Using Agent-based Simulation and Game Theory to Examine the WWII Bay of Biscay U-boat Campaign

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This paper presents research combining an agent-based modeling and simulation paradigm with game theory for an in silico historical analysis of the Bay of Biscay submarine war during WWII. The U-boat threat was of great concern to the Allies, prompting initial operational research efforts to devise counterstrategies. Focusing search efforts in the Bay of Biscay enabled an effective Allied response. Using the historical record as a means to create a reasonably accurate model of the U-boat campaign, we allow the resulting agents within the model to adapt their strategies to counter-opposition strategies. Model output data are examined with respect to the historical record and game theory. The results hold promise for extending the agent-based modeling paradigm into more complex military-based domains.

Keywords: Agent modeling, game theory, search games, military modeling, simulation

1. Introduction

We present research using an agent-based simulation for mission-level military modeling in which empirical results are compared to those predicted by game theory in the context of an in silico study of the WWII submarine (U-boat) war in the Bay of Biscay. This work was motivated by recent trends in military modeling, simulation, and analyses to glean lessons from "what if" studies of historical combat, to better bound the outcome space of future combat, and to eventually better model critical human aspects of combat. An agent-based simulation paradigm was used to create a system of interacting, autonomous entities (search aircraft and evasive U-boats). An adaptation algorithm was defined and implemented governing the behavior of each group of simulation agents. Agent interactions drove subsequent agent behavior changes guided by their adaptation algorithm, thereby modifying simulation output trajectories as each agent sought to maximize that output to their advantage. These emergent output are shown to agree not only with history but also as predicted by game theory and thus this initial study provides a promising basis for further analytical uses of combat models built using the agent-based modeling and simulation paradigm.

The military is the largest user of models [1], spanning a plethora of purposes from prediction of future defense needs and potential conflict outcomes, to reflection on past combat experiences. However, no model perfectly reflects the "real world." This has led to concerns regarding the use of modeling (particularly simulations) to gauge potential combat outcomes [2] and to conduct thorough "what if" analyses of historical combat. While perfect modeling and perfect prediction are unattainable, a greater degree of modeling fidelity is attainable through the definition and instantiation of models that "capture" historical outcomes and provide a reasonable level of extensibility beyond the historical specifics modeled. We focus on the former aspect, defining a model to capture the historical outcome.

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An agent-based paradigm promotes the modeling of complex systems; warfare is widely accepted as extraordinarily complex. Human involvement in combat, with our cognitive capabilities and our human frailties, have produced a landscape of combat history replete with non-linearity, emergent behavior, and general unpredictability. Combat truly is a chaotic system [3]. Emergent behavior is a feature of agent models offering promise for both the military analyst and combat historian to extend their influence and analytical contributions by using models that provide emergent behaviors as a result of agent interactions versus specific software engineering interventions. We note as emergent behavior the agent tendencies toward day-versus-night operations both in terms of search effort and in terms of U-boat surfacing.

Agent-based models potentially overcome several drawbacks inherent in current combat modeling techniques and methods. An agent model provides a means to directly model factors such as leadership, courage, morale, and other human traits versus indirect methods currently employed, such as behavior degradation factors or lethality scale multipliers. Agent models provide mechanisms to display adaptability within a simulation scenario, ideally in a manner similar to how actual human decision makers react. Our agents are not overly sophisticated; the agents do however change, or adapt, their behaviors based on environmental perceptions during the actual simulation run.

> A danger inherent in detailed, complicated computer simulations of combat is that they reflect current doctrine; their ability to intimate radically new tactics is limited [4].

An agent-based simulation changes the nature of model-based military analyses [5,6,7]. An agent-based simulation may not provide classical statistical output, but instead may demonstrate trends that collectively encompass actual combat behaviors. These trends, along with the embellishment of the agent model beyond usual parameterizations, can provide enhanced insight into the combat phenomena of interest, particularly phenomena associated with non-classical applications of military power.

Any historical study of warfare includes game theory, i.e., the study of conflict between opponents. However, the preponderance of historical studies involve manual simulation techniques which can be time-consuming, error-prone, and rife with the biases associated with human decision-making. Classical computerized simulation techniques process quicker and overcome many biases, but may fail to incorporate the human aspect of decision-making. Agent-based simulation offers a promising hybrid; a simulation-modeling environment that can accommodate adaptive behavior patterns thus offering a unique opportunity to examine the historical record through an entirely new set of analytical lenses.

This work develops and demonstrates such a hybrid environment in which the simulation entities, the agents as we have defined them, incorporate game-playing attributes. The specific scenario is based on the famous U-boat-hunting operations within the Bay of Biscay during World War II. In the next section we provide technical background concepts pertinent to our work. We follow this with a terse summary of the Bay of Biscay U-boat campaign scenario. We then present the modeling environment developed for the research along with the methodology employed to embed game theoretical constructs within this agent-based simulation environment. Results of the study are then presented and we close with summary statements, conclusions, and avenues of further work.

