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Modeling the Decision Process of a Joint Task Force Commander

John Anthony Sokolowski
Old Dominion University

MODELING THE DECISION PROCESS OF A JOINT TASK FORCE COMMANDER

by

John Anthony Sokolowski
B.S. December 1974, Purdue University
M.E.M. May 1998, Old Dominion University

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Approved by:

Mikel D. Petty (Director)

R. Bowen Loftin (Member)

Frederic D. McKenzie (Member)

Gary E. Luck (Member)

Joseph Psotka (Member)

ABSTRACT

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John Anthony Sokolowski
Old Dominion University, 2003
Director: Dr. Mikel D. Petty

The U.S. military uses modeling and simulation as a tool to help meet its warfighting needs. A key element within military simulations is the ability to accurately represent human behavior. This is especially true in a simulation's ability to emulate realistic military decisions. However, current decision models fail to provide the variability and flexibility that human decision makers exhibit. Further, most decision models are focused on tactical decisions and ignore the decision process of senior military commanders at the operational level of warfare. In an effort to develop a better decision model that would mimic the decision process of a senior military commander, this research sought to identify an underlying cognitive process and computational techniques that could adequately implement it. Recognition-Primed Decision making (RPD) was identified as one such model that characterized this process. Multiagent system simulation was identified as a computational system that could mimic the cognitive process identified by RPD. The result was a model of RPD called RPDAgent. Using an operational military decision scenario, decisions produced by RPDAgent were compared against decisions made by military officers. It was found that RPDAgent produced decisions that were equivalent to its human counterparts. RPDAgent's decisions were not optimum decisions, but decisions that reflected the variability inherent in those made by humans in an operational military environment.

This thesis is dedicated to Marsha, Amy, and Whitney for all their patience, understanding, and love.

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TABLE OF CONTENTS

Section | Page

1 INTRODUCTION . . . 1
- 1.1 Thesis Statement . . . 1
- 1.2 Problem Statement . . . 1
- 1.3 Motivation . . . 3
- 1.4 Approach . . . 7
- 1.5 Contributions . . . 8
- 1.6 Dissertation Organization . . . 8

2 BACKGROUND . . . 10
- 2.1 Decision theory . . . 10
- 2.2 Military decision making . . . 26
- 2.3 Computational techniques for implementing the CJTF decision process 31
- 2.4 Summary of the state-of-the-art . . . 50

3 RESEARCH PROJECT . . . 53
- 3.1 RPDAgent design and implementation . . . 53
- 3.2 Validation methodology . . . 80
- 3.3 Data analysis and results . . . 88

4 CONCLUSION . . . 97
- 4.1 Future work . . . 98

5 REFERENCES . . . 100

APPENDICIES

A RPDAGENT COMPUTER DISK . . . 108

B DECISION SCENARIO AND ASSOCIATED DATA . . . 109

C ODU IRB INFORMED CONSENT DOCUMENT . . . 118

D PERSONALITY MEASUREMENT QUESTIONNAIRE . . . 121

Section Page

E TURING TEST INSTRUCTIONS 123

VITA 126

LIST OF TABLES

Table		Page
1	Example utility values	13
2	Kahneman decision experiment	15
3	Roles and associated agent classes	55
4	Hydrography cue structure	60
5	Goal evaluation example	68
6	Location cues and associated environmental variables	76
7	Location goals and associated cues	77
8	Location actions and associated environmental variable values	78
9	Timing cues and associated environmental variables	79
10	Timing goals and associated cues	80
11	Timing actions and associated environmental variable values	81
12	Change cues and associated environmental variables	81
13	Change goals and associated cues	81
14	Change actions	82
15	Continue cues and associated environmental variables	82
16	Continue goals and associated cues	82
17	Continue actions	83
18	Hypothesis and test statistics for significance testing	87
19	Role player location decision results	89
20	Role player timing decision results	89
21	Role player change decision results	90
22	Role player continue decision results	90
23	Location decision descriptive statistics	91
24	Model location decision results and analysis	91

Table		Page
25	Timing decision descriptive statistics	92
26	Model timing decision results and analysis	92
27	Change decision descriptive statistics	92
28	Model change decision results and analysis	92
29	Continue decision descriptive statistics	92
30	Model continue decision and analysis	92
31	Equivalency test summary	93
32	Turing test results	95

