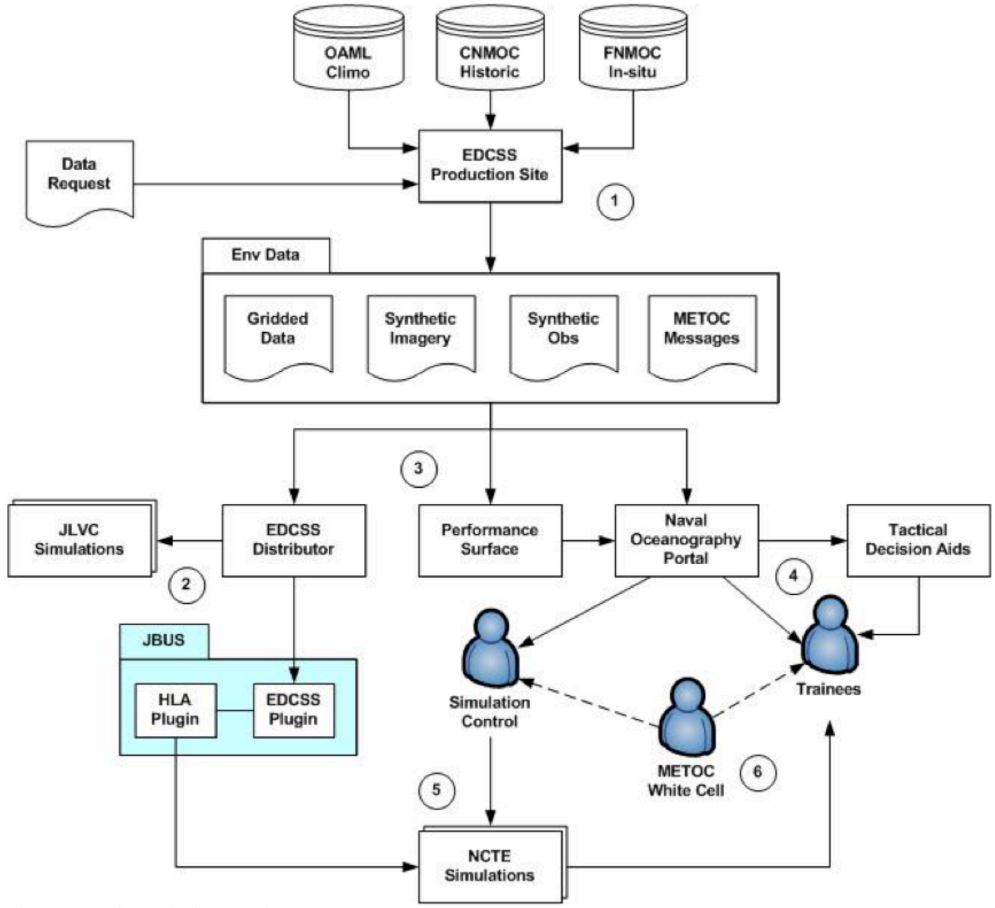

Figure 12. JSAF Schematic (Guest 2012)

Military operations at every level of war are impacted by the environment and accounting for this variable in training and mission planning contributes to the realism, fidelity, and confidence level of the simulation. JSAF uses this data to set the simulation environmental parameters, as shown in Table 2.

Table 2. JSAF Environmental Parameters

Surface Weather 2-D Grids (at 10 m)	**Sea Conditions 2-D Grids**	**Undersea Ocean Conditions**
Air Temperature Surface Pressure Relative Humidity Surface Winds Precipitation Rate and Type Visibility or Visual Extinction Coefficients Radar Duct Information	Sea State Category or Significant Wave Height Surface Current	Temperature Salinity

2. Next Generation Threat System (NGTS)

The Navy also uses other physics-based simulations to run tactical and operational training and exercises. Next Generation Threat System (NGTS) is another government owned synthetic environment generator developed by Air Force Research Laboratory (AFRL) and transitioned in 2008 to the Naval Air Warfare Center Aircraft Division (NAWCAD) for sustainment and follow-on development (Boyle 2008). NGTS is the primary simulation system of the Navy's Naval Aviation Simulation Master Plan (NASMP). This simulation generator is the backbone of the majority of Naval Aviation ground-based simulators. NGTS's focus is on the air domain; however, it has physics-based datasets of ground, maritime surface, and maritime subsurface objects. NGTS and JSAF have similar capabilities in regard to entities, environmental models, and the ability to connect geographically separated users through network connections. The difference between the two synthetic environments is NGTS's higher fidelity air environmental model, expanded and comprehensive Link-16 modeling, datalink modeling for net enabled weapons, and a dedicated graphical user interface (GUI) for entity behavior responses. Figure 13 shows the GUI for NGTS. Behavior responses can be built for friendly or adversary entities from Navy TTPs or doctrine by warfare domain and from intelligence of adversary TTPs or doctrine. This GUI enables a user to build customized behaviors through the layering of established actions into the desired behavior for an entity in the simulation. NGTS and JSAF also share the same drawback, these simulations can be run at maximum at five times real-time. This factor limits the ability of these synthetic environment generators to produce large amounts of adjudicated interactions between friendly and adversary forces.

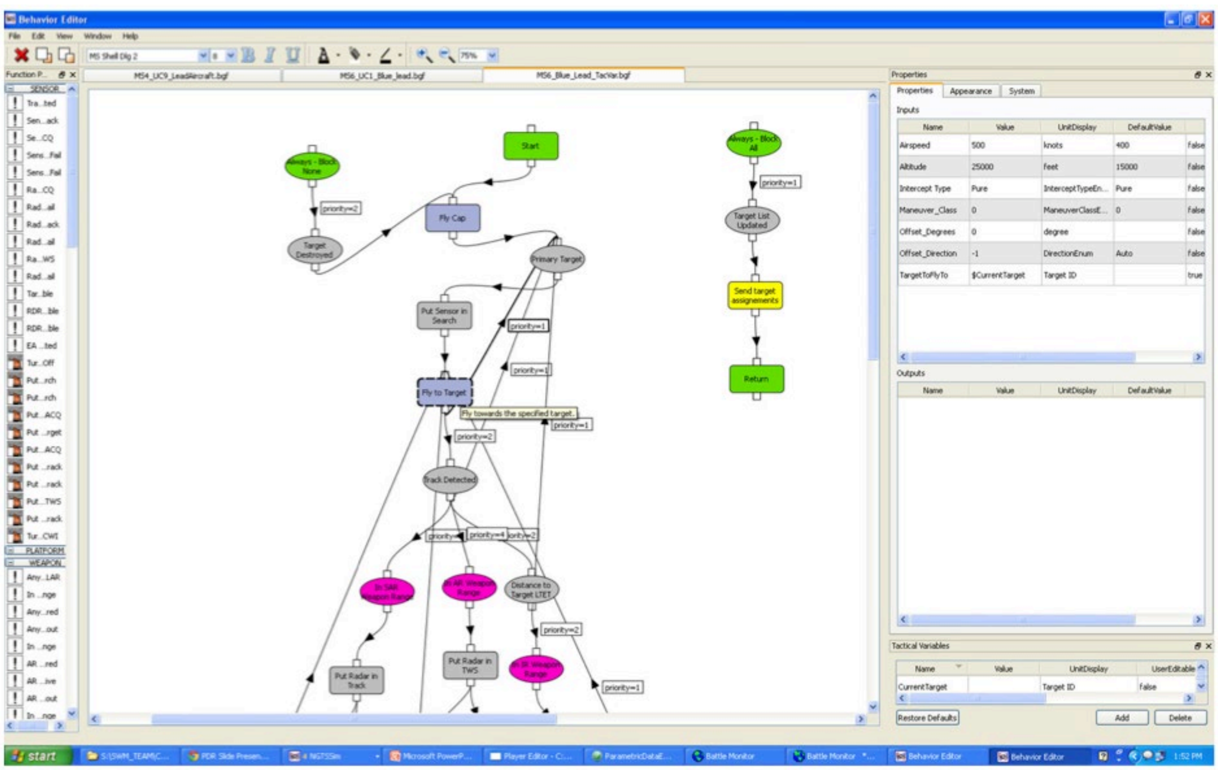

Figure 13. Graphical User Interface for Behavior Modeling in NGTS (Boyle 2008)

3. Naval Simulation System (NSS)

The Navy utilizes modeling and simulation capabilities developed by industry to conduct mission analysis at the operational level of war. The Naval Simulation System (NSS) developed by METRON is an example of one such capability. NSS advertises its abilities as "a comprehensive force-on-force modeling and simulation capabilities" to represent "C4ISR, logistics, forces engagement, and commander's logic simultaneously for multiple players at a common level of fidelity" (Stevens 1999). NSS uses a five-step process to create and develop a scenario. The five steps in this process are:

1. **Define Force Alignment:** Friendly and adversary Order of Battle (OOB), allies and partners of each force are defined, and units are assigned to friendly and adversary commanders.
2. **Define Command and Control (C2) Plans and TTPs:** "Initial plans and responsive tactics are defined for each commander." (Stevens 1999)
3. **Define Fleet Operational Plans:** Movement plans for surface, subsurface, and land platforms/units are defined. "Communications networks/pathways, surveillance reconnaissance operations (SRO), and logistics plans are defined." (Stevens 1999)
4. **Define Platform/Unite Mission Plans:** Preliminary Intelligence Surveillance Reconnaissance (ISR), Air Warfare (AW), Anti-submarine Warfare (ASW), Surface Ware (SUW), and Strike Warfare (STW) plans for aircraft are defined. (Stevens 1999)
5. **Define Metrics:** "The user specifies and defines the metrics to be collected. Over 100 metrics are pre-defined. Additional metrics maybe specified by users." (Stevens 1999).

Figure 14 is a screen capture of the NSS GUI that shows an operational scenario and the information from the five-step process displayed to the user. NSS also has an integrated "fully-defined" classified database, yet modifiable, containing data on specific U.S. and foreign platforms, communications, surveillance, weapons, and C2 systems that are immediately available to the user (Stevens 1999). This capability enables the NSS to be customizable for future scenarios where the addition of new capabilities (platforms, sensors, or munitions) can be modeled and analyzed with the over one hundred pre-defined metrics. NSS's other notable feature is ability to conduct quantitative analysis through the program's "study mode" capability. "The study mode GUI permits determination of the number of Monte Carlo simulation replications for each simulation run, and parameter ranges for each run (Stevens 1999). This study mode has the ability to automatically collect measures of performance (MOPs) and measures of effectiveness (MOEs) during the simulation execution (Stevens 1999). The results of the collected data can be exported for Microsoft Excel to graphically display the data and to conduct visual trend analysis from the Monte Carlo simulation executions. NSS, unlike JSAF and NGTS, has this analytical ability to capture and plot data to explore at an operational level, the movement, placement, or use of different units/platforms regarding achieving mission success or completion against an adversary.

NSS also has mode that lets the embodied decision makers in the model make decisions based on their perceived common operational and tactical picture, not the actual picture, which is unique to NSS. This means in theory that if cyber weapons are designed to skew tactical and operational pictures, NSS can model those behaviors and effects.

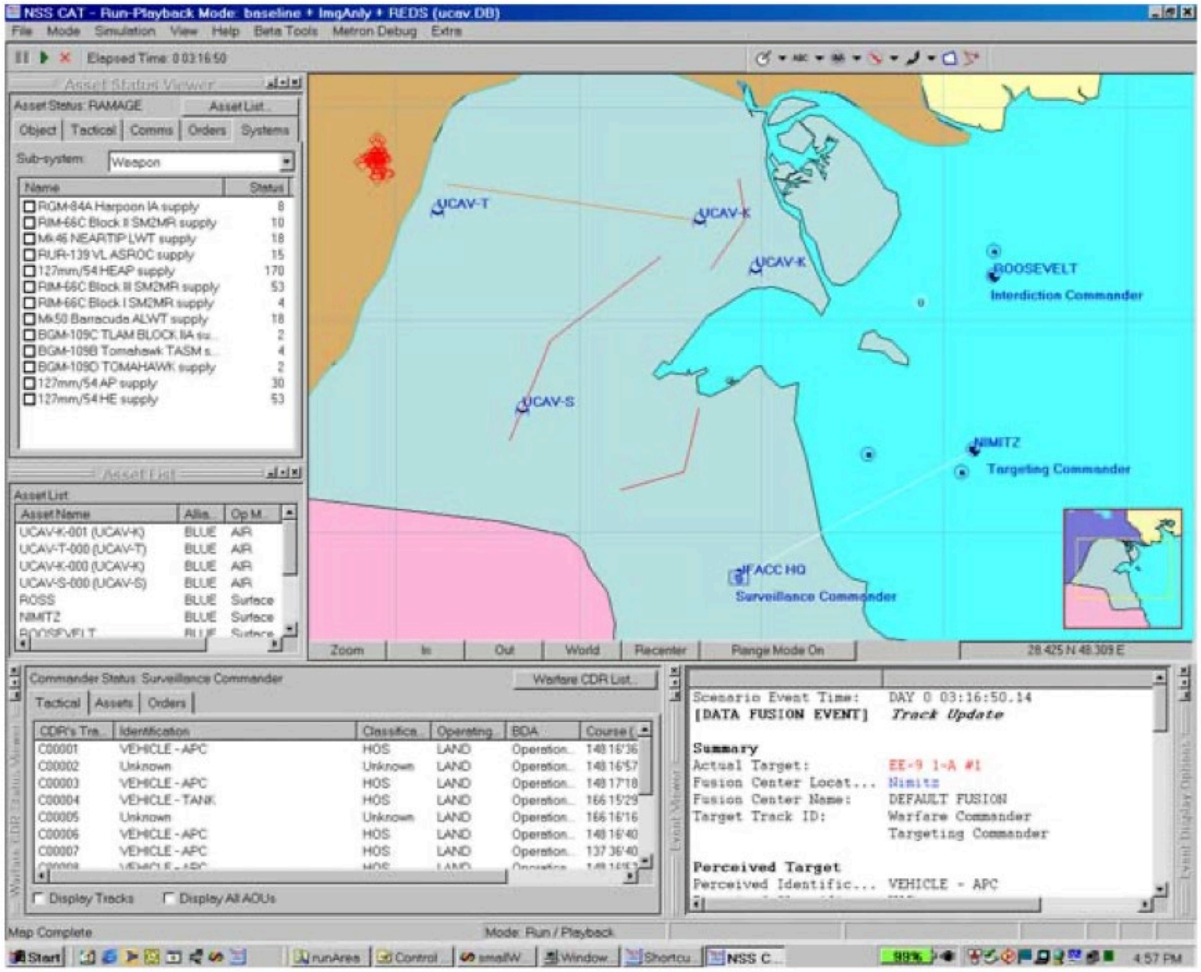

Figure 14. NSS Graphical User Interface (Stevens 1999)

4. BRAWLER

Like the Navy and Marine Corps, the USAF has comparable modeling and simulation tools that it uses for training, analysis, and experimentation. BRAWLER is an example of a tactical level air analysis tool that is used by the Headquarters of the Air Force (HAF) Air Force Studies and Analyses Agency (AFSAA). The BRAWLER capability is an "air-to-air combat simulation model used for engagement-level analyses of few-on-few air combat" (Buschor 1998). BRAWLER provides a "high resolution" model because of its engineering level models of system hardware, such as aircraft and radar, and physics-based physical effects of drag and lift (Buschor 1998). This simulation also has the ability to portray three distinct skill levels or mental models for pilots- Rookie, Pilot, and Ace. These differing skill levels allows users of BRAWLER to model and train interactions of pilots at diverse experience levels to explore how effective USAF pilots will be with a force that has various skills levels against an adversary that could be rookies or novices, pilots or journeymen, and aces or highly skilled.