2. Background

There are three key concepts pertinent to this research. These concepts are agent-based modeling, the application of game theory, and the tie between game theory and search applications known as search games.

2.1 Agent-based Modeling

Agents are entities "distinguishable from [their] environment, …, possess some kind of identity, …, have some autonomy of action, that they can engage in tasks in an environment without direct external control" [8]. Agents are governed by a set of rules and act based upon what they can perceive in their environment [9]. An autonomous agent is a physical or virtual entity

1. that is capable of acting in an environment;
2. that can communicate directly with other agents;
3. that is driven by a set of tendencies (has autonomy);
4. which possesses resources of its own;
5. that is capable of perceiving its environment (although limited);
6. that has only a partial representation of this environment;
7. which possesses skills and can offer services;
8. that may be able to reproduce itself; and
9. whose behavior tends toward satisfying its objectives, taking account of the resources and skills available to it, and depending on its perception, its representations and the communications it receives [10].

Expanding to a multi-agent application requires adding

1. an environment;
2. a set of objects that can be perceived, created, destroyed, and modified by the agents;
3. an assembly of agents (the active entities in the system);
4. an assembly of relations linking the agents;
5. an assembly of operations enabling agents to perceive, produce, consume, transform, and manipulate objects; and
6. operators whose task is to represent the application and reaction to these operations [10].

We later use the above nine agent characteristics and six multi-agent characteristics to characterize our simulation entities as simulation agents.

Agents are commonly classified into two types: reactive (or dynamically coherent) and adaptive (dynamically incoherent) [8]. Reactive agents determine their next action (or state) based on their current internal state and the state of their environment. Adaptive agents incorporate memory, thus allowing decisions based not only on the current state of the environment but also on any internalized information. Adaptive agents provide a richer set of behaviors than reactive agents particularly when given an ability to adapt over time. A collective of individualized adaptive agents is the basis of a multi-agent system [11].

Various forms of agents have been used in a wide variety of applications. Artificial intelligence applications are detailed in [9], computer related applications are reviewed in [11], Batty and Jiang [12] examine the use of agents in geographic information systems, McDonald and Talbert [13] employ agents for the management and retrieval of simulation data for military simulation models, and Allsopp, et al. [14] discuss the use of agents to promote interoperability among various software systems. Other agent applications involve computer networks and information retrieval. Details of a number of agent-based models and their contributions can be found in [8], while Epstein and Axtell [15] provide a detailed account of building and examining such models. This wide variety of agent applications has led to ambiguity in the definition of an agent [11]. Within constructive simulations, the ambiguity has led some to perceive an agent simply as an object. The characteristics we provide above attempt to distinguish an agent from an object within the context of a simulation model.

The exploitation of agent-models for combat analyses is less mature than other applications. The earliest example is arguably [16]. The first example of agent-based modeling applied to combat to gain serious attention within the military modeling community is the Irreducible Semi-autonomous Adaptive Combat (ISAAC) model. ISAAC is designed as a "conceptual playground" of agent-based combat modeling, and is not intended as a full combat model [17]. Each agent in ISAAC represents a combat unit, each with different "personalities." ISAAC is used to examine factors influencing unit level combat success. Examining a full range of combat parameters generates a landscape of outcomes used as the basis for the combat analyses.

The ISAAC work, sponsored by the U.S. Marine Corps, led to their Project Albert initiative to specifically examine emergent behavior in agent models to explore questions of interest to the military. Recent Project Albert efforts are described in [18] and [19]. ISAAC influence extends into the defense graduate research realm as well. ISAAC-inspired thesis work from the Air Force includes [20,21,22] while Naval efforts include [23,24,25]. Recently published defense modeling and simulation works stemming from ISAAC influences include [26,27,7]. The work presented in this paper follows this line of research.

2.2 Game Theory

Game theory is the science of conflicting interest [28]. Conflicting interest exists when two or more opposing "individuals" must make decisions, resulting in several possible outcomes, outcomes dependent on their opponent's decisions. These individuals have a preference structure in conflict with that of their opponent. Game theory analyzes these conflicts, describes the choices of each individual, and examines the possible resulting outcomes from the competitive game.

Game theory outlines a few common characteristics of games. First, the game must have two or more rational players, some of which are competing against each other. Second, there is a type of payoff, or utility, that each player desires to maximize. A rational player may be defined as one who adheres to utility maximization in a consistent fashion. This utility may be represented by a number of things: money, time, or in combat situations, survival and measures of mission success. Each player makes decisions without knowledge of their opponent's decisions while seeking to maximize attainment of their individual preferences. The propensity, or probability, to make a certain decision is a player's strategy. Game theory attempts to determine which strategies allow the player to maximize their payoff, usually at the expense of the other players. Our particular research employs two-sided game theory such as described by Rapoport [29] and detailed in [30].

2.3 Search Games

Search games involve a search problem formulated as a game theory problem [31]. The conflict involves a searcher and a hider, or evader, who does not want to be found. The hider may be stationary or mobile. Search game payoffs vary, for instance whether the hider is found or not or how long it takes to find the hider. Benkoski, et al. [31] detail a good number of search game references in their survey of search theory literature.