LIST OF FIGURES

Figure		Page
1	Decision under risk	11
2	Utility function	13
3	Recognition-Primed Decision Model	22
4	The decision-making cycle in the OODA model [36].	28
5	Processes, data flows, and feedback loops in the OODA model [38].	29
6	Finite State Machine structure	32
7	Expert system structure	34
8	Neural Network Architecture	38
9	Composite Agent [64].	45
10	Hydrography fuzzy sets	61
11	RPDAgent UML class diagram	64
12	Goal: Accomplish Mission fuzzy sets	69
13	Complete RPDAgent UML class diagram	72
14	One-sided hypothesis tests for significance testing [92]	87
15	Map of Joint Operations Area (JOA)	113

1 INTRODUCTION

1.1 Thesis Statement

Multiagent system simulation technology can be used to implement the cognitive decision-making process described by the Recognition-Primed Decision model. Further, one can employ this implementation to model the decisions made by a Joint Task Force Commander at the operational level of warfare.

1.2 Problem Statement

To maintain its warfighting capability, the United States Department of Defense (DoD) must train its personnel; it must continue to analyze and refine its war plans and operating strategy; it must design, procure, and test new weapons systems; and it must experiment with new warfare concepts to maintain its military advantage in a rapidly changing world. The cost to accomplish these tasks on a recurring basis, in terms of using actual combat personnel and equipment, has become prohibitive [1]. To reduce personnel and operational costs, DoD has sought to replace many of these tests and exercises involving live equipment and personnel with computer simulation. To ensure effective results in the above areas, these simulation systems must accurately portray the battlespace. Included in the simulated battlespace are not only the physical equipment such as tanks and airplanes, but also the humans who must make many decisions in the course of carrying out their warfare responsibilities.

Human behavior representation (HBR) in military simulations has received much attention ever since the National Research Council published its comprehensive review of HBR modeling in military simulation systems [2].[1] This review covered many aspects of HBR including individual and group behavior, human decision-making, memory and learning, situational awareness, and planning. Germane to this research

[1]Citation and reference list format for this manuscript are taken from the journal *SIMULATION: Transactions of the Society for Modeling and Simulation International.*

were their findings in the area of decision modeling. Specifically, they found that decision models within military simulations were too stereotypical and too homogeneous. In their words:

> "First, the decision process is too stereotypical, predictable, rigid, and doctrine limited, so it fails to provide realistic characterization of the variability, flexibility, and adaptability exhibited by a single entity across many episodes. Variability, flexibility, and adaptability are essential for effective decision making in a military environment ... Second, the decision process in previous models is too uniform, homogeneous, and invariable, so it fails to incorporate the role of such factors as stress, fatigue, experience, aggressiveness, impulsiveness, and attitudes toward risk, which vary widely across entities."

The shortfall in military decision modeling is especially evident at the operational level of warfare.[2] While many decision models exist for the tactical level of warfare, very few military simulations model any type of decision-making at the operational level. Most obvious is the lack of a model for the decision-making of senior military commanders such as the commander of a Joint Task Force (CJTF).[3] In simulation exercises, human role players make CJTF decisions and then manipulate the simulation system to carry out orders generated by the decisions. In a large military exercise where simulation is the primary representation of military forces in the field, several hundred role players are required to produce and to carry out these decisions. This manpower requirement significantly adds to the cost of an exercise [5].

[2] There are three levels of warfare within the U.S. military. The strategic level of warfare refers to national military objectives and theater war plans. The operational level of warfare is concerned with planning, conducting, and sustaining campaigns and major operations to achieve strategic objectives. The level at which battles and engagements are planned and executed is called the tactical level of warfare [3].

[3] A Joint Task Force Commander is typically a two or three star admiral or general from one of the military services who commands military forces from two or more services that are jointly working to achieve military objectives [4].

One reason that an adequate decision model for a senior military commander is not available is the lack of a complete understanding of how people make decisions. Michael Bauman, Director of the Army Training and Doctrine Command Analysis Center put it this way: "We cannot represent how humans make decisions. If we understood how people make decisions, we could tailor simulations and training to enhance people's abilities [6]."