5. Advanced Framework Simulation, Integration, and Modeling (AFSIM)

The USAF Air Force Research Laboratory (AFRL) uses Advanced Framework for Simulation, Integration, and Modeling (AFSIM) for their modeling and simulation framework to enable research and development, operations research and analysis, and experimentation. AFSIM is a government-owned (transferred in 2013) contractor-developed (by Boeing) multi-domain simulation that models air, land, sea, and space-based platforms (West 2020). AFSIM, when compared to JSAF and NGTS, has similar Joint Force models for naval vessels, tanks, airplanes, and helicopters. But AFSIM also has additional platform models in satellites and cyber agents to model and simulate the impacts of Space and Cyber in this multi-domain simulation environment. The AFSIM environment employs "National Air and Space Intelligence Center (NASIC) approved threat models of many threat systems" and National Geospatial Intelligence Agency (NGA) Digital Terrain Elevation Data (DTED) for high fidelity rendering of adversary capabilities and environmental terrain (West 2020). The modeling and simulation system accounts for unit and platform control through "the reactive integrated planning architecture (RIPR), messaging systems, commander subordinate structures, generic programming logic, and conceptual ways to interact with the agents" (Choate 2017). AFSIM is a robust multi-domain modelling tool with a comprehensive ability to emulate conditions and platforms ranging from the seabed to space, and even cyberspace. Table 3 depicts the timescale for the varying range of scenarios and the time needed to complete each different simulation level. Operational level multifaceted scenarios that are more complex than the "Campaign" level with many platforms in different domains against a large adversary force could take up to months to complete (West 2020).

Table 3. Levels of Wargaming Simulations (West 2020)

Simulation Level	**Complexity Scale**	**Time Scale**
Campaign	Many v. many	Days
Mission	Several v. several	Hours
Engagement	One v. one	Minutes
Engineering	Subsystem interaction	Seconds

6. One Semi-Automated Forces (OneSAF)

The USA uses One Semi-Automated Forces (OneSAF) as its simulation system to support "Advanced Concepts and Requirements (ACR), Training, Exercises, and Military Operations (TEMO), and Research, Development, and Acquisition (RDA) domains" (Wittman 2001). OneSAF enables squad (four Soldier team) to Brigade level (three to five thousand Soldiers) simulations that support LVC environments for ACR, TEMO, and RDA. The Army's Training and Doctrine Command (TRADOC), the four-star command that is responsible for developing Soldiers, oversees all training, evaluates current doctrine or TTPs as well as creates new doctrine or TTPs in response to adversaries, technology, or environmental conditions. The ACR is aligned under TRADOCs subordinate command of the TRADOC Analysis Center (TRAC). TRAC's interest include "the analytical application of modeling and simulation" (Wittman and Harrison 2001). TEMO falls under National Simulation Center, another TRADOC subordinate command. The domain of RDA is affiliated within the U.S. Army Material Systems Analysis Activity (AMSAA), which is aligned under the Army's Futures Command. Table 4 shows how the USA intents to use OneSAF to support tactical doctrine and TTP reviews and updates, training at the operational level, and systems development for acquisition.

Table 4. Intended Uses for OneSAF (Wittman and Harrison 2001)

Advanced Concepts Requirements (ACR)	**Training Exercise and Military Operations Domain (TEMO)**	**Research Development and Acquisition Domain (RDA)**
To explore new and advanced concepts with respect to equipment, organizations, doctrine, and operational environments.	Unit training – OneSAF will be used as a simulation driver for round out forces.	Weapon systems development and product improvement using appropriate military settings and context
To develop and evaluate tactics and Operational Plans for organizations at Brigade and below	Unit commander and staff training at battalion and below in a training exercise, workshop, or seminar environment	Technical development, test, and evaluation support for Army modernization objectives
To create data that can be used as input to other closed form analytic simulations.	Unit division commander refresher training.	Communications design and laydown experiments,
To provide training associated with a specific location prior to real-world developments.	As a mechanism to link live, virtual, and constructive Synthetic Theater of War-like environments.	

OneSAF employs comparable physics-based models of land, air, and maritime units/platforms similar to JSAF, NGTS, and AFSIM. The simulation also has similar environmental capabilities for air, land, and ocean domains. The simulation also has an After Action Review (AAR) component that allows users to data mine scenarios to select MOEs and MOPs that can be used to analyze results in graphical charts. OneSAF's focus is the land domain, and it provides higher fidelity in this domain by having the functionality to model units down to the fire team level (four Soldier team). This higher fidelity enables the Army to assess and develop new TTPs down to this level, since this level is the basic force structure for most combat arms (infantry, armor, cavalry, combat engineers, and military police) units. JSAF, NGTS, and AFSIM model land-based units, but do not have this level of unit fidelity because each of the services modeling and simulation systems are concentrated within their specific domain of operation.

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III. AUTOMATED WARGAMING FOR OPERATIONAL PLANNING

A. BACKGROUND

The formation of today's United States (U.S.) Combatant Commands began with the unified combatant command system outlined in the Goldwater-Nichols Department of Defense (DoD) Reorganization Act of 1986. Previous to 1986 the Commanders of Combatant Commands reported to their service chief. This earlier military construct of task organization enabled a Service (U.S Navy, U.S. Army, U.S. Air Force) focused paradigm in the planning and execution of theater specific warfighting. The Goldwater-Nichols Act changed this Service oriented model by realigning the Commanders of Combatant Commands under the Chairman of the Joint Chiefs of Staff (CJCS), the principal military advisor to the President of the United States. The Act also gave Combatant Command Commanders "the authority and power to call up and deploy forces from the different services" (Scott and Rosati 2021). This authority puts the ownership of developing Joint Force strategic operational plans (OPLANS) on the Combatant Commands. These OPLANS must integrate all-domains (land, air, maritime, space, and cyberspace) with the seven joint functions (intelligence, movement and maneuver, fires, information, protection, sustainment, and command and control) to enable the Joint Force to project non-kinetic or kinetic effects into the operational environment at the Commander's choosing and/or aligned with the plan.

Scott and Rosati (2021) outlines the CJCS guidance on joint planning. This document provides the foundation and states the fundamental principles and methodology that guide the Armed Forces of the United States in the planning of joint campaigns and operations. Strategic and operational planning is a combination of "art" and "science." Where the "strategic art" is the "formulation, coordination, and application of ends, ways, and means to implement policy and promote national interests" and the "operational art" is the "cognitive approach by commanders – supported by their skill, knowledge, experience, creativity, and judgement – to develop strategies, campaigns, and operations to organize and employ military forces by integrating ends, ways, means, and evaluating risks" (Munsch 2020). The "science" is the Joint Planning Process (JPP) methodology which is an orderly and analytical set of logical steps "to frame a problem; examine a mission; develop, analyze, and compare alternative COAs; select the best COA; and produce a plan order" (Munsch 2020). The seven steps of the JPP are:

Planning Initiation (Step 1)
Mission Analysis (Step 2)
COA Development (Step 3)
COA Analysis and Wargaming (Step 4)
COA Comparison (Step 5)
COA Approval (Step 6)
Plan or Order Development (Step 7)

These seven steps are grouped into the four planning functions of Strategic Guidance, Concept Development, Plan Development, and Assessment as illustrated in Figure 15. The figure depicts the seven steps of JPP and the four functions of planning in the Operational Design Methodology.

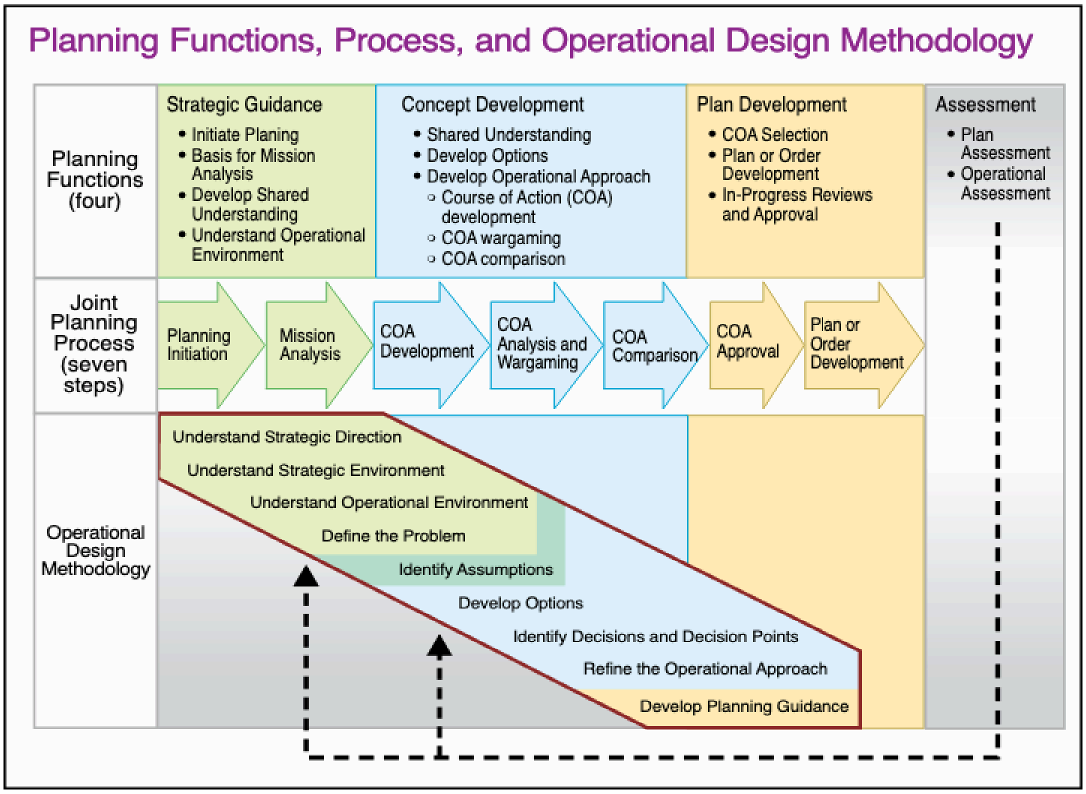

Figure 15. Operational Design Methodology for Planning (Munsch, 2020)

Each Combatant Command uses the Operational Design Methodology, the JPP, and the four planning functions to develop their Operational Plans (OPLANS). These OPLANS are unique strategic plans that detail at the strategic level the phasing or sequencing of military end states which will lead to specified military objectives against a regional threat.

Each regional threat or adversary is unique and presents a different level of risk for the U.S. and DoD. The Unified Command Plan (UCP) outlines the geographic boundaries that form the specific geographic regions or "Area of Responsibility" (AoR) for each Geographic Combatant Command (GCC) as well as stating the role and function for each Functional Combatant Command. Figure 16 shows the regional responsibility for the seven GCCs and four FCCs.

The GCCs are:

- United States Space Command
- United States Northern Command
- United States Southern Command
- United States European Command
- United States African Command
- United States Central Command
- United States Indo-Pacific Command

The FCCs are:

- United States Special Operations Command

- United States Transportation Command
- United States Strategic Command
- United States Cyber Command

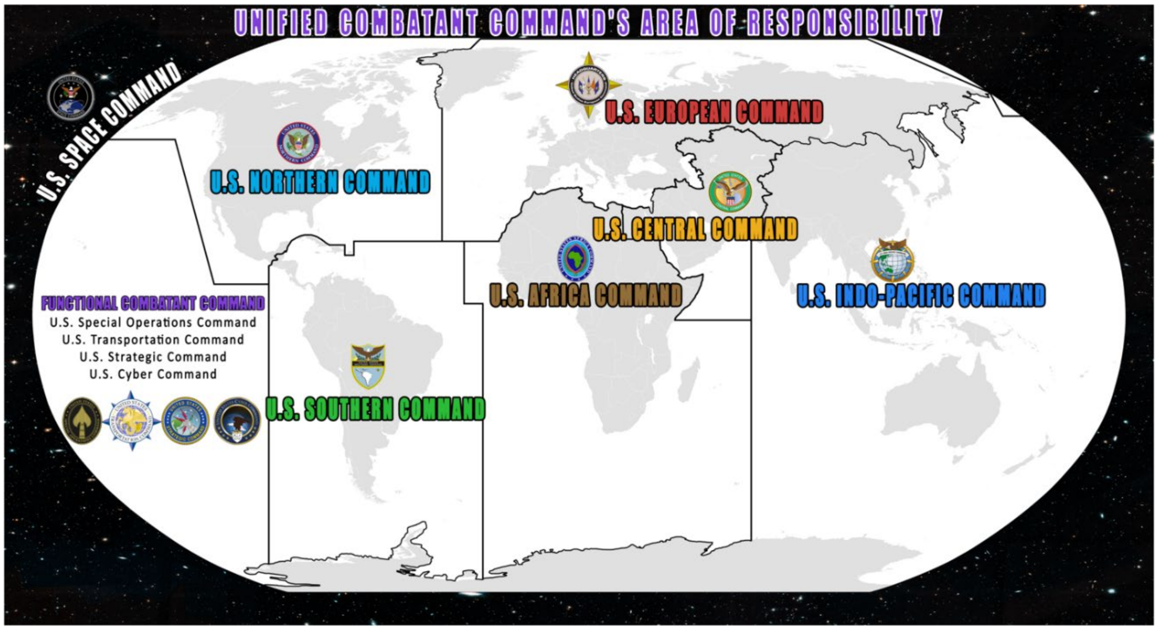

Figure 16. Geographic and Functional Combatant Commands Worldview

Each GCC and FCC four-star Joint Commander reports directly to the United States Secretary of Defense (SecDef). This unique command and control (C2) relationship reinforces the precedence that the military is under control of civilian authority. This also means that every GCC or FCC OPLAN needs to be reviewed and approved by the SecDef. Every four to five years the SecDef publishes the National Defense Strategy (NDS). The NDS is the DoD strategic guidance that transforms National Security Strategy, which is published from the White House, into guidance for military planning, military strategy, and Joint Force modernization and structure.

The NDS outlines to Joint planners the planning guidance and the planning factors to incorporate into Joint plans and combatant command OPLANS. The 2018 NDS published by then SecDef Jim Mattis outlines strategic guidance for the Joint Force, but also highlights the necessity for Joint Force planning to enable the fully developed plans to counter regional threats around the world. A few of the key takeaways from the 2018 NDS are:

“Today, every domain is contested—air, land, sea, space, and cyberspace” (Mattis 2018).

“America can expand the competitive space, seizing the initiative to challenge our competitors where we possess advantages, and they lack strength” (Mattis 2018).

“Modernization is not defined solely by hardware; it requires change in the ways we organize and employ forces. We must anticipate the implications of new technologies on the battlefield, rigorously define the military problems anticipated in future conflict, and foster a culture of experimentation and calculated risk-taking" (Mattis 2018).

The Armed Forces of the United States and the Joint Force must now be prepared to face the peer and near-peer adversaries on the modern battlefields that are hyper-contested and exponentially more complex and lethal than those encountered during the previous decades. We become vulnerable when our opponents can plan effectively and efficiently, thus putting themselves inside our decision-making cycle.

By all indications, our adversaries are putting their focus and attention in developing these planning and decision-making tools to create a significant capability gap that we must address. The GCCs who confront these adversaries do not have the adequate tools to rapidly produce complete and analyzed course of actions (COAs) for execution. This includes the development of OPLANS and Contingency Plans in today's steady state operations, as well as for the ability to transitions plans to Operation Orders for execution in the crisis space where time is limited. Today the Joint Force has a multitude of high-end weaponry, communications equipment, space-based enablers, aircraft, sea craft, and armored vehicles available for operations. However, to quickly plan at the strategic and operational level we are unable to digitally manipulate the myriad of inputs for both blue and red forces in a digital environment. Combatant Command planners are tasked with constructing concepts of operations (CONOPS) to employ our high-tech weapons and enablers without access to the tools required to wargame numerous COAs at machine speeds. We must get better and faster as the next fight will most assuredly depend on it. USINDOPACOM has an emerging operational need to integrate machine learning and other advanced technologies into the COA development and COA analysis / wargaming steps of strategic and operational planning and campaigning, in order to keep pace with near-peer competitors in the Indo-Pacific. China and Russia are already enabling and enhancing their planning and decision-making with advanced technology to include machine learning at machine speeds. If this is not addressed the Armed Forces of the United States will lose the initiative in the decision space to our competitors. Established computer simulations and models are not suited to strategic and operational planning and campaigning.

USINDOPACOM has in the recent past conducted a series of wargames using primarily traditional means. These traditional means consist of physical map boards divided into hexes, dice, relative combat power charts, and the use of experienced organizations (such as the Naval War College) to facilitate the execution of these games. Although some automation was present, this was limited to isolated scenarios.