The problem of searching for an evading target is addressed in [32]. Dobbie's problem space is defined as a two-cell problem where a single evader tries to avoid detection by moving away from the searcher when the searcher's presence is detected. Dobbie finds the strategy for the searcher's effort that maximizes the probability of detection in a given amount of time. Stewart [33] extends Dobbie's formulation using some special cases. First, the evader has a goal or objective to complete, and when completed, continuation of the search is no longer productive. Second, the searcher is subject to resource constraints prohibiting searching during every time period of the game. Alpern and Gal [34] present results regarding agents that do not necessarily wish to be found by the searchers.

Washburn [35] considers a similar problem, except the target is moving in discrete time and space. During each time step, the searcher tries to detect the evader and to maximize the chance of immediate detection (a myopic strategy). Washburn gives a necessary condition for optimality in this case.

Baston and Bostock [36] present a one-dimensional helicopter versus submarine game, modeled as a two-person zero-sum game. Both players move along a straight line, and neither player can see the other over an extended range. The helicopter has bombs with which to attack the submarine, and the payoff is whether or not the submarine is destroyed. The authors solve the game when one bomb is available, and extend it to multiple bombs given certain constraints. Our work involves a two-dimensional, airplane versus submarine game.

Eagle and Washburn [37] address two-person zero-sum search games where play continues for some period of time with neither player receiving feedback. Each player moves according to a preset plan. The authors present two methods to solve the game: an empirical method of fictitious play and an analytical method using mathematical programming.

3. The Bay of Biscay Scenario

Although introduced and employed during World War I, it was during World War II that the Germans first effectively used the submarine for aggressive purposes. Their primary targets were the logistical forces supporting the Allied war effort. U-boats (from the German word for submarine, *unterseeboote*) were primarily used to sink Allied merchant ships crossing the Atlantic Ocean to resupply the Allied forces in Europe. For a period of time in 1943 and 1944, the U-boat effort was so effective, and their efforts so devastating to the Allies, that Winston Churchill [38] later wrote that "the only thing that ever really frightened me during the war was the U-boat peril."

From 1941 through 1944, U-boats operated out of captured ports on the western coast of France. From these captured ports, the U-boats transited the Bay of Biscay enroute to the Atlantic where their Allied convoy targets were located. U-boats spent a significant amount of travel time in the Bay departing from and returning to their French ports as the Bay provided the only access route between the open waters of the Atlantic and the captured ports. The Allies concentrated their aerial U-boat search effort within the Bay in an offensive endeavor to counter the U-boat threat. These offensive efforts consisted of locating, attacking located U-boats, and hopefully sinking attacked U-boats before the U-boats reached the vast open waters of the Atlantic, or the heavily defended U-boat ports.

The Bay of Biscay represents roughly 130,000 square nautical miles (NM) of potential search area. Although a formidable search area, the U-boat density in the Bay was high enough to warrant a dedicated search effort. Furthermore, unlike modern submarines, U-boats of the time could not stay submerged indefinitely. U-boats operated on the surface using diesel engines and operated submerged on batteries, lacking a snorkel for submerged diesel operations. Battery operation limited submerged travel distance to approximately 100 nautical miles before three hours of surface transit were required to fully recharge the batteries. This meant U-boats surfaced often during any transit of the Bay of Biscay thus increasing the ability of Allied aircraft to locate and potentially destroy U-boats.

3.1 Previous Analyses

The first analysis of the Bay of Biscay campaign was written in 1946 shortly after WWII (not cleared for publication until 1973). In this work, Waddington [39] details the efforts of the Operational Research Section (ORS) of the Royal Air Force Coastal Command in countering the U-boat threat. This work provides firsthand insight of how scientific techniques were applied to promote effective operational decisions - hence operations research. McCue [40] re-examined the WWII analyses using modern analytical techniques. Other interesting, and pertinent, works covering various aspects of the U-boat war include [41,42,43]. Our work is the first to apply agent-simulation to a Bay of Biscay analysis.

3.2 Benefits of Examining the Bay of Biscay Scenario

The historical record of the Bay of Biscay U-boat campaign is quite complete and detailed, a benefit in any modeling effort. The U-boat war was rich in measure versus countermeasure strategies. U-boats were four times faster on the surface than when submerged (approximately 10 knots versus 2.5 knots, respectively). However, U-boats were also much easier to detect, and thus attack, while surfaced. Nighttime surfacing abated much of the detection vulnerability, but pure nighttime surface operations provided too high a level of operational predictability. Finally, electronic devices, such as search receivers were just being introduced. While such receivers helped detect (and avoid) patrolling aircraft, the electronic signatures of these devices helped patrolling aircraft detect the U-boats. In other words, the Bay of Biscay was rich in game-theory considerations. Thus, the Bay of Biscay experience is an ideal choice for a game-theoretic study using an agent-based simulation model.