To solve this decision modeling problem, much research has been conducted not only on how humans make decisions, but also on how to represent the decision-making process in a computational form. A survey of this research is presented in Section 2 of this manuscript. This dissertation furthers decision modeling research by developing a computational model of the decision process of a CJTF based on cognitive decision theory and multiagent system simulation techniques. It is important to note that this model is not intended to produce optimum decisions for a given situation (although it may). Instead, it is meant to mimic a human's cognitive decision process and thereby produce realistic and possibly suboptimum decisions.

1.3 Motivation

This portion of the dissertation serves two purposes. First, it describes the role of a CJTF in modern warfare so the reader has a clear understanding of why CJTF decisions are important. Second, it draws on the CJTF's role to explain the motivation behind developing a computational model of his[4] decision process.

1.3.1 Joint doctrine and the CJTF

The Goldwater/Nichols Act of 1986 [7] mandated that U.S. warfare at all levels no longer be fought along separate Service (Army, Navy, Air Force, and Marine Corps) lines. Instead, U.S. military operations would be "joint", combining forces from

[4]Throughout this paper "he" and "his" are not gender specific but refer to both sexes.

different services to suit the situation. This was a significant shift in the way U.S. forces would carry out their wartime missions. Before Goldwater/Nichols, a military commander had no operational forces directly assigned to him. He had to request support and permission to carry out his wartime tasks from each Service. After this congressional act, a CJTF was given direct command authority over those forces.

To illustrate this dramatic shift, consider the command structure for the invasion of Panama, which was the first significant U.S. military action to employ the new Joint Task Force (JTF) organization. General Maxwell Thurman, Commander of the U.S. Southern Command, took advantage of his power under the Goldwater/Nichols act to select Lieutenant General Carl W. Stiner, U.S. Army, and the Commander of the XVIIIth Airborne Corps, to command a JTF of 22,000 Soldiers, 3,400 Airmen, 900 Marines, and 700 Sailors. The result was a force with unity of command and good interoperability, which would rapidly achieve its operational objectives of protecting U.S. citizens in Panama and maintaining the Panama Canal free of Noriega's control [8].

To further joint concepts, U.S. Joint Forces Command, which evolved from the U.S. Atlantic Command, was assigned the mission of developing joint doctrine for the Chairman of the Joint Chiefs of Staff and was tasked to train CJTFs and their staffs in the area of joint warfare [4, 9].

JTFs, made up of forces from two or more services, are now formed to handle most types of military operations, from peacekeeping to major theater war. A JTF exists long enough to accomplish its assigned mission and to transition control back to civil or political authorities. Its size varies depending on the assigned mission.

At the head of a JTF is the CJTF. He is charged by the National Command Authority (President, Secretary of Defense, and theater commander) to translate strategic guidance into operational level warfighting decisions. He is supported in his planning and decision-making by a JTF staff composed of hundreds of officers and enlisted personnel who are drawn from each Service. A CJTF can come from any of the Services but he will have been specifically trained in joint warfare policy and doctrine. The JTF staff provides the operational planning support and situational assessment necessary to enable the CJTF to make military decisions that tip the scale of victory in his favor.

A CJTF makes hundreds of decisions in the course of his assignment as the leader of a JTF. These decisions span a large domain from those of a strategic nature to those of an operational type. At times, they even venture into the tactical area although tactical decisions are not usually the norm. He is assisted with his decision-making by the JTF staff. One of the staff's jobs is to develop multiple courses of action (COAs) for the CJTF to consider before choosing the most appropriate one. For example, suppose a CJTF is faced with the decision of when to conduct an amphibious assault. His staff may propose the following COAs:

- COA 1: Attack immediately to gain the element of surprise even though only 85% of the required troops are in place to support the assault. The staff judges this as an acceptable risk.

- COA 2: Wait 96 hours until 95% of the troops arrive. Intelligence estimates that there is a 50% chance the enemy will be alerted to the assault by that point.

- COA 3: Build up additional forces over the next week to 100% strength and keep the enemy guessing as to when the assault will occur.