B. NEEDS ANALYSIS

1. Stakeholder needs

The genesis of the SODA system concept originates from the following problem statement: USINDOPACOM requires a high fidelity, planning and decision-recommending tool which rapidly generate numerous viable courses of action (COA) options for RED, BLUE, and WHITE. The tool analyzes, wargames, applies game theory, and compares these options, and produces suggested casual reasoning and insights as to why outcomes might occur, thereby broadening the planners and decision makers' mental model. Further, this tool must also replan almost continuously, and produce modified course of action options, alternatives, and recommendations during plan execution. This tool must be easy to learn and use, provide useful feedback that helps improve the user's experience and performance, and be reliable and easy to maintain. The tool should easily ingest relevant historic, live and forecasted data, information, and knowledge. While not required, it would be best if it contained a module that added "common sense" to its reasoning algorithms. This tool does not exist today.

The most important stakeholders of SODA is the Commander, INDOPACOM and his or her subordinate commanders. SODA is expected to deliver well-reasoned recommendations based on the consideration of many possible courses of action, yet SODA will never be perfect. These decision makers add insight from years of operating experience, and if designed properly SODA will provide the input for robust and constructive discussions before a final decision is reached.

The primary stakeholders for SODA are the planners in the J5 Plans Directorate at USINDOPACOM, as well as the planners at the component commands in the theater. The planners at these commands are in the N5 Plans Division at Pacific Fleet (PACFLT), the A5 Plans Division at Pacific Air Forces (PACAF), and the G5 Plans Division at Army Pacific (USARPAC). The other primary stakeholders would be the J2 Director of Intelligence who would be responsible for the mission analysis inputs from step 2, the operators, and the maintainers of the SODA system. Figure 17 shows the command relationship and the information flows of orders and military intent from DoD echelon level from SecDef down to the COCOM and component levels. In the diagram, PACFLT is the Joint Force Maritime Component Commander (JFMCC), USARPAC is the Joint Force Land Component Commander (JFLCC), and PACAF is the Joint Force Air Component Commander (JFACC). This illustration also depicts the communication of strategic guidance from the SecDef of strategic end-states that is aligned with national policy which OPLANs will achieve from a military perspective. Planners at the CCMD level are responsible for leading the Operational Planning Teams (OPTs) that develop OPLANs per the guidance from the Joint Publication 5.0 on Joint Planning. These OPTs follow a deliberate planning process which encompasses the seven steps, from step one planning initiation to step seven plan/order development. These seven steps take months and many meetings to accomplish.

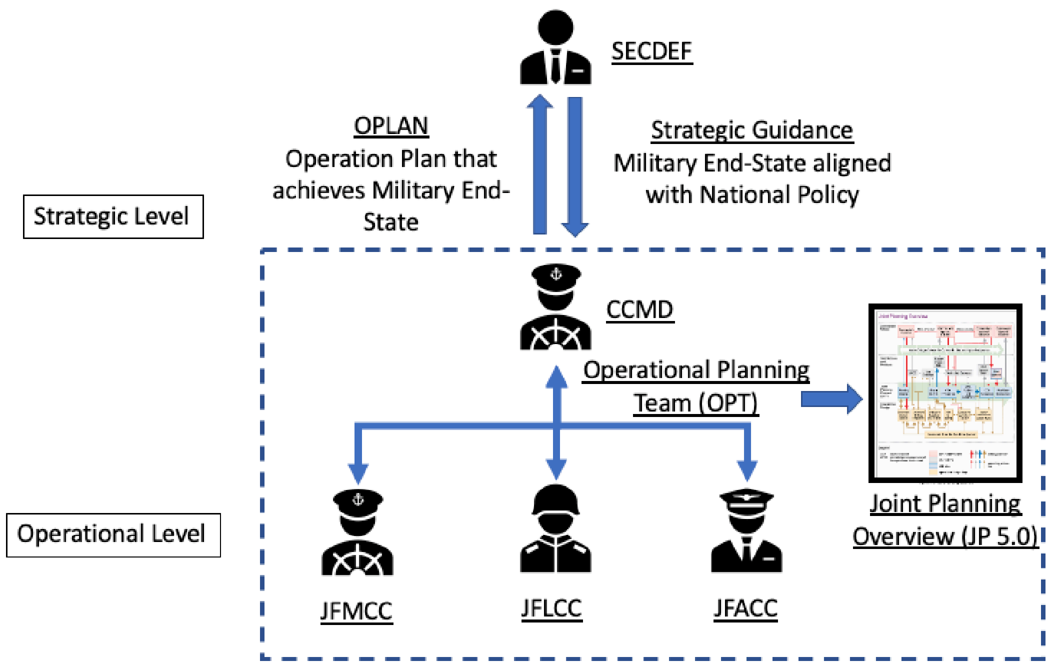

Figure 17. Stakeholder Relationships for Joint Planning

Planners at the USINDOPACOM and at other CCMDs as well as component Maritime, Air, and Land planners require planning toolsets to speed up the planning process, through the rapid development of multiple COAs, that can be analyzed with wargaming, to produce COA metrics and reports that are customizable in easily assimilated graphically and numerical form, and which could be operated by novice users or skilled planners. Maintainers of this system need the SODA system to have low maintenance requirements for software updates and equipment updates best aligned with commercial off the shelf (COTS) information systems.

2. Requirements

SODA system requirements were developed based on the problem statement and stakeholder needs. For the purposes of this thesis, the requirements were developed at a high-level and are organized into four categories: functional, performance, human factors, and reliability/ maintainability. System requirements have been codified through discussions with the primary stakeholders, the USINDOPACOM planners.

a. Functional Requirements

The stakeholder requirements for the SODA system can be traced back to the Joint Publication 5.0 on Joint Planning. The stakeholder requirements and the JPP functional requirements are aligned with regards to the functional needs of the system. Joint and component planners have identified the capability need within the established Joint Staff seven step JPP doctrine at step three (COA Development), at step four (COA Analysis and Wargaming), and at step 5 (COA Comparison). The SODA functions for each of the corresponding steps in the planning process are based upon the outputs of each prior step in the JPP. The high-level functional requirements for the SODA system based upon these steps are listed and described in Table 5.

Table 5. High-Level SODA Functions

SODA Function	Description
Mission Analysis	Convert Commander's guidance into actionable description from which COAs can be developed.
COA Development	Enables users/planners to develop COAs that takes into account all-domains (land, air, maritime, space, and cyberspace) and higher-level strategic guidance to develop at machine speeds and with the assistance of automation technologies such as blue and red simulated engagements as well as the use of ML to drive these agents to output a COA that has objectives, key tasks, timeline, task organization, main and supporting efforts, and deployment concept and transportation feasibility (Time-Phased Force Deployment Data (TPFDD)).
COA Analysis and Wargaming	Independently analyzes each developed COA through blue and red interaction and collects data of each COA wargaming iteration to meet selectable user evaluation criteria metrics with the outputs of potential decision points as well as potential branches and sequel.
COA Comparison	Presents recommended COA along with all evaluated COAs based upon user/planner selected evaluation criteria metrics in user selected visual or data formats to display the data in a simple straight forward manner.

Figure 18 shows the required functional requirements within the JPP along with how these requirements are integrated into the overall planning process. The SODA system is a bounded system engineering effort to inject technology/automation into the JPP at the steps (2-5) that will have the largest benefit for the Joint Force by transforming a very deliberate process into one that potentially can accommodate dynamic planning situations. Intelligent automation enhancements such as blue and red simulation and ML software agents can reduce the time between the Commanders approvals and guidance as well as condensing the staff actions and products. Technology can make the JPP more efficient in time critical situations.

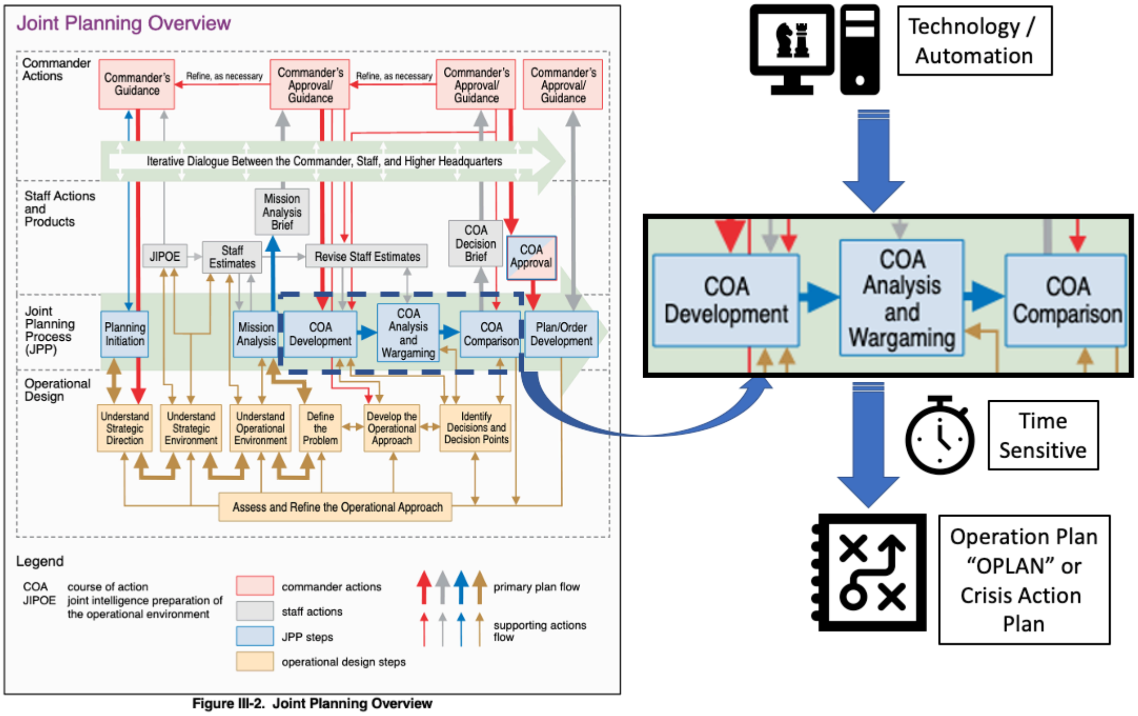

Figure 18. Functional Requirements of SODA within the JPP

b. Performance Requirements

The SODA system will need to produce results for COA development, COA analysis and wargaming, and COA comparison in minutes. Any longer, hours or days would mean that the system could not meet crisis action planning standards or when an emergent situation happens. These time critical situations are driven by external events that make Joint planning a time-constrained endeavor. "Crises may evolve over time (e.g., escalating civil war, humanitarian crisis) or develop quickly (e.g., hostage rescue, natural disaster) with little or no warning and require accelerated decision making" (Munsch 2020). The goal of crisis planning is to inform senior leaders and decision makers about military response toward a situation so they can evaluate if it is worth the cost or risk from a national, political, or military viewpoint.

c. Human Factors

The decision aid will have a GUI to interact with novice level users. This is a requirement from the planners as the primary stakeholders for the system. The majority of military planners do not have a programming or computer science background to program modeling and simulation systems through code insertion. For COA development, users will need to be able to customize through the GUI the strategic or operational intent from the commander, the scenario, environment, geolocation of the conflict, all-domain blue and red force composition, C2 structure, and force posture. The COA Analysis and wargaming GUI will need to have a novice level visual interface to modify the selectable evaluation criteria metrics, the number of iterations, decision points, and COA specific branches and sequels. The last GUI for COA comparison will also have to be interpretable for novice level users. This visual interface should display the customizable metrics in a clear discernable way so planners can recognize which is the recommended COA and the reason for this assessment based upon the evaluation criteria.

d. Reliability and Maintainability

According to the stakeholders, the SODA system will need to have a 95% availability rating. This high-level of dependability is required because of the performance requirement of Crisis Action Planning. Crisis Action Planning does not have set timeframes for execution but requires a high-level availability to meet emergent nature of the crisis and the time constrained situation for planning. Maintenance of the system shall not extend over the 5% non-availability rating. This will synchronize the maintenance of the system with the mission requirement of 95% availability rating to enable no gaps in mission coverage.

C. CONCEPTUAL DESIGN

The SODA system context hierarchy diagram is shown in Figure 19. This hierarchy diagram is solution neutral and depicts how the SODA system is related to the world and the universe. The figure depicts the solution neutral system on the left side of the diagram with the world on the right. The SODA system is composed of SODA software, operators, maintainers, and resources needed to support the system. This system will interact with world at the specified locations of CCMDs, component commands (PACFLT, PACAF, USARPAC), and at other DoD locations which require the dissemination of planning information.

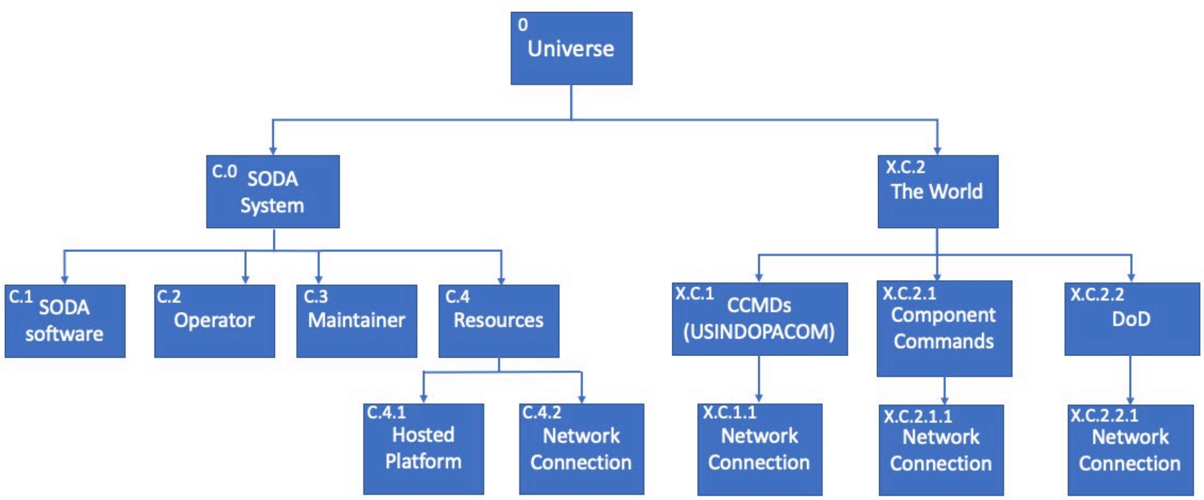

Figure 19. SODA System Context (Solution Neutral)

1. Functional Architecture

The functional architecture of the SODA system focuses in on the primary functions of the system and abstraction at this level permits system engineers to map out representative associations of the relationships between the principal functions. Each function shows the necessary roles for the system and supports the discovery of boundaries and limiting factors. Figure 20 highlights the main function of the system. This function is the COA recommendation or step 5. The other primary functions support this function, with 1.0 COA development (step 3) on the left and 1.1 COA analysis and wargaming on the right (step 4). This is because this system replicates the JPP process in a system form and COA development as well as COA analysis and wargaming support COA recommendation due to the processes being in sequence. These primary functions also share the same function of 2.1 and 2.2 blue and red simulated engagements. However, for 2.2 COA analysis and wargaming require the additional functions of 2.3 evaluation criteria selection, 2.4 data collection, and 2.5 data output of evaluation criteria to complete primary function 1.1.