4. Agent Model Description and Methodology

The Bay of Biscay agent-based simulation was coded in JAVA to utilize its multi-threading capabilities [44] consider multi-threading a key characteristic of an agent model). Model design data pertaining to the historical record was researched and utilized in the following order of importance: 1) historical fact as found directly from sources credited to

Allied and German participants; 2) published studies directly related to the offensive search in the bay; 3) data derived from raw numbers in one or more of the credible sources; and 4) good judgment (operational expertise) when sources failed or contradicted [45].

4.1 Model Agents

There are two primary types of agents within the model: the Allied aircraft agent and the U-boat agent. Each type of agent reports to a commander: an Allied aircraft squadron commander and the German U-boat command. The agents act autonomously within the simulation although each instance of each type of agent share common attribute sets.

4.1.1 Aircraft Agents

Aircraft agents are assigned by their commander to a specific search area and within that search area employ a barrier search pattern (see Figure 1 discussion below). Each agent employs a set of predefined waypoints to implement the search pattern trajectory within the assigned sector. The aircraft agents travel at a rate of 120 knots and remain in the search pattern while fuel permits. Aircraft agents scan for surfaced U-boats within a visibility range and attack any U-boat detected. Aircraft attacking a U-boat will expend all on-board ordinances during that attack and return to base upon completion of the attack, and any damage assessment efforts.

Aircraft agent behavior follows a hierarchy of actions during each period of aircraft agent execution:

1. Attack U-boat;
2. search for U-boat;
3. determine fuel level;
4. move along current path.

If an aircraft is in attack mode, and within range of the U-boat target, the attack against the U-boat will commence. If the aircraft is not in range, the aircraft continues moving along the defined path to the target. If not in attack mode, the aircraft will search for U-boats. If a detection occurs, a path to the U-boat target is set, the aircraft switches to attack mode, and commences movement toward the U-boat target. Without detections, the aircraft will check its fuel status. If fuel levels are sufficient, the aircraft continues along its search or attack path trajectory; otherwise a path to home base is set and the plane commences its return to home base.

Some aircraft activities at home base are considered. Each aircraft agent schedules its next mission. A maintenance failure can potentially ground the aircraft for that day. Weather considerations additionally may ground the entire Allied aircraft fleet for the day.

4.1.2 U-boat Agents

U-boat agents move between their assigned ports and the open seas of the Atlantic using either battery power or diesel power. Battery power usage dictates submergence time, with fully charged batteries providing 100 NM of submerged range. Recharging requires three hours of surface time under diesel power. Battery charging and battery discharging rates are modeled as a linear function of elapsed time. U-boats communicate daily with the U-boat command, as was the historical experience. The U-boat command sets the fleet surfacing policies incorporated by each of the U-boat agents. U-boats leave with 30 days worth of supplies and fuel, although 25% of U-boats in the Atlantic are extended beyond 30 days to model the effect of the limited tanker U-boat resupply operations that occurred during the actual campaign.

U-boat behavior also conforms to a decision hierarchy during each period of U-boat agent execution:

1. Avoid contact with any searching aircraft;
2. check state of battery power;
3. conform to fleet surfacing policy; and
4. move along current path.

If surfaced, a U-boat will scan for a search aircraft and if aircraft are detected, the U-boat will commence submergence. If no aircraft are detected, the battery state is checked. If the U-boat is surfaced, with fully charged batteries, the U-boat can submerge. Conversely, if the U-boat is submerged, with fully depleted batteries, the U-boat can surface. Intermediate levels of battery charge results in the U-boat maintaining its current status (submerged or surfaced). A U-boat prepared for surfacing or prepared for submergence will do so based on current fleet submergence policies and the environmental state (day or night). Finally, the U-boat moves to the next point along its current path. The U-boat path is either a port-to-Atlantic or Atlantic-to-port path.

U-boat activities, while in the Atlantic or at its assigned captured port, are modeled as delays; convoy hunting period in the open seas of the Atlantic and maintenance/resupply period during their times within their home port.

4.2 Model Environment

The Bay of Biscay model explicitly accounts for day-versus-night operations. “Daytime” in the model is defined as the period between nautical sunrise and nautical sunset (nautical sunrise and sunset occur when the sun is 12 degrees below the horizon). Both aircraft and U-boat agents have detection sensors corresponding to the inverse cube law [40]. The inverse cube law states that detection probability varies with the inverse cube of the distance between seeker and target. Aircraft takeoff times are randomly distributed over each simulated day (24 hours), with at least 12 hours between each aircraft mission. Actual takeoff times employed ensure the correct proportion of aircraft operate during the daytime and during the nighttime; missions do not overlap daytime and nighttime operations. Maintenance cancellations occur stochastica lly based on historical break rates, grounding the aircraft for that day. Weather is modeled based on average weather conditions for the time period modeled. Weather cancellations affect the entire flying day and cancel all aircraft sorties for that day. U-boats remain in port 30–45 days whereupon the U-boats are assumed to return to combat operations. Allied attacks against U-boats experience 40% success during day hours and 11% success during night hours, which are again historically derived rates [40].