This decision is typical of those that a CJTF faces. Joint doctrine specifies a methodical approach to developing these COAs [4]. COA development generates and examines two or more solutions to a problem, establishes the pros and cons of each solution, and makes a recommendation to the CJTF on which COA to choose. However, there is no doctrine or training for the CJTF on how to choose the best

COA. How he makes the decision is left up to his years of military experience and his personal assessment of the situation. Modeling this personal decision process is the subject of this dissertation.

1.3.2 Motivation for modeling the CJTF

The U.S. military relies heavily on constructive simulations[5] to train its JTF staffs and their supporting Service components. Unfortunately, they only receive training about once every two years. These staffs and the CJTF are drawn from the Services. The commander that would normally act as the CJTF has many other duties that must be carried out, which precludes him from being available to conduct JTF training on a regular basis. If a computer model of a CJTF existed, then the staffs would be able to conduct JTF training more frequently because the computer could play the role of the CJTF when he was not available.

Besides training, military simulations are used for COA analysis and for experimenting with new warfighting doctrine.[6] To achieve realistic analysis and to validate new doctrinal concepts, a CJTF decision model must produce decisions that are typical of an experienced CJTF as opposed to generating non-doctrinal or artificially optimized decisions. As noted earlier, military simulations have not measured up to this demand. Because of this, the quality of simulation-based training, analysis, and experimentation has suffered [6, 11, 12]. The military community would greatly benefit from improved models of CJTF decision-making within constructive simulations.

[5]A constructive simulation can be thought of as one or more computer-generated forces acting against other computer-generated forces as opposed to a virtual simulation where a human interacts with computer entities. For example, a flight simulator, where a real pilot flies a simulated aircraft, is a virtual simulation. A computer war game where one set of computer-generated entities fights against another set is considered a constructive simulation [10].

[6]Training simulations take the place of live military forces so that a commander can train a CJTF and his staff at a reduced cost and with more robustness than if live forces were used. Analytical simulations are used to help refine war plan scenarios, to predict the outcome of specific military maneuvers, and to conduct mission rehearsals for pending operations. Simulation supports experimentation by providing a venue for testing new warfighting concepts.

1.4 Approach

This research formally sets forth an architecture for a multiagent system (MAS) simulation that implements the cognitive decision process described by Recognition-Primed Decision (RPD) Making as used by a CJTF. RPD was evaluated as the cognitive decision model closest to representing the CJTF decision process. RPD has as its base the premise that a decision maker, who is an expert in his area, relies heavily on his past experience to interpret a current decision situation, to recognize, in an intuitive manner, what decision must be made, and then to assess that decision to ensure it fits the context of the current situation.

RPD attempts to capture the intuitive interactions that go on inside the human brain as decision situations are being evaluated. The RPD process was captured with a MAS design, hereafter known as *RPDAgent*, by using agents to simulate the various steps involved in RPD. The agents within the simulation interact to assess the situation, draw on past experience to produce potential decisions, and evaluate those decisions against competing goals that must be satisfied.

Capturing an expert's past experience was a crucial part of implementing RPD in a computational form. A data structure was developed to represent the key concepts of the decision recognition process, to capture a human's internalization and interpretation of his environment, and to represent a personal evaluation process of potential decisions against the goals that he is trying to achieve.

For a model to produce credible results, it must be validated. RPDAgent was validated using a decision scenario typical of the types of decisions facing a CJTF. The scenario was provided to a group of senior military officers, each playing the role of a CJTF. The same decision scenario was provided to RPDAgent. The set of role player decisions was then statistically compared to the model decision set to evaluate validity. As a final measure of validity, a set of role player decisions and a set of model decisions were presented to senior military officers who had previously commanded a JTF. They were asked to distinguish between the model results and the human results.

The approach described above was intended to produce a model capable of mimicking the decision process of a senior military commander. The model was not meant to produce optimized decisions, but rather to follow, as closely as possible, the sometimes imperfect decisions produced by humans who are the experts in their field.

1.5 Contributions

This dissertation provides a new approach to modeling the cognitive decision process of a decision maker experienced in his particular decision domain. The following are the specific contributions of this research:

- A computational model of the RPD process capable of mimicking decisions made by experts in their field. It is not limited to the military domain.
- A data structure capable of modeling a person's past situational experience, of capturing a human's internalization and interpretation of his environment, and of capturing personal preferences for evaluating potential decisions against possibly conflicting goals.
- A model capable of explaining its reasoning process rather than produce a "black box-type" decision with no explanation of how the decision was made.
- An experimentally validated implementation of a model of CJTF decision-making for a class of operational decisions.