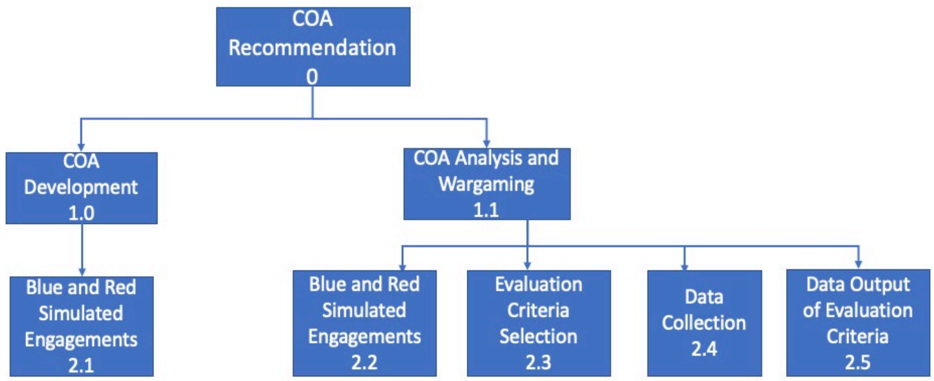

Figure 20. SODA Functional Architecture

2. Physical Software Architecture

The physical architecture of the SODA system equates to the software architecture of the system. The SODA system will be composed various software components. These components will constitute the entirety of the SODA system. The physical decomposition of a SODA system into software components allows system designers to examine the interrelationships between the components and how they relate to the overall system. Figure 21 depicts the system's three primary software components: Blue and Red Simulated Engagement System (1.1); Data Collection System (1.2); and COA Assessment System (1.3). The Blue and Red Engagement System is further comprised of Blue Intelligent Software and Red Intelligent Software agents as well as the scenario GUI. The Blue Intelligent Software agent contains the automated ML intelligence which manipulates all-domain (land, air, maritime, space, and cyberspace) blue forces within the simulation environment. This software agent also holds the software program that assesses transportation feasibility (3.2) through TPFDD, assignment data, readiness levels, and location of blue units. The scenario GUI will provide the vital human system interface between the user and the system for the entering of mission analysis data (step 2) and Commander's intent. The Red Intelligent software agent will also hold the automated ML intelligence for red forces and control red forces actions.

The data collection system component executes the automated data collection of individual iteration scenario data. This computerized collection of data is enabled by the human system interface of the evaluation criteria GUI. This GUI allows the user to customize the important data variables which need to be collected by the evaluation criteria data logger (2.4) and analyzed by the COA assessment system (1.3). These data variables are user/planner selected MOPs and MOEs that are selected and weighted in terms of importance to evaluate the performance of a COA.

The COA assessment system is the software component which will analyze the collected data. The data will be transformed into data tables or graphs that can easily be interpreted by the user/planner regarding how each COA performed over various iterations performed by the blue and red simulated engagement system. The data output GUI will permit the user to select the data format for the results from the assessment engine (2.6). The assessment engine will calculate and summarize tabulated results from each of the weighted and selected data variables to score each of the COAs. The COA with the highest rated result will be selected as the recommended COA. Users/planners will have the ability to rerun assessment scoring in the event variables or weighting has changed due to deviations in the operational environment or with Commander's intent.

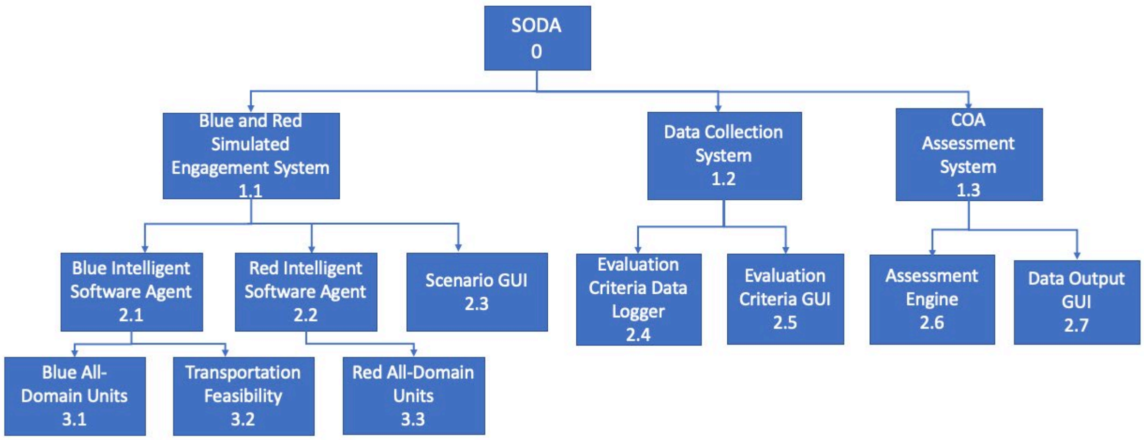

Figure 21. Software Architecture of the SODA System

3. System Architecture

The system architecture combines the functional and software architecture views of the SODA system. This combined view of SODA supports system design integration analysis of form and function within a solution neutral context. Mapping the form and function of the system together enables a comprehensive view of SODA in order to discover external dependencies. These comprehensive views gave the designer insights into the system constraints that are outside the system boundaries and the mapping of the system inputs and outputs. Figure 22 illustrates the mapping of these two different views together. In the diagram the SODA process starts with a COA recommendation initiation. This initiation has one dependency that could influence the outputs, whether this is for a deliberate planning process (normally months long) or for crisis planning where a result is needed in minutes or hours. This starts the SODA process where the system will require an input from the user/planner for scenario parameters that describe the Commander's intent or guidance and the Mission Analysis Data (step 2) in the JPP. The mission analysis data is primarily comprised of the results from the Joint Intelligence Preparation of the Operational Environment (JIPOE) process. The JIPOE process is made up of four steps:

1. Defining the operational environment
2. Describing the impact of the operational environment
3. Evaluating the adversary
4. Determining the adversary's potential COAs to include most likely and most dangerous.

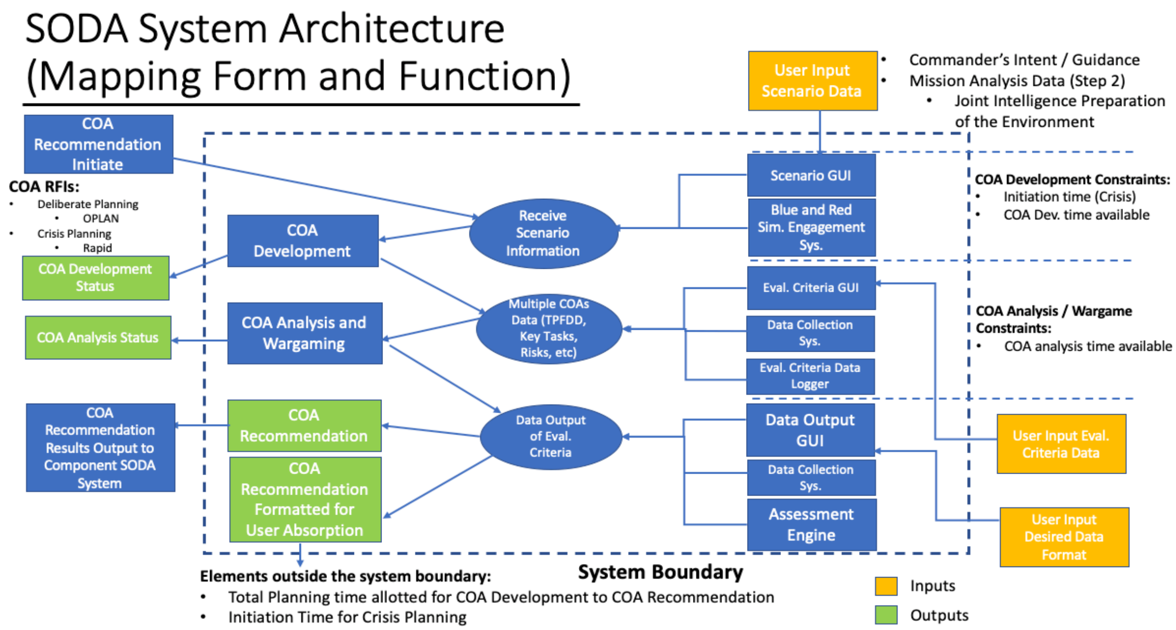

Figure 22. SODA System Architecture (Mapping Form to Function)

Once the user enters this information and states the number of desired COAs into the scenario GUI the system will begin COA Development. The information from the Commander's intent/guidance and the JIPOE will be inserted into the blue and red automated intelligent agents to set strategic and operational objectives for each force. This will give each agent what is needed for the "theory of victory" for each side. The COA development portion of automated planning process has a timing constraint, due to the external factors of starting time and time available to plan. The COA development function will send a status update output to the user concerning COA development status in case planning timelines changes.

COA analysis and wargaming can start once COA development is complete and the user inputs the evaluation criteria data into the GUI. The main output of the COA development is the COAs. Each of the COAs will have supporting information that could be key components of the next step of COA analysis and wargaming. The key COA information includes (in no priority of importance) key tasks, objectives, major capabilities required, task organization, sustainment concept, and TPFDD. This portion of the process also has the same dependency or constraint, time. The blue and red simulated engagement system will need to have the ability to execute multiple simulations concurrently and faster than real-time to obtain results with the number of iterations to have deterministic qualities for multiple COAs. The COA analysis and wargaming function will send a status update output to the user concerning COA development status in case planning timelines changes.

The output of the COA analysis and wargaming will be a rating of each COA to determine which COA that has the highest rating based upon evaluation criteria. The COA assessment portion of the process will take the information from the COA analysis and wargaming process along with the user inputted data from the data output GUI to transform this information into a format that can be easily understood. The output for this final section of the process is a formatted COA recommendation that can be inserted into the COA approval brief that will presented to the Commander. The COA recommendation results will also be sent via network connection to the component commands so they can load the COA analysis data without the need of entering it manually.

4. Component Nested Planning

Planning at the CCMD level requires a team of teams to plan for strategic and operational operations at the CCMD and component level. Plans for these types of operations are nested in terms of Commander's intent/guidance, objectives, key tasks, and sustainment concepts. The only difference being the scope of these plans are limited to the domain of the component. The SODA system, with various instantiations at the CCMD and component level, allows planners to transfer information at the current speeds of network connectivity. The ability to share this information into the same systems at other locations will enable planners at the component level to begin planning as soon as the CCMD approves the COA. This time advantage could make the difference, especially during crisis planning, where complete plans may have deadlines in hours.

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IV. AUTOMATED WARGAMING FOR TACTICAL DECISION-MAKING

A. BACKGROUND

Advances, proliferation, and the build-up of tactical weaponry and warfare systems by peer competitor nations and by the U.S. Joint Forces are leading to complexity in warfare. Battlespace intricacy, characterized by increased pace, lethality, and uncertainty, is proliferating as a result of new technologies, capabilities, weapons, and actors (Zhao, Mackinnon and Gallup 2015). Figure 23 illustrates an instance of complex tactical warfare, showing many varied blue and red force weapons in a close-in ground and urban scenario.

Figure 23. Complex Ground-Operations Battlespace (Fresconi et al. 2018)

The escalation of battlespace complexity is causing a knowledge gap in tactical decision-making. US Joint Forces are establishing a presence in previously unrealized places, such as the Arctic Ocean (Larter 2020) and the South China Sea (Jennings 2021). Novel military weapons are continuously being developed, both domestically and overseas. Innovative new threats are emerging such as cyber-attacks, with the US and Russia targeting national power infrastructures, as an example (Atherton 2018). Adversarial directed-energy weapons, autonomous systems, advanced intelligence surveillance and reconnaissance (ISR) techniques, and space pose potential risks, hazards and threats that are unfamiliar in a new-age combat environment. Applicable training may not be available, and crews may not be familiar with these new operating environments, leaving a gap in both knowledge and capabilities. This knowledge-gap presents challenges for human operators making tactical decisions, in the form of delays in action, unfamiliarity and uncertainty. These factors all bring new challenges that require a new set of tactics, techniques, and procedures (TTP), rules of engagement and approach logic. Defense researchers are actively pursuing Artificial Intelligence (AI) as a source of methods, algorithms, and systems that can address the growing battlespace complexity. Researchers are studying the ability of AI to process large amounts of data and information to significantly improve tactical decision superiority in complex combat environments and provide the most accurate information available to the warfighters (Layton 2021). The implementation of AI systems into current military scenarios is at the forefront of warfighter capability and lethality (Vincent 2017). AI has the potential to provide real-time decision responses in complex situations with many variables and unknowns. A real-time decision aid that uses AI to provide wargaming functionality may be able to rapidly produce course of action (COA) recommendations while handling many variables, many scenarios, and many unknowns, in a highly dynamic situation.

Global actors are racing to develop and integrate AI (Forthomme 2019). Considered as the next frontier within both commercial and defense industries, AI is a fundamental step in technological advancement. President Vladimir Putin has stated that whichever country develops AI first will dominate global affairs (Vincent 2017). With the rapidly multiplying number of defense systems and defense operations, human decision making is becoming increasingly more difficult and "narrow;" implying that decisions are not made with all the information at hand, but only a select, readily available portion of it. Losing the race in integrating AI into defense operations is one of the largest risks for the U.S Joint Forces. To emphasize, Figure 24 displays the Peoples Republic of China's (PRC) roadmap for the incorporation of intelligent systems (i.e., AI) into both military and socio-economic systems.

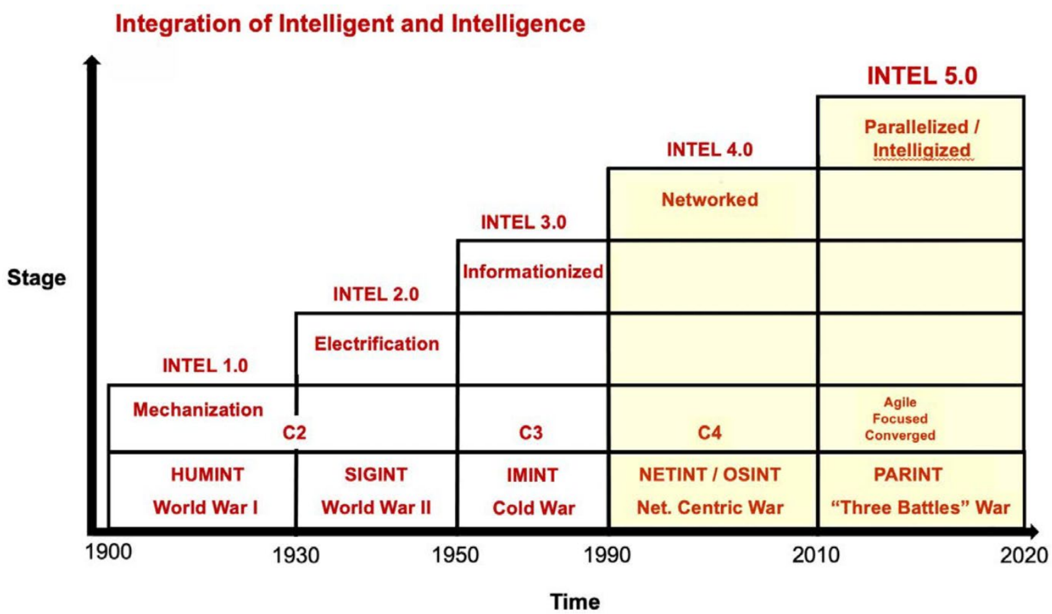

Figure 24. China's Integration of Advanced Data (Bruzdzinski 2021)

Advances in computational capabilities, AI methods, and increased amounts of information point to potential solutions addressing battlespace complexity through the development and use of automated decision aids to support warfighters making tactical decisions (Johnson 2019). Computers can support human operators by developing recommendations quickly that incorporate large quantities of data that would overwhelm humans. In tactical situations, the time to make critical decisions may be very short and situational awareness may be very limited. Throughout human history, military leaders have strived to command a level of order and predictability during war; "…the history of command in war consists essentially of an endless quest for certainty – certainty about the state and intentions of the enemy's forces; certainty about the manifold factors that together constitute the environment in which the war is fought, from the weather and the terrain to radioactivity and the presence of chemical warfare agents; and last, but definitely not least, certainty about the state, intentions, and activities of one's on forces" (Bousquet 2008).

The intent of military operational planning is to develop a series of blue force COAs based on Commander's intent and working within many constraints and assumptions. During execution of plans, changes in the situation often require replanning—which entail reprioritizing COAs or implementing new COAs. The use of AI to develop military plans and perform replanning can be referred to as COA engineering. An AI-enabled decision aid has the potential to improve situation awareness and "rapidly replan from the now known information" (Miller, et al. 2021). Without the use of an automated decision aid, the ability to replan is so time consuming and overwhelming, requiring vast amounts of data to be captured and processed to produce an outcome, that it is not performed at all. The potential of an AI-enabled decision aid is that this "approach will enable multi-mission planning across tactical and operational levels, enable a more nuanced way to understand uncertainty about the enemy, and enable replanning so quickly as to make it a viable approach" (Miller, et al. 2021). This will create multiple dynamically updated COAs that change based on critical information and generate insight into operational execution. Figure 25 shows an example of many different COAs that can lead to the overall objective of winning a war.