The search region modeled is a 200 x 350 square NM rectangular area within the heart of the Bay of Biscay further subdivided into 28 50 x 50 square NM non-overlapping search sections. Screen display discretized an 800 x 680 pixel screen display such that each pixel represented approximately 0.90 NM. Figure 1 provides a representation of the Bay on the left side, the search area as the overlaid rectangle, the individual search grids as expanded out from the search area, and on the right side a graphic of the barrier search pattern employed by each of the search aircraft. Further details on other search patterns that can be modeled can be found in [46].

4.3 The Game Theory Aspects

The Bay of Biscay campaign represents a competitive game with two "players" or agents, defined as the collective Allied aircraft search forces versus the collective of German U-boats. The Allied aircraft agents seek to maximize the number of U-boats detected, and hopefully destroyed. The U-boat agents want to minimize detection by Allied aircraft, and thus survive. The game is a two-person, zero-sum game.

The Allies had two pure search strategies available to them: search only by day, and search only by night. Daytime search was more effective than nighttime search and attacks were more lethal during the day. The Germans had two pure

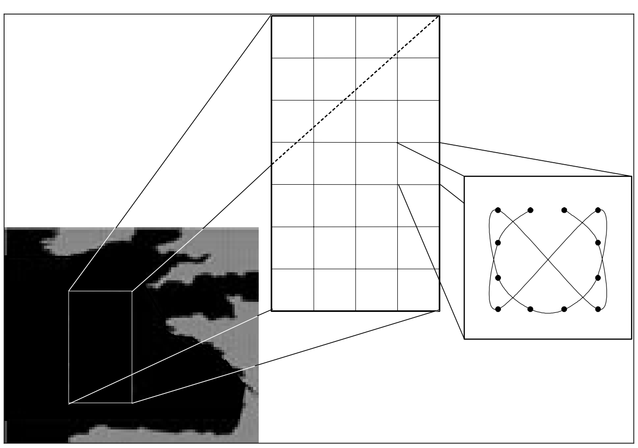

Figure 1. Collage of Bay of Biscay screen, search girds, and search pattern

surfacing strategies: surface only during day hours or surface only during night hours. Daytime surfacing was riskier than nighttime surfacing due to aircraft detection capabilities. The U-boats also were much faster surfaced than submerged, thus affecting the time required to transit the Bay. Any pure strategy by a side yields predictability in behavior, an advantage exploitable by the opposition. Thus, pure strategies are not particularly interesting especially if the strategies are strictly adhered to throughout the simulation.

Each side of a game wants unpredictability in its behavior. Therefore, when one formulates a mixed strategy game, the results are more interesting, especially when each side is allowed to adapt based on perceptions of strategy effectiveness in the model environment. This is the approach adopted in this research.

Each side starts with a day-versus-night strategy, defined as the proportion of effort during daytime hours and during nighttime hours for each time period. For aircraft, this is the proportion of search missions assigned to daytime hours. For U-boats, this is the proportion of surfacing to occur during daytime hours. A simple adaptation algorithm, based largely on sightings, allows commanders on each side to modify their strategy each time period (updates occurred at the end of each month within the six-month time period modeled). The algorithm for each side is similar and is presented below in a general fashion. Note, however, that sightings by an Allied aircraft need not equal sightings by a U-boat within any particular time period.

Define P^i_{day} as the proportion of effort (Allied search or U-boat surfacing) allocated to daytime operations in time period (month) i, with $P^i_{night} = 1 - P^i_{day}$). Next define S^i_{day} and S^i_{night} as sightings realized in time period i during daytime and nighttime operations, repsectively. Thus, total sightings for the period is defined as $TD^i = S^i_{day} = S^i_{night}$. Then,

(1) $$P^{i+1}_{day} = W_1 AVE^i_{day} + W_2 P^i_{day} + W_3 F^i$$

with the components defined as:

(2) $$AVE^i_{day} = \frac{1}{i}\sum_{t=1}^{i} P^t_{day}$$

(3) $$F^i = S^i_{day} / TD^i$$

(4) $$\sum_{j=1}^{3} W_j = 1$$

(5) $$P^{i+1}_{night} = (1 - P^{i+1}_{day})$$

Equation (1) produces a strategy for the next period based on three weighted components. Equation (2) provides an average of the preceeding daytime proportions, thus providing a smoothing effect. The second component is the current daytime proportion. The final component, defined in equation (3), provides a "projected" strategy based on the effectiveness of the current strategy as measured by the ratio of daytime sights to total sightings. Weight values of 0.25, 0.35, and 0.40, for W_1, W_2, and W_3 respectively, were employed in this study. Equations (1) - (5) calculate a projected strategy based on perceptions of current strategy effectiveness. More complicated adaptation algorithms are left for future research as is further work involving sensitivities to assigned values of W_i.

4.4 Defining the Game Agents

Criteria were previously provided defining an agent. Our agents encompass most of the criteria provided for both the characteristics of an agent and those of multi-agent systems. In Table 1 the applicable agent criteria previously listed is displayed with a short rationale for its applicability to our simulation entities. In a similar fashion, Table 2 lists the applicable multi-agent system criteria with a short rationale for its applicability.

Agent Criteria	Rationale
1	Decision hierarchy based on environment
3	Tendencies based on detection
4	Resources include fuel, engines, batteries, weapons
5	Environmental perceptions drive the detections
6	No entity has global knowledge
9	Each entity has specific objectives

Table 1. Agent criteria versus simulation entities employed

Agent Criteria	Rationale
1	Bay of Biscay environment includes weather, daytime, nighttime
2	Agents detect other agents, aircraft can destroy U-boats
3	Sets of agents exist on both sides
4	U-boat and aircraft agent actions effect one another
5	The agent decision hierarchy provides these operations

Table 2. Multi-agent criteria versus simulation entities employed

Our modeling framework and research involves sets of opposing agents, search aircraft versus U-boats. Agents within each set act to maximize their objectives, detections of U-boats for the aircraft and non-detections by aircraft for the U-boats. Each of these agents also make decisions regarding their actions based on environmental conditions and experiences. Thus, the agents within our simulation, and within this research, can also be deemed game agents.

5. The Experiment

Define the coordinates (P^i_{day} , P^i_{night}) for each one-month period in the simulation scenario. For Allied forces, these coordinates indicate search effort during the day and search effort during the night, while for U-boats, these indicate proportionate surfacing during the day and surfacing during the night. The period of history simulated is April 1943 through September 1943. This time represents a period of relatively stable technological advancements, making the period a logical choice for the day-versus-night, two-person game studied here. For each modeling scenario, a 12-month warm-up period was used to remove initialization bias due to random initial U-boat locations throughout the Bay of Biscay. Champagne [47] details how this 12-month warm-up yielded a distribution of U-boats in the Bay in agreement with historical U-boat density distributions. Preliminary studies indicated 20 replications of this initialization deletion approach provided sufficiently stable variances.

5.1 Scenario One—No Adaptation

Analytical game theory suggests that non-adaptive, opposing strategies lead to an equilibrium point in the fixed strategy coordinate space. With two factors, Allied strategy and U-boat strategy, and three levels, pure daytime, equally mixed daytime and nighttime, and pure nighttime efforts, a full 32-factorial design was executed. Table 3 contains the experimental points and simulation results. Figure 2 is the resulting surface discussed below.

5.2 Scenario Two—Adaptation

For the second scenario, both sides are allowed to adapt their strategies using the algorithm in (1)-(5). Three design points and the corresponding results are depicted in Table 4.

Design Point	Allied Strategy	U-boat Strategy	U-boat Detections
1	(1,0)	(1,0)	275.10
2	(1,0)	(0.5, 0.5)	233.45
3	(1,0)	(0,1)	0.00
4	(0.5, 0.5)	(1,0)	77.45
5	(0.5, 0.5)	(0.5, 0.5)	273.80
6	(0.5, 0.5)	(0,1)	146.20
7	(0,1)	(1,0)	0.00
8	(0,1)	(0.5, 0.5)	374.65
9	(0,1)	(0,1)	746.75

Table 3. Scenario one design and results

Three points are actually sufficient in scenario two since regardless of the starting strategy employed, adaptation yields convergence to similar strategies. These three points also represent interesting initial conditions: two pure opposing strategies, and a mixed strategy.

Design Point	Allied Strategy	U-boat Strategy	Allied Ending Strategy	U-boat Ending Strategy	U-boat Detections
1	(1,0)	(0,1)	(0.542, 0.458)	(0.164, 0.836)	183.75
2	(0.5, 0.5)	(0.5, 0.5)	(0.522, 0.478)	(0.259, 0.741)	182.60
3	(0,1)	(1,0)	(0.625, 0.375	(0.327, 0.673)	180.45

Table 4. Scenario two design and results

6. Discussion of Results

At first glance the empirical results of Figure 2, an equilibrium point at Allied strategy, (0.699, 0.301) and U-boat strategy, (0.534, 0.466) seems unbalanced and illogical. However, this emergent behavior result actually agrees with history. During the months simulated, April 1943 through September 1943, the Bay of Biscay location provides 16 hours of daytime, or 66% of the total 24-hour period. Historically, the Allies allocated search effort in proportion to daylight hours thereby forcing the U-boat command to adopt an equal level of effort between day and nighttime surfacing, which is observed in the simulation results. The values realized in the simulation nearly perfectly align with the proportion of daylight as an artifact of the model assumption that all aircraft search strictly daytime or strictly nighttime.