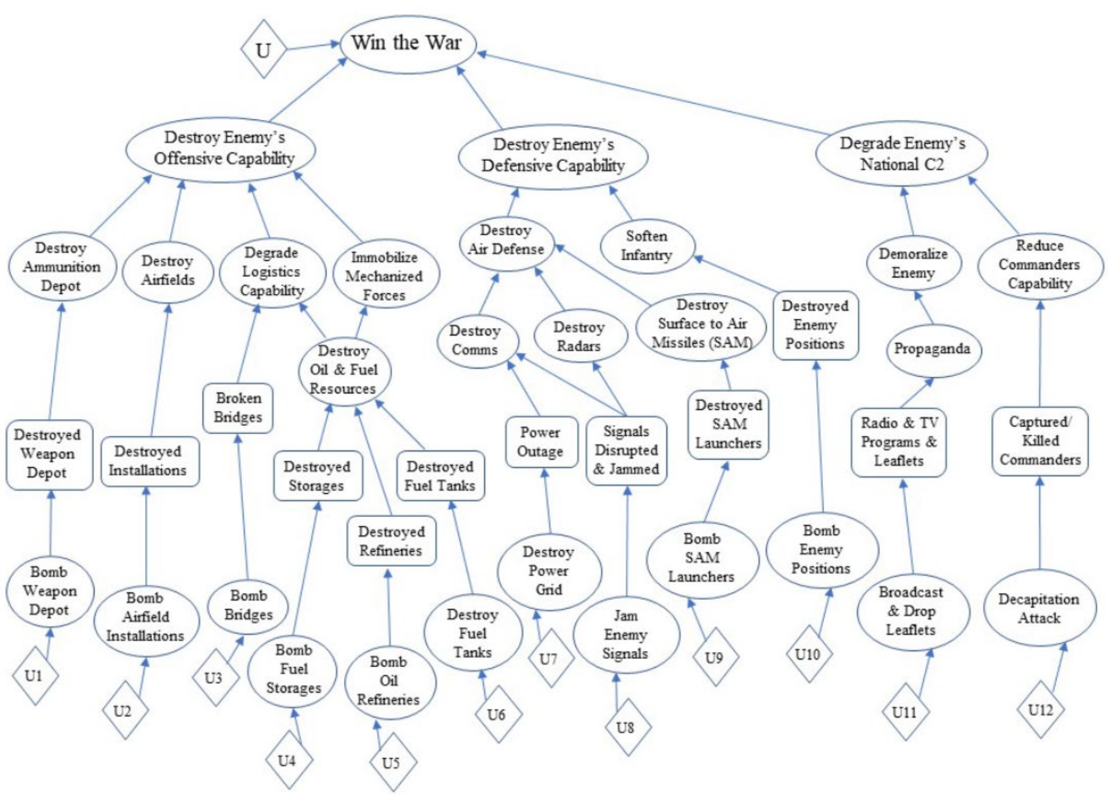

Figure 25. Military Courses of Action Diagram (Johnson 2020)

B. NEEDS ANALYSIS

With the rapid evolution of today's combat environments due to state-of-the-art technology and high-speed lethal threats, the required reaction time to make combat decisions has significantly reduced. Prioritization of warfare assets, combat units, and combatant requests now depends on an overwhelming amount of information which in turn further complicates human decision making. The number of potential future scenarios in any unique combat situation becomes almost overwhelming for a human to base combat decisions.

In a military combat situation, every second spent deciding on a COA or countermeasure influences the result. For example, in a naval blue ship vs red aircraft scenario, the amount of time to decide to engage the red aircraft with the Close-In Weapon System (CWIS) Phalanx will influence whether the countermeasure is effective. One second too late and the red aircraft could potentially fire a missile, causing catastrophic damage to the blue ship. In another example, the prioritization of tactical assets such as individual combat units, ISR systems, and logistics alter the success of the mission.

With ever-increasing complexity, lethality, and pace of warfare, there is an extreme risk of undermining the global prowess of the United States military unless research and development focuses on improving the tactical military decision-making process.

1. Example Scenario

An example scenario was explored to support a better understanding of stakeholder needs and operational requirements. Figure 26 illustrates an expeditionary mission to reinforce some islands and establish defense of the area.

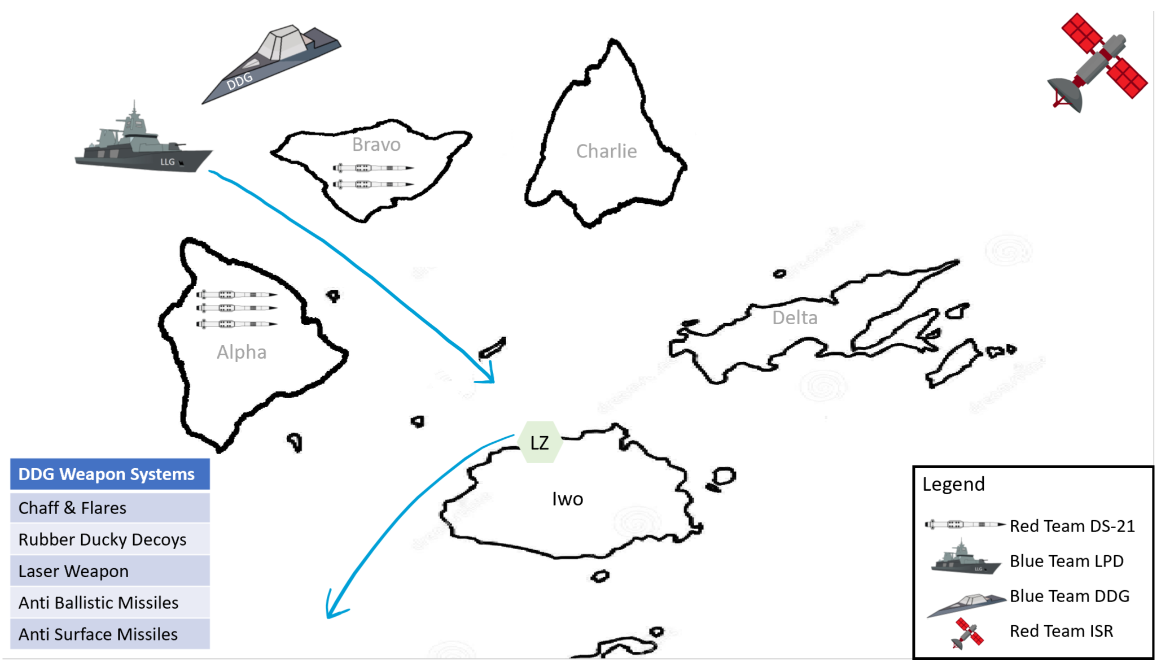

Figure 26. Five Island Scenario (Miller 2022)

The U.S. BLUE forces use five islands as possible launch sites for surface-to-surface anti-ship missiles (SSM). The enemy RED forces have suitable intelligence of the five islands and know the BLUE will likely only use three of them at any one time. The SSM poses a considerable threat to RED.

The BLUE mission is to deploy expeditionary forces and their accompanying missiles to Island Iwo covertly. Warfighters are loaded onto a Navy Landing Platform Dock (LPD), and will approach island Iwo covertly at night, with no radiation. A Guided-Missile Destroyer (DDG), OSCAR AUSTIN, will provide defensive cover, but is required to keep its distance from the LPD. Covertly inserting Marines on to Island Iwo is a high priority. USS OSCAR AUSTIN has been told their next mission involves providing defensive support to an attack Surface Action Group (SAG), where there will be no time to rearm between missions.

RED believes that BLUE will be trying to reinforce one of the islands soon and is using intelligence surveillance and reconnaissance (ISR) systems to observe BLUE operations. RED will attack if they detect the LPD or Marines. The LPD itself is essentially defenseless. RED will use decoys, a variety of surface and air to surface anti-ship missiles to attack the LPD if discovered. RED also has shore-based DF-21 ballistic anti-ship missiles, which were designed to be used against a carrier. It is unknown if RED would use them against an LPD. USS OSCAR AUSTIN also employs a decoy mode, that makes its electronic and hull signature appear more like an LPD, and at night augments its IR signature to appear as an LPD. AUSTIN OSCAR has chaff and flares, rubber ducky decoys, laser weapon, close in weapon system, rolling airframe short range missiles, and three different standard missiles, two for use against a regular surface strike missile, and one that works against ballistic missiles.

AUSTIN OSCAR's protection mission is complete when the expeditionary forces are on island. Once offloaded, the LPD will move at best speed into a safer area. Mission planners are in pursuit of significant information to develop a strategy.

- Are there viable COAs that will work to support this mission?
- As more knowledge about RED is acquired, are there amendments to the plan that make sense to change?
- Is there an allocation of missiles that should be assigned for this mission, and a minimum reserve for the next mission?
- If the operators can wargame this in real-time, what new insights might that process deliver?

This scenario was used to inform the needs and stakeholder analysis. The scenario is an example of how a wargaming style analysis that studies the possible effects of different COAs could be useful to mission planners and tactical decision makers.

2. Stakeholder Analysis

As an R&D program and future potential implementation into the Naval Fleet, the list of stakeholders involved in automating tactical decision-making is expansive. An AI-enabled wargaming system capability of this scope will encompass stakeholders beginning at the source of military capital thru to the end users (ex: Naval Combatant Commands, Commanders of Naval

Strike Groups). Figure 27 illustrates the most relevant stakeholders and their most applicable relationship with the WRAID system. The four domains of involvement include:

- Funding
- Integration and Logistics
- Research and Development
- End Users, or "Owners" of the WRAID system.

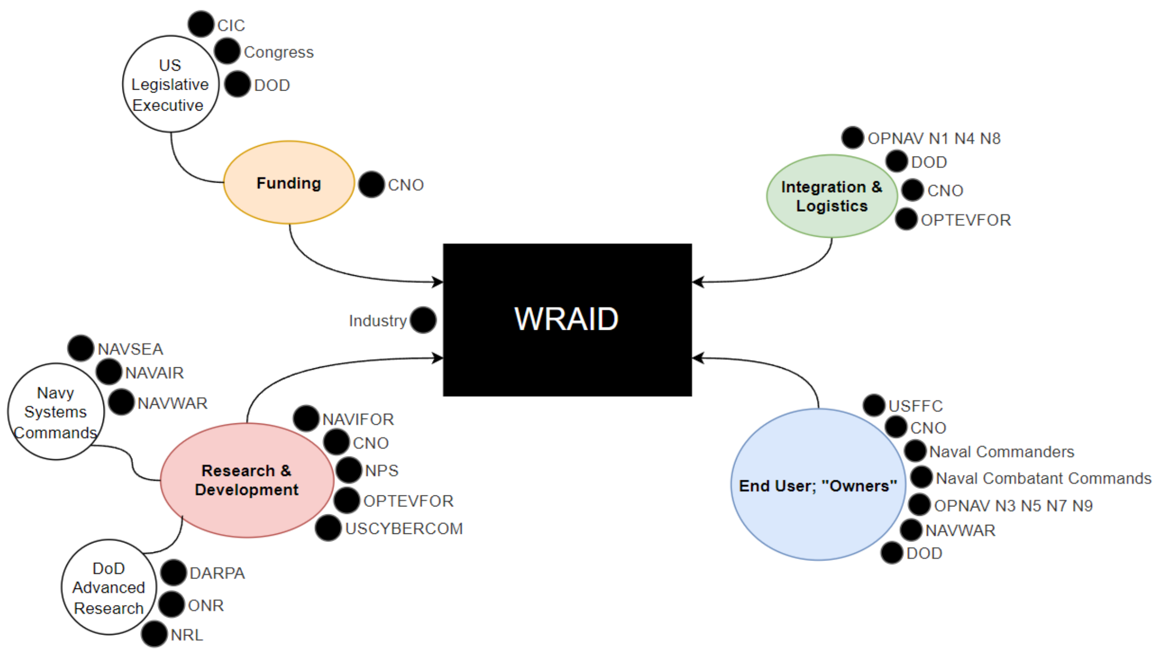

Figure 27. Stakeholder Tree Diagram

Several key stakeholders, most notably the CNO's staff (OPNAV) and the Department of Defense (DoD) are assumed to be involved, due to the nature of it being a DoD R&D project as well as specifically a naval one. Key organizations would include Fleet Forces (i.e., N2, N3, N4, etc.), Naval Warfare Development Command, Naval Combatant Commands, Naval Commanders, and representatives of the end users. The R&D efforts of a future AI-enabled wargaming system will encompass most of the advanced research organizations within the DoD, specifically Office of Naval Research (ONR) and the sub organization Naval Research Labs (NRL), as well as the Defense Advanced Research Projects Agency (DARPA).

3. Requirements Analysis

An NPS student capstone team generated requirements for a real-time automated wargaming system (WRAID 2022). The team developed the requirements with future warfighter users in mind. The team developed requirements in four categories: hardware/software requirements, human-machine interface requirements, functional requirements, and ethical requirements.

a. Hardware and Software Requirements

The NPS student team captured requirements for a future automated wargaming system from a hardware and software perspective. The team's requirements consider data collection, supportability requirements, reliability metrics, cybersecurity information assurance requirements, AI training avenues, and computational power maximums. The requirements are listed in Table 6.

Table 6. Hardware and Software Requirements

Hardware/Software Requirement	Unit
System shall operate at a minimum of XX% full performance with at least X hardware failure(s).	%, Quantity
System shall have a minimum mean time between failure (MTBF) of XX in operational environments.	MTBF (hrs.)
System shall continue to operate at full performance with a total loss of communications.	%
System shall be able to operate with a complete loss of communications for a minimum of XX minutes.	Y/N
System shall continue to operate at full performance for a minimum of XX hours with a loss of ship power supply.	Hrs.
System should be able to transfer full operations and decision authority to another installation within XX seconds.	Seconds
System shall have a system availability metric of ##% (including preventative maintenance, overhauls, repairs, and logistical downtimes) when in intended operational environments.	%
System shall be installable on currently available COTS hardware, as well as supportable on COTS hardware to be issued in the future.	Y/N
Systems shall be installable on COTS hardware.	Y/N
System shall communicate on an encrypted channel.	Y/N
System shall be compliant to operate on ship networks.	Y/N
System shall be compliant with governing Information Assurance (IA) protocols.	Y/N
System shall be installable on current hardware, as well as hardware to be issued in the future.	Y/N
Users shall be issued unique logins (Ex: CAC and PIN) with access only to the components and roles they are authorized to view. Access to sensitive data shall only be permitted as necessary for job duties.	Y/N
System shall conceal AI/ML algorithms inside a "black box" that cannot be deconstructed by any authorized or unauthorized personnel with access to the system.	Y/N

b. Human-Machine Interfacing Requirements

The NPS student team develop requirements for human-machine interactions for a future automated real-time wargaming system. The requirements consider data dashboarding, order generation, custom user inputs, and human-machine trust building. The team envisioned the future system as responsible for communicating its operations, recommendations, and orders to the human operator (warfighter). The team considered the future interaction as human-machine teaming, which requires three functions to ensure success: observability, predictability, and directability, between the human and the machine (Johnson, et al. 2014).

The team studied the DARPA Artificial Social Intelligence for Successful Teams (ASIST) program. This project is studying an AI system capable of modeling the world and problem-solving scenarios the same way humans do, by building a similar state-of-mind called "Theory of Mind," or ToM. Humans predict future actions based on inferences generated by "their ToM skill to infer the mental states of their teammates from observed actions and context" (DARPA 2019). "These models are built on each individual's existing experiences, observations, and beliefs. Within a team setting, humans build shared mental models by aligning around key aspects of their environment, team, and strategies. ToM and shared mental models are key elements of human social intelligence that work together to enable effective human collaboration" (DARPA 2019). Figure 28 illustrates DARPA's human-machine teaming model for the ASIST program. This model was used by the NPS team as a way to envision the future AI-enabled real-time wargaming system.