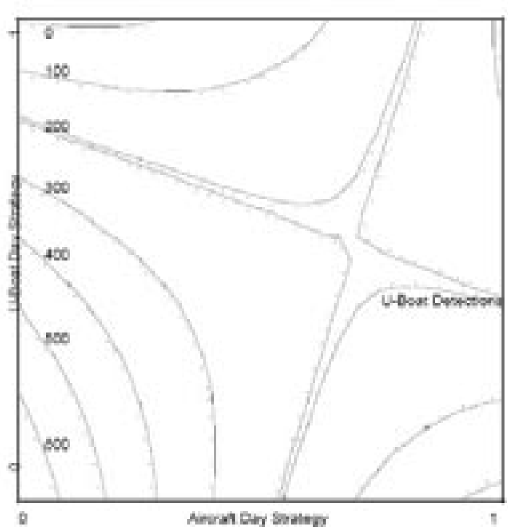

Figure 2. Contour plot of scenario one with equilibrium point

If both players are allowed to adapt, we should continue to see convergence to some equilibrium point. The data show that each side did in fact converge to a mixed strategy. The average ending strategies for the aircraft are very close to an equal distribution of effort, while for the U-boats the ending strategies favored nighttime surfacing when U-boats were less vulnerable. As far as the historical record, Allies adopted a balanced force concept to make it equally dangerous for U-boats to surface during both day and night. "Great emphasis was placed on the necessity for a properly balanced force, capable of attacking throughout the twenty-four hours" [39]. Looking at a time series graph for the first design point (Figure 3) and third design point (Figure 4), both from scenario two, depicts the quick convergence to the stabilized points. The U-boat side uses surfacing both night and day, although favoring nighttime surfacing, thereby forcing the Allies to continue their search effort around the clock, not allowing them to focus on one particular part of the full day.

7. Summary and Concluding Remarks

This paper presents research that coupled agent-based simulation with game theory to examine a data-rich historical combat scenario: the U-boat war in the Bay of Biscay. Our results show promise. First, like traditional simulation methods, an agent-based simulation can accurately represent a historical combat scenario. Second, as with other computer-based empirical approaches to game theory, an agent-based model can produce results consistent with game theory predictions of equilibrium points. Finally, a simple adaptation algorithm, that incorporates past behaviors and agent-based predictions of improved behavior, can find equilibrium points in competitive games as predicted by the theory.

The promise of agent-based modeling for military combat simulation still is largely unfulfilled. Agent-based models purport to bring new modeling capabilities to capture human behavior more accurately and to capture the non-linear interactions among combat agents so often found in warfare. However, agent-models for combat analyses, in general, are still largely focused on one-on-one modeling (i.e., shooter-versus-shooter). Our research not only couples agent-based modeling and game theory for the first time in a combat analysis context, but the model also represents an initial effort at modeling longer time-frame, force-versus-force, combat campaigns within an agent-based modeling paradigm.

Future research avenues abound. The Bay of Biscay historical record is full of game theory components; for