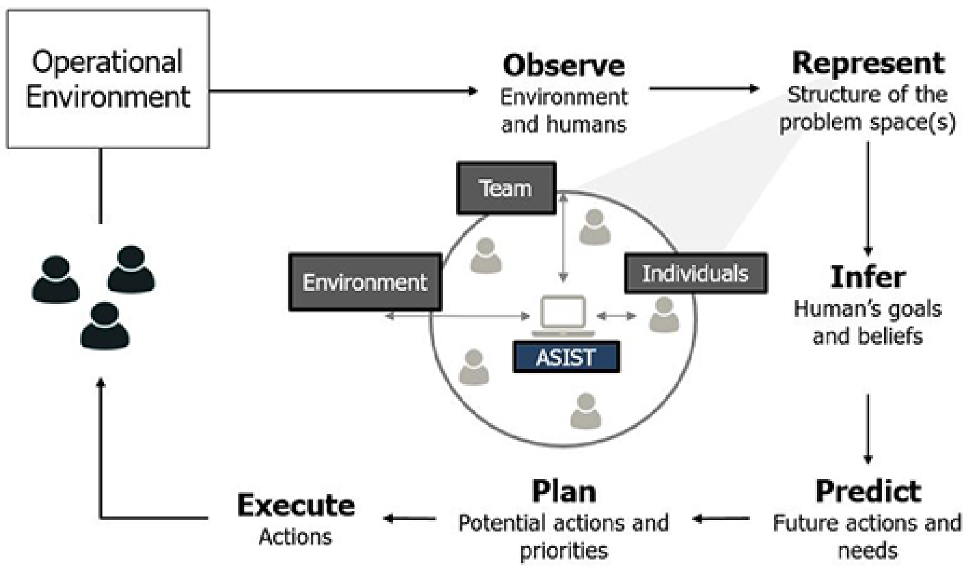

Figure 28. Human-Machine Teaming Model (DARPA 2019)

The NPS student team envisioned the AI-enabled system as a useful cooperator with future warfighters for tactical decision-making. Table 7 shows the informational needs of the human and the machine in a human-machine teaming arrangement. Both the human and the machine need mutual observability, predictability, and directability of their partner.

Table 7. Fundamental Human-Machine Teaming Flow (M. Johnson 2015)

Human Informational Needs	Topic	Machine Informational Needs
Machine Actions	Observability	User's Intent
Machine Next Steps	Predictability	User's Expectation/Needs
Human-Machine Language	Directability	User's Communication (Input)

An important component of successful human-machine teaming is the graphical user interface (GUI). Human-machine teaming requires the ability to eloquently display or communicate the operations, recommendations, and orders of the automated machine. The GUI display need to be able to expand and expedite the mental model and decision-making capabilities of both the human operator and the machine. As an example, U.S. Army researchers are investigating how to "thrive in [combat] uncertainty" and have developed a draft template of how tactical information should be conveyed most effectively (Adamski and Pence 2019). Named the "Multi-Horizon Event Template", mission objectives, enemy decision points, a chronological "roadmap" and simplified graphical representation of the progression of battle are all presented to the user (shown in Figure 29). Figure 30 also provides an example of a GUI, or "dashboard" presented to the human for their cognizance.

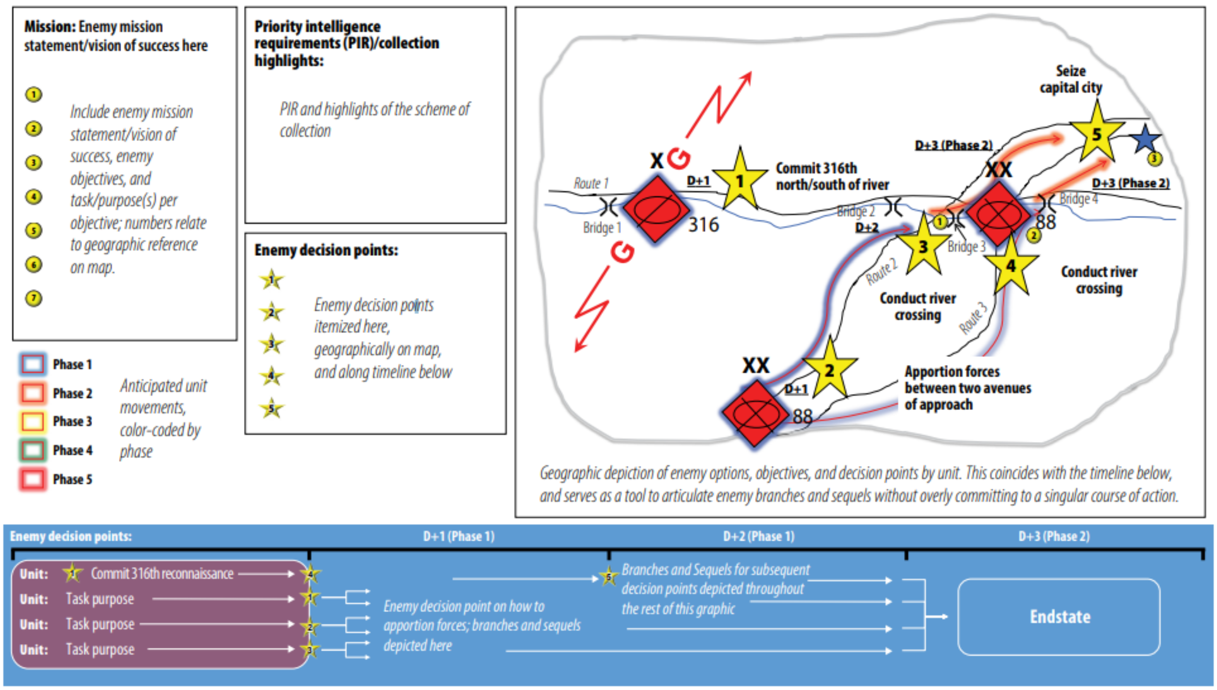

Figure 29. US Army Multi-Horizon Event Template (Adamski and Pence 2019)

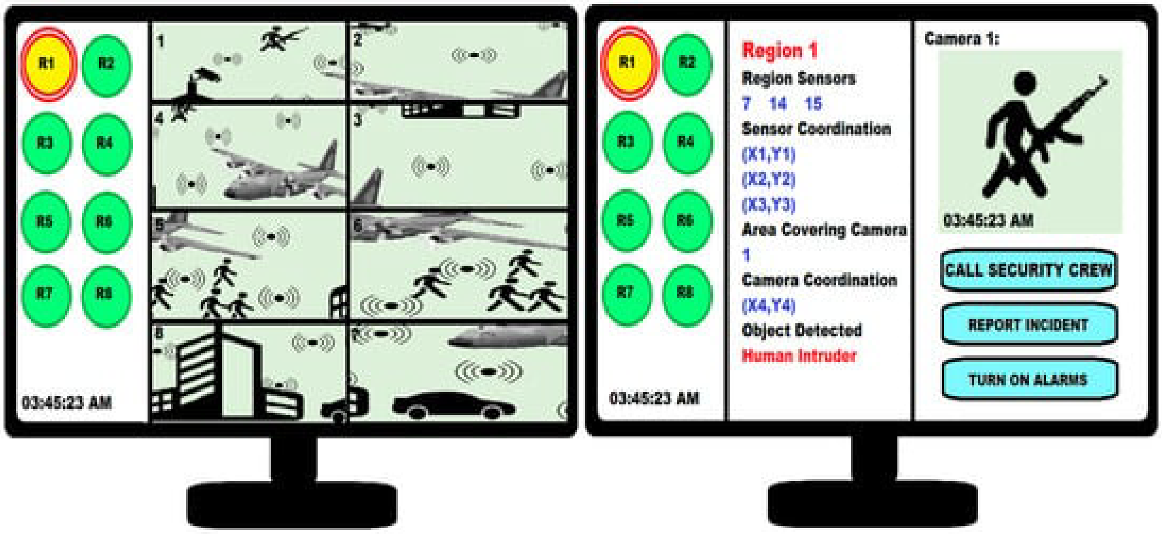

Figure 30. Example User Interface and Data Visualization (Madni and Madni 2018)

The NPS student team developed a set of human-machine teaming requirements based on their research. Table 8 lists these requirements.

Table 8. Human-Machine Teaming Requirements

Requirement	Units
System shall display information in a user interface contained to a total screen area of # square inch.	Area, Square Inches
System shall display operational information (i.e., current tasks, computing processing, computing statuses, asset tracking.)	Y/N
System shall provide auditory feedback for critical or alarming information.	Y/N
System shall provide touch-screen operation for navigating the user interface.	Y/N
System shall support traditional user input via keyboard and mouse.	Y/N
System shall limit displayed information to minimum (to prevent over-stimulation, obscuring important information).	Y/N
System shall present recommended courses of action in a tabulated format with columns containing statistical confidences.	Y/N
System shall provide explanative reasoning for COA recommendations and wargaming analyses upon user request.	Y/N
System shall allow human operator to input information or preferences as needed.	Y/N

c. *Functional Requirements*

The NPS student capstone team developed a set of functional requirements for the future AI-enabled automated wargaming system for tactical decision making. These functional requirements are listed in Table 9.

Table 9. Functional Requirements

Functional Requirements
System shall be capable of importing data and associated meta data from all available sources within the operational scenario naval group.
System shall be capable of computationally deciphering the naval commander's intent, adapting the intent to the mission.
System shall provide a method for the user to convert the commander's intent into digitizable objective.
System shall be able to receive and be input with ISR data.
System shall be able to analyze resources available to create COAs.
System shall be able to iteratively wargame the operational scenario at a defined frequency.
System shall be able to provide a list of COAs to human operators.
System shall be able to provide an order generation list to human operator specific for each COA.
System shall iterate the recommended COA list in tandem with the wargaming iteration to provide updated COA.
System shall provide statistical confidences for each of the Red team assumptions in the wargaming iterations.
System shall be trainable using prior wargaming simulations and historical battles.

d. Ethical Requirements

The team identified the importance of ethical considerations for the development of a future AI-enabled system that make recommendations that support tactical operations. The team noted that the AI-system could develop and recommend COAs that result in the use of weapons that can impact humans. The team developed a set of ethical considerations that should be considered as requirements are developed for the future system. These ethical considerations are described in Table 10.

Table 10. Ethical Considerations and Impacts on Requirements

Area of Consideration	Explanation	Potential Effects on Requirements
Human-In-The-Loop (HITL)	In HITL, the AI will make recommendations, but will not take actions or decide without a human operator. This allows the human to check for errors and ensure that the system makes the desired decision. With HITL, the system is used as a decision aid, not a complete solution.	What would happen if the system developed and suggested a COA, and after presenting it to the operator, no action was taken? How long should the system wait for an action? Should the system act, or should it continue to operate? If it were to react, consideration must be made as to what the desired action should be in the event the human side of the interface is inoperable.

Area of Consideration	Explanation	Potential Effects on Requirements
Value of Human Life	Putting a value on a human life is difficult. Even if no explicit dollar amount is assigned, a break-even analysis can be performed (Bardach 2012, 65-66). People put a wide range of values on a human life, impacting the trade-offs when developing and analyzing a COA. For example, if one force values a human life significantly more than another, they may choose to focus on infrastructure and equipment, rather than personal. Additional care may be taken to avoid human casualties.	During the COA analysis and COA ranking stage, the system will place different weighting based on the value of a human life. Additionally, this value may change depending on the operator and commander, and the system shall be able to adapt to different values. With AI/ML, the system will undoubtedly develop different COAs depending on the values assigned. The system shall also account for if the value for a civilian life versus a military life is different. Relevant information should be presented to the decision maker and human operator.
Bias	When training an AI/ML model, there is always the opportunity for bias or an anomaly in outputs based on prejudiced assumptions made during the development or presented in the training data. In the judicial system, AI has been explored and trialed, but time and time again, it has discriminated against people of color, recommending more severe sentences. Could an AI/ML system discriminate against foreign-sounding names when developing a COA or choosing a target?	Care must be taken throughout the system development and implementation to minimize the potential for bias. Requirements should be developed to minimize or eliminate the potential for bias. But what the requirement would look like or how it would be measured is still a topic of debate.
Explainability "XAI"	Explainable AI allows the human users to understand the impact and potential biases, leading to better transparency. It leads to a responsible approach, generating greater confidence in the system. While explainable AI has its benefits, there are potential downsides in security. The ability to dissect and reverse engineer the system black box, opens the door to bad actors who may be able to change the system behavior.	Whether to make the system explainable or leave it as a black-box system is beyond the scope of this report. Should experts decide that it should be explainable, this needs to be transformed into requirements, in such a way that it can be measured. It is not feasible to have a requirement that states the system must be explainable because requirements should be agnostic and relatable, regardless of the implementation chosen.

C. CONCEPTUAL DESIGN

The NPS student capstone team developed the acronym WRAID – which stands for Wargaming Real-Time Artificial Intelligence Decision Aid as a name for the system they envisioned as part of their capstone project. This section summarizes the team's conceptual design for the WRAID system.

The WRAID system mimics the traditional planning and decision-making process with the key difference being the "brain" behind the process. WRAID leverages AI's ability to perform computations on large datasets without loss of information, while recognizing and minimizing the biasing of data. The same inputs in traditional methods for the planning process are required for WRAID. The decision making ultimately lies with the commander whether the traditional or WRAID process is used. The WRAID system is not designed to supplant the commander, but rather expand the decision maker's mental model to ensure as much information is considered in each decision and CoA made. Expanding the mental model of the decision maker is synonymous with:

- Increasing the maximum amount of information or key inputs into a decision.
- Decreasing or negating the effect of human biases on decisions; including cognitive biases (given biases are not introduced into the capability programming).
- Increasing the decision-making speed in contrast to the overwhelming amount of information at which the most efficient and effective decision can be deduced.

The team envisioned the use of the WRAID system as a human-machine teaming arrangement to support human warfighter's tactical operations.

1. System Description

Incorporating an AI into combat and tactical decision making has the potential to automate and improve much of the decision-making process. Essentially, AI can bring the advantages of speed, efficiency, and effectiveness. The traditional 7-step planning process will take on a more simplified form when an AI system is incorporated. A system of this scope will have many inputs and outputs. The NPS student team developed a black-box system diagram shown in Figure 31 to identify WRAID system inputs, outputs, and stakeholder interactions.

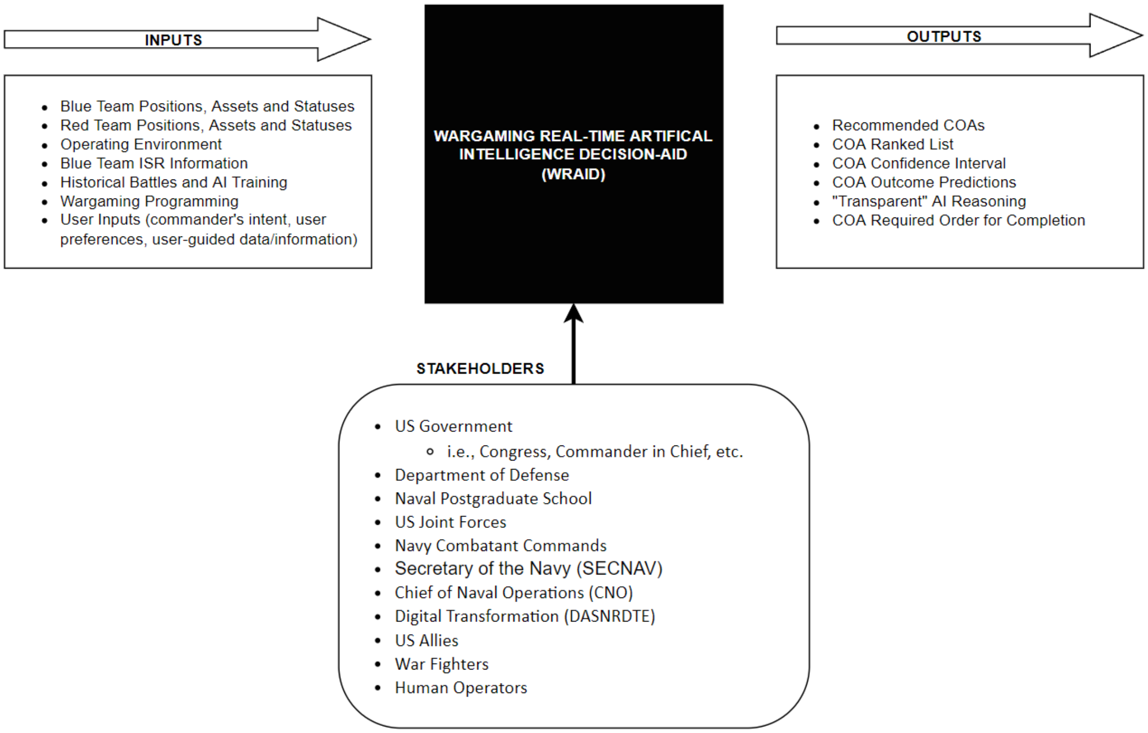

Figure 31. Black-Box System Diagram

2. Concept of Operations

The student team develop an operational view of the WRAID system and how it might be used in the real-world to support warfighter tactical decision-making based on inputs from ISR, sensors, and Commander's intent. Figure 32 shows the team's OV-1 diagram.