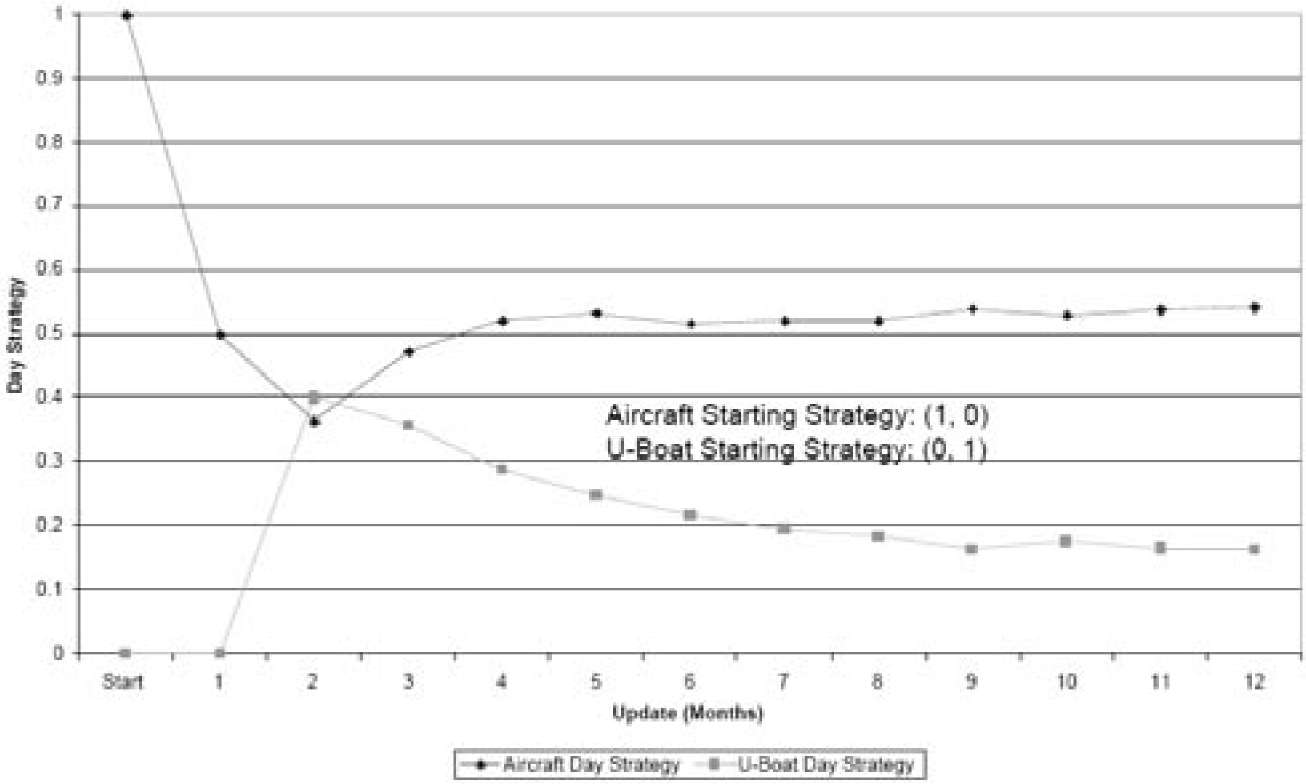

Figure 3. Two-player adaptation, design point 1

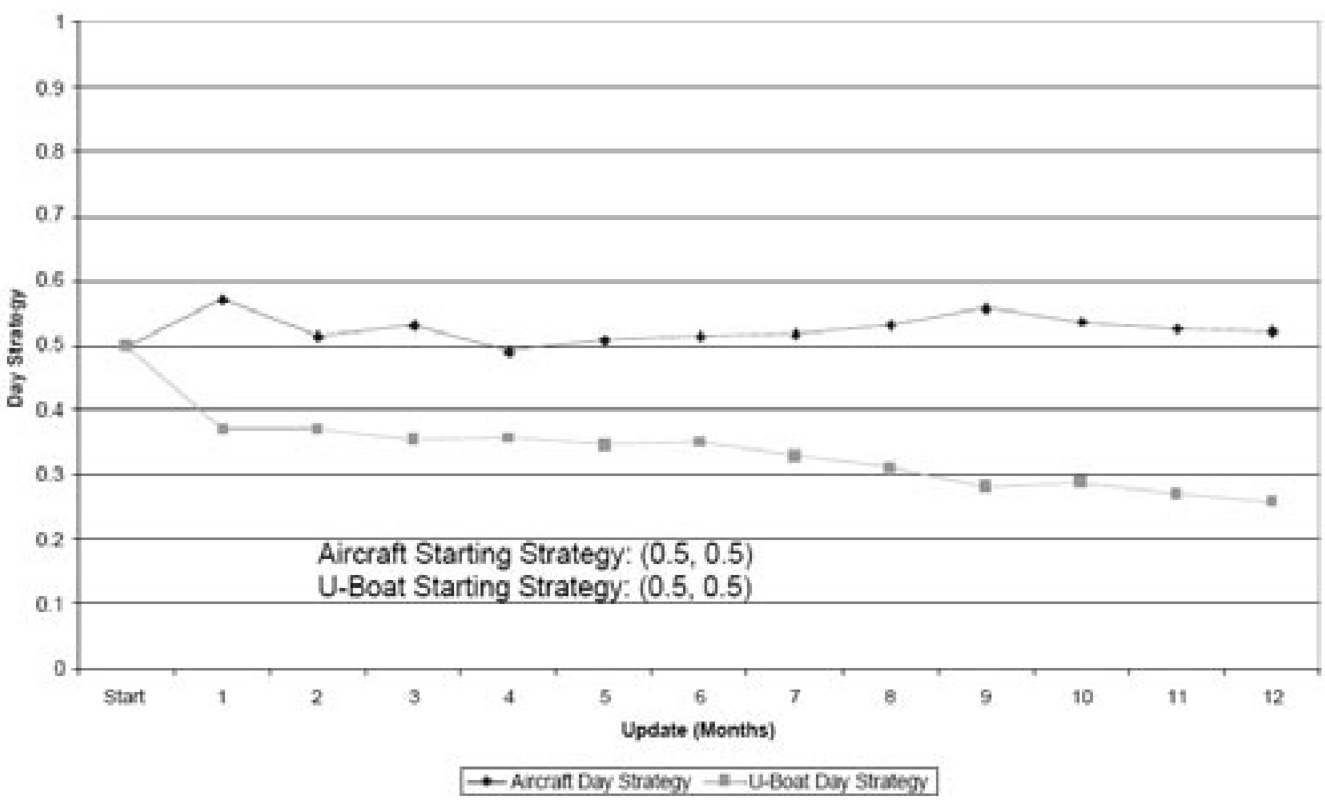

Figure 4. Two-player adaptation, design point 3

instance how new technology was countered with improved operational tactics, and the reverse. Expansions of our efforts to accommodate the modeling of such innovations, backed by the historical record, provide a means to gain experience which can then be applied to more modern applications in areas such as illegal immigration, drug smuggling (both aircraft and watercraft approaches), treaty verification, missile hunting, and possibly even chemical weapons production search efforts.

The goal, of course, is to eventually create models and simulations that provide better bounds on the range of potential outcomes as they pertain to various types and manners of conflict. However, until models adequately capture human capabilities, such as adaptation, attaining such bounds are likely unrealizable.

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