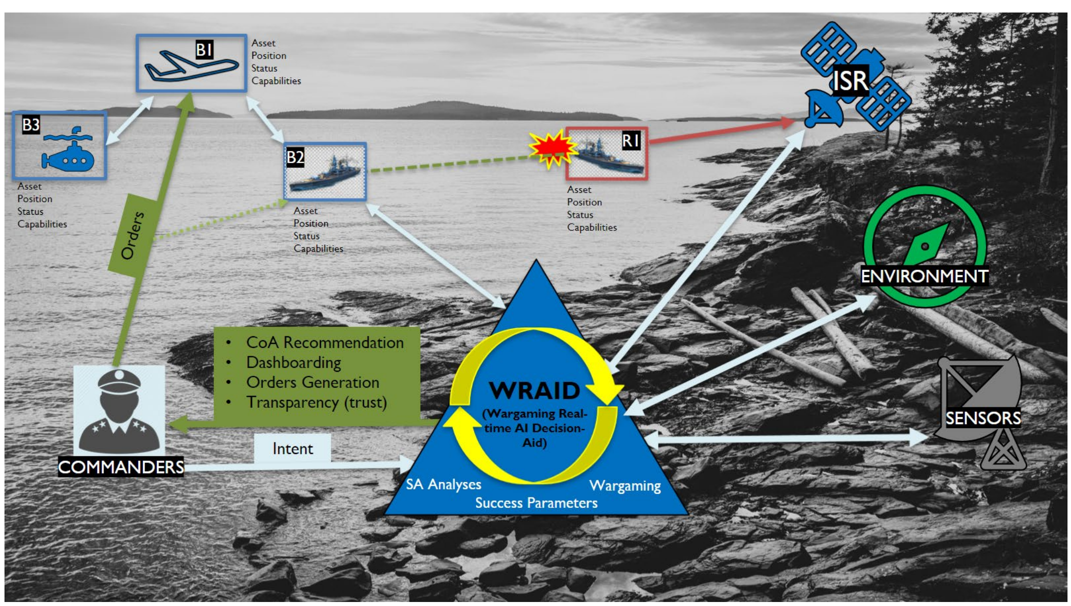

Figure 32. OV-1 Diagram for the WRAID System

The WRAID system will receive input from situational, environmental, and circumstantial sources including Blue Force's assets (ex. ships, aircraft, and equipped weaponry), any operational ISR information, and all sensors communicating within Blue force's operational environment. Red Force's assets positions, capabilities (i.e., weaponry, range, endurance, manpower) and status will consequently be obtained. Within the black-box WRAID system, these inputs and the assigned Commander's Intent (i.e., the main objective) will be used to generate respective wargames. These wargames will be used to determine the likely progression of the confrontation. The WRAID system will continue to iterate these wargames on a frequency suitable for the "speed" of the confrontation; this provides an ever-increasing confidence of Red Force intent and ensures the decision recommendations to follow suit. For example, an active skirmish between Blue and Red force vessels would require an iteration time substantially less than that of one in cease-fire. COA recommendations will be generated by the WRAID system and presented in an understandable yet encompassing manner (i.e., "dashboarding") to the staff and decision makers. The COAs presented will have respective likelihood and severity rankings, as well as mission readiness. If the WRAID system generates a COA with an extremely high-risk combination (likelihood/severity) and an urgency for immediate action, the COA will be presented to the users with an alert. As with any human-machine teaming, trust between the human operator and machine must be built. To foster this, the WRAID system will attempt to provide transparent reasoning for each of the COAs it generates. Finally, the decision maker will select their preferred COA and the WRAID system will generate a list of necessary orders to be executed for that specific COA. This process will iterate at an interval determined by the user and the available computational prowess.

3. System Process Workflows and Sequences

The NPS student team developed a system view of the envisioned WRAID system (shown in Figure 33). The WRAID system is shown on the right and consists of wargaming analyses, AI training, data fusion and AI algorithms. The diagram shows the WRAID system receiving information from the environment, from blue force ISR sensors, from Blue team forces and assets, and from the Commander. The figure shows that WRAID produces a list of recommended COAs and sends these to the Commander.

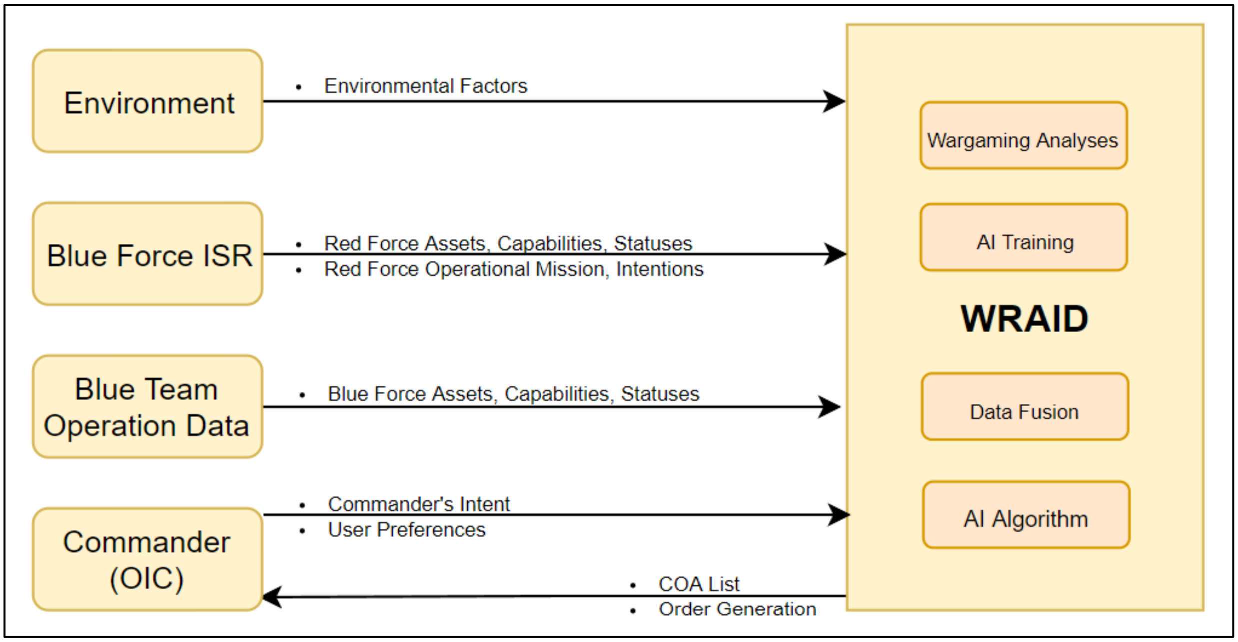

Figure 33. SV-1 Diagram

The NPS student team developed a workflow process diagram for the conceptual WRAID system as shown in Figure 34. The workflow diagram shows the flow of information as knowledge of the Red forces, knowledge of the situation, and knowledge of the Blue force capabilities and readiness is used by the WRAID to develop and evaluate COAs and recommend them to the human warfighters. The outer red arrows in the workflow illustrate the continuous and dynamic nature of this tactical decision-making process. The NPS student team used Systems Modeling Language (SysML) activity diagramming to capture the WRAID decision-making process in a software tool called Innoslate. Figures 35 and 36 show WRAID diagrams made in Innoslate. Figure 35 in intended to show the traditional planning and decision-making process and Figure 36 shows the same process using the WRAID system.

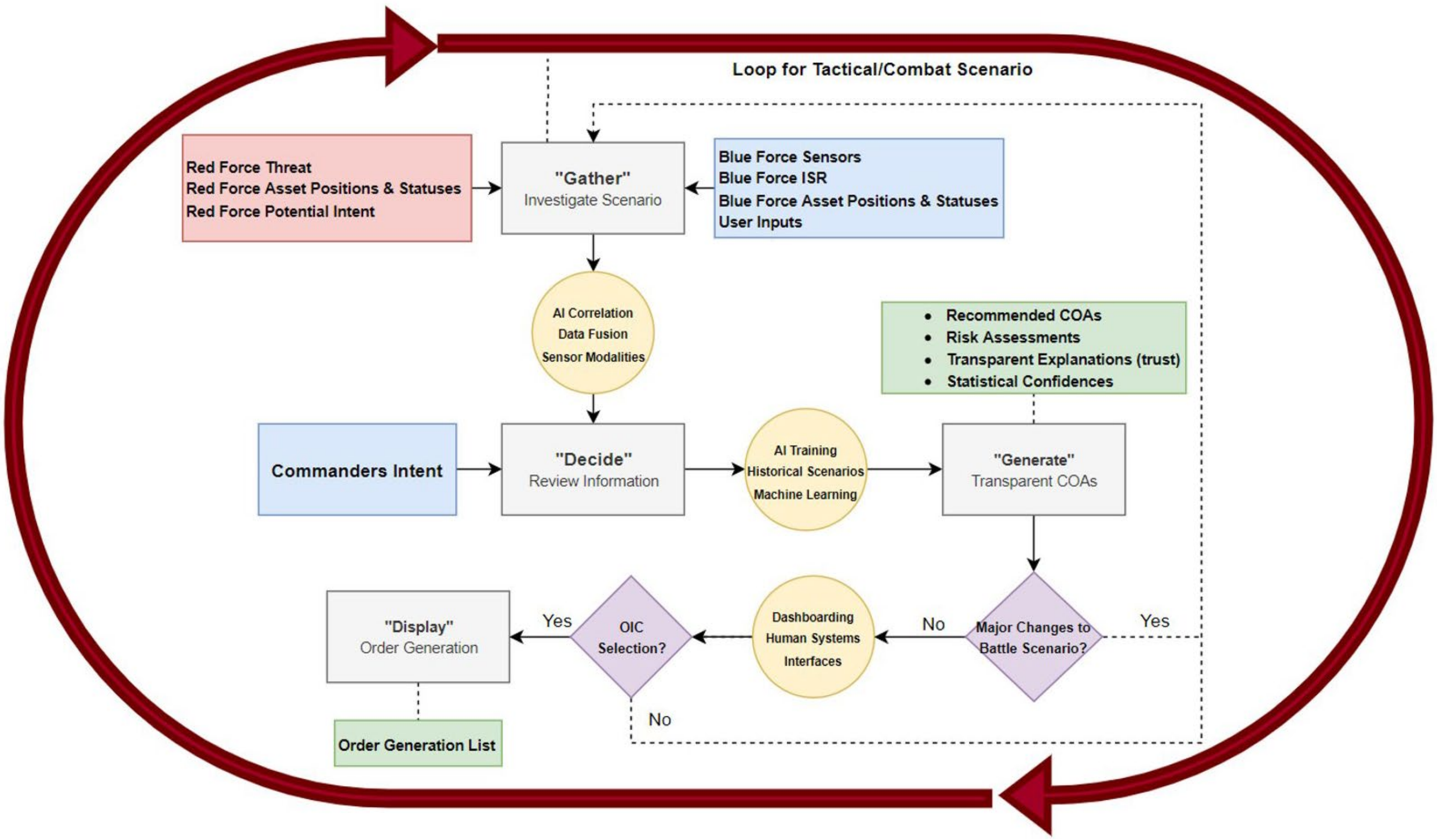

Figure 34. WRAID Planning and Decision-Making Process Workflow

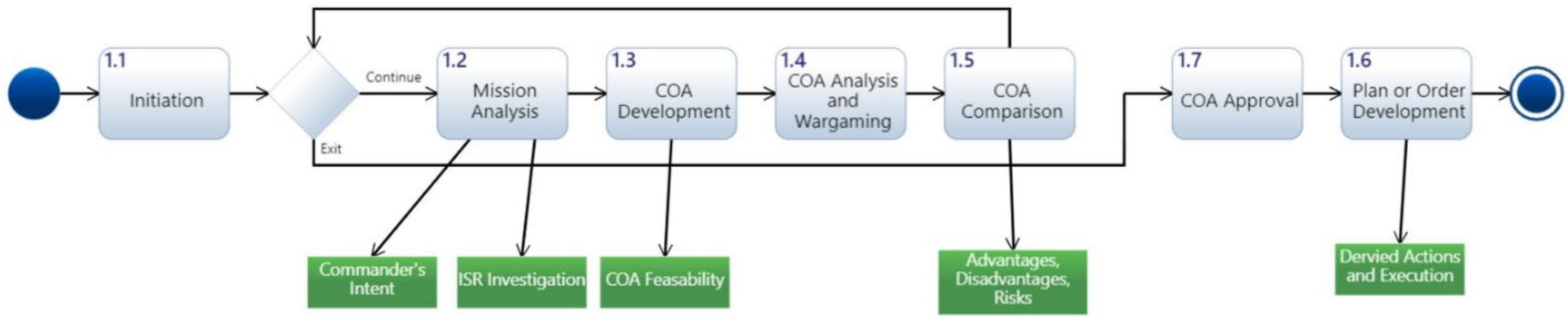

Figure 35. Traditional Planning & Decision-Making Process

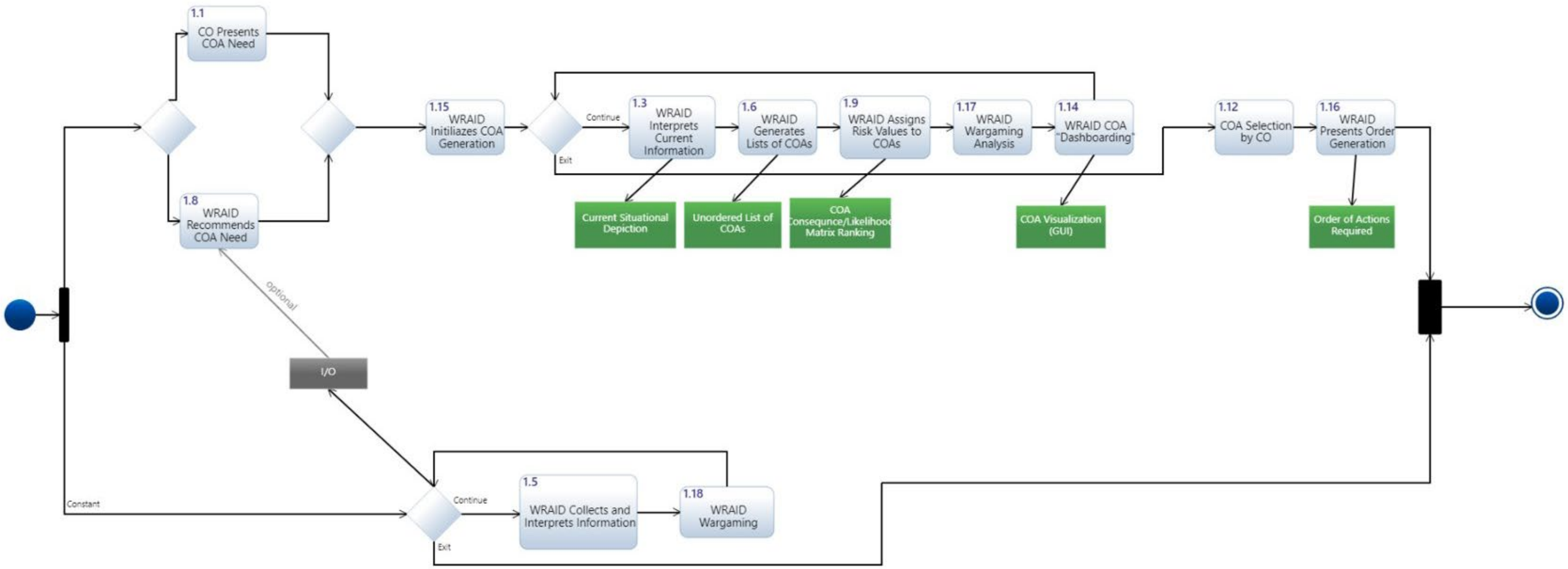

Figure 36. Planning and Decision-Making with WRAID

4. Scenario Analysis

In traditional planning and decision-making, a plan is created in a linear fashion and reiterated when information changes. The process is done manually which makes change slow. In the scenario presented in the needs analysis section, the goal is to deploy Marines onto the island Iwo without being noticed by red defenses on nearby islands.

A traditional plan would come up with limited likely scenarios and options for the commander and would require a long time to develop. If the scenario changed and intel suggested a sub was in the area and that was not planned for in the likely scenarios the commander has limited options and limited time. The limited options and time would require that the mission be called off with the slow response of traditional planning. Combat situations are always guaranteed to change and preparing for as many changes as possible is invaluable. However, with traditional planning and decision making the scenarios are limited and incomplete or slow to develop. The following is a hypothetical walkthrough of the scenario.

As illustrated in Figure 37, the Blue Team receives orders to proceed with mission navigating between islands Alpha and Bravo without radiation at night to the landing zone. Blue Team ISR reports that there are Red Team DS-21 missiles on both islands.

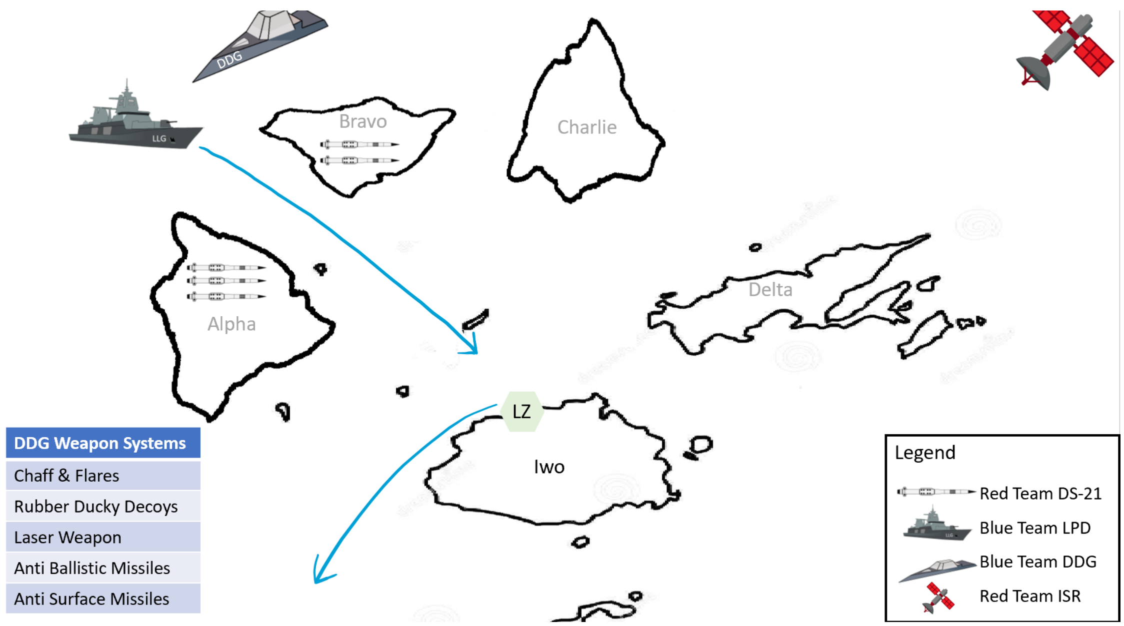

Figure 37. Traditional Planning First Battle Scenario

An updated order is given to the commander to reroute between the islands Charlie and Delta to the Landing Zone. The Blue Team DDG is to follow at a safe distance to provide protection should the mission encounter surprises.

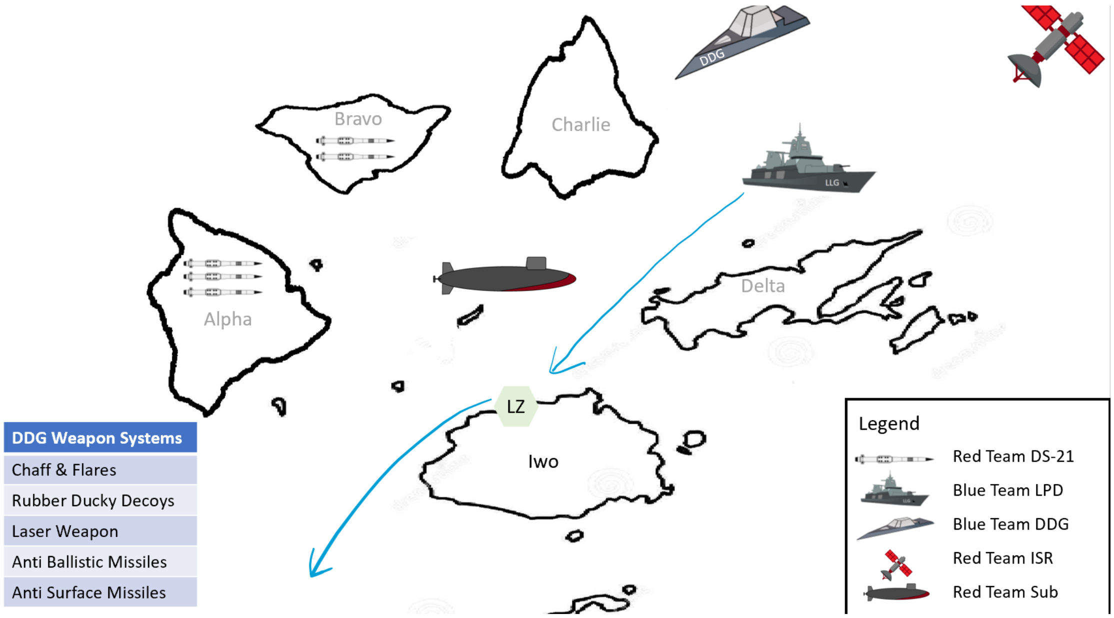

Figure 38. Traditional Planning Second Battle Plan Scenario

Blue Team ISR now reports that a sub is in the area between the five islands (as shown in Figure 38). The commander must either pull the LPD out and abort the mission, or continue with the set plan and attempt to skirt the sub. The planning process is once again executed, and a change of action is selected. Due to time constraints the mission is aborted, and by the time the LPD repositions, and a new landing zone (LZ) is identified, it will be morning and the Red Team will have reinforcements on the way.

The WRAID AI can run simultaneous scenarios with different changes in each of them and offer a best path forward to the commander when the situation inevitably changes. Last minute knowledge of a sub can be one of the simultaneous scenarios WRAID runs, providing an alternative path for the blue ship to follow or sending in further military assets in the area. Ultimately the Commander will oversee the decision but with WRAID more actionable options are available and presented.

Leveraging WRAID's ability to run multiple similar scenarios with small changes in variables, coupled with an experienced commander who understands what WRAID outputs are meant to accomplish (expanding the mental model and trade space) will lead to better, quicker decisions, and ultimately additional preparedness. The ability to quickly analyze and pivot to alternate plausible solutions will prove invaluable to military commanders as the battlespace and scenarios continue to become increasingly complex. WRAID's AI architecture must be conveyed so commanders understand what WRAID is, and how to use it to their benefit. As with any disruptive technology there will be a learning curve. However, the realized benefits of a fully developed WRAID system will foster acceptance of, and additional collaboration with WRAID's transparent human-machine teaming.

WRAID presents several possibilities to the commander, once it cycles through the possible variables to establish different plans of attack based on the various scenarios and their likelihood. The WRAID system runs through variables and likely scenarios are outlined:

- A Red sub/ship in the middle of the five islands.
- Moving the LZ to the other side of the island.
- Other islands have more DS-21 missiles than first anticipated.
- Using the DDG as a decoy to pull the sub from its current location.
- Several approaches to the island.

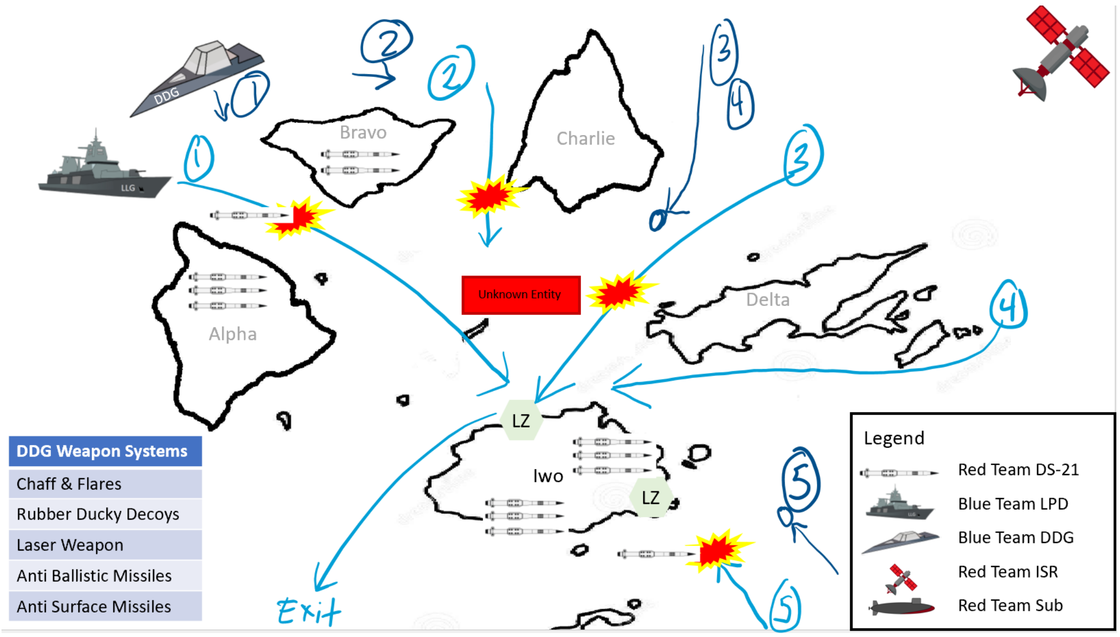

Figure 39. WRAID Battle Plan Scenarios

WRAID generates five (5) COAs, as illustrated in Figure 39, and recommends a plan for the best chance of success. The LPD inserts from the east, between islands Delta and Iwo, with the DDG camped between islands Charlie and Delta ready to engage should an enemy entity appear (a speculation WRAID determined to be highly likely, based on past mission history and wargaming scenarios).

WRAID provides the commander the opportunity to choose an appropriate and actionable COA in a timely manner, rather than be forced to abort the mission due to repositioning and time constraints. To emphasize, the commander does not have to pick any of the options given to her, WRAID is a decision aid tool. The WRAID system will require commanders to be trained on how to use and interpret WRAID results. Understanding how to use the system and training material for commanders will be just a valuable as the WRAID algorithm. The system does not output fixed COAs but rather aids the commander in decision making. Re-running the algorithm with different parameters will yield different results. In this case the potential threat of an enemy vessel in between the islands proves to be valuable input to the commander. This is a simplified scenario; however, it clearly demonstrates the benefits of an AI system integrated in the planning and decision-making process.

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V. CONCLUSIONS

A. SUMMARY

Game theory and prescriptive analytics offer two potential game changing capabilities for naval battle management superiority. Tactical operations can take a significant leap in progress with the aid of automated wargaming systems for real-time course of action (COA) decisions and for mission planning. Automated wargaming systems can predict the success of different COA options and consider possible second and third order effects. Future automated wargaming systems could accompany current development in the use of artificial intelligence (AI) to improve battle space knowledge and battle management.

The study leverages research in decision science, predictive analytics, AI, and causal inference. The study incorporated work being done in game theory, regret minimization and equilibria, counterfactual regret minimization, and recent experiments with AI systems playing games. The study drew upon methods and concepts for predictive modeling and influence diagrams. The study took a closer look at research that has focused on the application of these methods and capabilities in the military domain.

The Navy is taking advantage of advances in computational technologies and data analytic methods to automate and enhance tactical decisions and support warfighters in highly complex combat environments. Novel automated techniques offer opportunities to support the tactical warfighter through enhanced situational awareness, automated reasoning and problem-solving, and faster decision timelines. This study investigated how game theory and prescriptive analytics methods can be used to develop real-time wargaming capabilities to support warfighters in their ability to explore and evaluate the possible consequences of different tactical COA to improve tactical missions. This study explored data analytic methods including game theory, prescriptive analytics, and AI to evaluate their potential to design and engineer automated wargaming capabilities.

This study applied a systems analysis approach to develop conceptual designs of wargaming capabilities for real-time tactical decision, for mission planning operations, and to assist table-top wargaming. An NPS student systems engineering capstone team studied the use of game theory and prescriptive analytics to generate requirements and develop a conceptual design for a real-time tactical wargaming decision aid (Badalyan et al. 2022). An NPS systems engineering thesis student developed requirements and a conceptual design for an AI-enabled wargaming system for mission planning (Lee 2022). An NPS faculty researcher studied the use of AI and game theory to develop an automated wargaming capability to improve table-top wargames.
The research team, consisting of NPS research faculty and systems engineering students, identified the three battle management applications. The team applied a systems analysis to two of the three applications: for mission planning and for real-time tactical decision-making. The team conducted a needs analysis and requirements analysis for each of these applications. Next, the team developed conceptual designs using model-based systems engineering tools to capture system and architectural design artifacts. The students developed names for each of the automated wargaming capabilities: the Strategic Operational Decision Aid (SODA) for the automated system that could support future mission planning, and the Wargaming Real-time

Artificial Intelligence Decision Aid (WRAID) for a future tactical decision aid. The team worked with researchers from the Naval Air Warfare Center China Lake to investigate the use of automated capabilities to support future table-top wargames as an automated adjudicating White Cell.

The NPS research team studied the operational need for a real-time naval wargaming battle management aid. The team drew upon former research that the P.I. performed that characterized instances of complexity in military operations that result in situations that require automated decision support systems. Highly complex tactical military decision spaces can be characterized as having extremely short reaction or decision timelines, significant levels of uncertainty in situation awareness knowledge, extreme dynamics in the threat tempo in terms of heterogeneity, number, and kinematics, and information confusion with too little or too much information. Complexity in the military mission planning domain is also a candidate for applying an automated wargaming system. Military mission planning is current a very manual and lengthy process. An automated system can identify and evaluate many more possible COAs than can be done manually.

The study topic sponsor can use the findings of this research project as a basis for funding the research and development of automated wargaming systems. One step is to continue studying means of automating game theoretics as well as prescriptive and predictive analytics. Another step is to continue studying the three application domains to identify a manageable scope for some proof-of-concept demonstrations. The topic sponsor could use the foundational knowledge from this study to develop an automated wargaming capability road map for the Navy.

B. RECOMMENDATIONS AND FUTURE WORK

The NPS study team recommends that automated methods leveraging game theoretics, prescriptive analytics, and AI continue to be pursued by the Navy for the three categories of applications identified in this study: (1) to provide white cell adjudication, game design support, and automated players for table-top wargames, (2) to support operational planners as a COA engine to identify, evaluate, and recommend COAs, and (3) to support tactical decision-making as a real-time automated wargaming aid to provide predictive causal analysis to tactical COAs. The team recommends the following specific research initiatives as future work:

- Operational concept studies – to understand how/when, and under what conditions, automated wargaming decision aids are useful and even necessary
- Development of ontologies to support the three naval applications
- Development of red cell modeling
- Study of information and system architectures needed to support real-time tactical wargaming decision aids (what information needs to be shared, whether a centralized or decentralized distributed architecture are needed)
- Cross-domain studies to determine how automated wargaming systems can support multiple domain and multiple mission areas
- Bottoms-up vs. top-down and general boundaries of the wargaming models and decision-making – are they necessary? Do they constrain solutions?

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