1.6 Dissertation Organization

The remainder of this dissertation is organized as follows:

- **Section 2. Background.** This section surveys research on decision theory, military decision-making, and computational methods available to implement cognitive decision model. Work that is most relevant is described in detail.
- **Section 3. Research Project.** This section provides an in depth description of the research including project design, validation methodology, data analysis, and research results.
- **Section 4. Conclusions and Future Work.** This dissertation concludes with a summary of the research results and a description of follow on work that could be undertaken to expand upon the basis of this effort.

2 BACKGROUND

This section provides a survey of past research relevant to this dissertation. It begins with a review of pertinent decision theory research and is followed by a description of the decision process currently employed by the military. It ends with a comprehensive evaluation of techniques available to implement cognitive decision models in a computational form.

2.1 Decision theory

This part describes the research that has taken place to model decision-making. It begins with a review of classical decision theory and its associated concepts. It is followed by discussion of a competing theory called *Naturalistic Decision Theory*. These two theories are the leading models of the human decision process.

2.1.1 Classical decision theory

People in all walks of life have realized the importance of the decisions they make. This is especially true where high stakes decisions are prevalent such as in the military, law enforcement, and the medical field. Much research has been devoted to understanding the human decision process. Classical decision theory is the result of many efforts.

Classical decision theory is the collection of axiom-based models of uncertainty, risk, and utility that provides a method to make an optimal decision from among an array of choices. The underlying model and its explicit rule that maximizes a decision maker's payoff defines optimality. Two mathematical models have characterized classical decision theory, one of uncertainty and risk called expected value theory, and one of utility, which includes subjective expected utility and multi-attribute utility theory [13]. Both models had their origins in the economical and statistical methods that von Neumann and Morgenstern used to describe optimal decision making in these fields [14]. These models do not concentrate on the outcome of the decision but

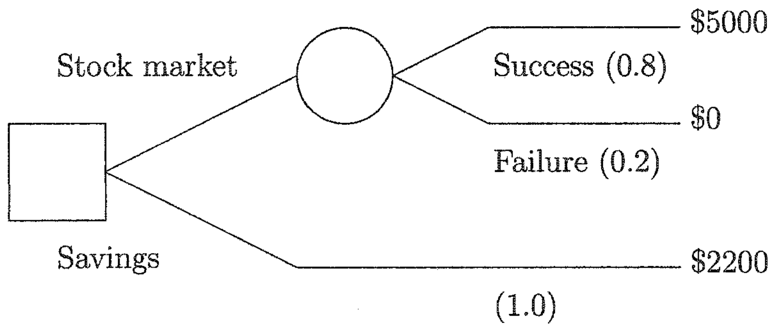

Figure 1. Decision under risk

rather on the logical process used to derive the decision. These models assume that a decision maker always acts in a logical or rational manner. Therefore, the formulas associated with these theories will always produce mathematically optimal decisions with respect to the available information.

Decisions under risk strictly use probability to calculate the optimal decision. They are most often described using monetary decision examples [15]. Figure 1 shows a classic decision tree used to represent a decision under risk. The decision is whether to invest a certain amount of money in the stock market or place the money into a savings account. The example shows that if the decision is made to place the money in a savings account, there is a sure payoff of $2200. If the money is invested in the stock market, there is a certain probability of either receiving $5000 or completely losing the investment. To calculate the payoff of this decision, one uses the expected value method.

$$\textit{Expected value} = (0.8)(5000) + (0.2)(0) = \$4000$$

Therefore, the logical decision would be to invest the money in the stock market with an expected payoff of $4000.

The above example is purely a probabilistic calculation. It does not take into account a decision maker's personal risk tolerance. Even with a probability of 0.8, an individual may not be willing to take the chance of loosing all his investment. However, expected value calculations do not account for personal risk tolerance.

Von Neumann and Morgenstern [14] saw this shortcoming in expected value theory. To account for personal risk, they transformed decision outcomes or consequences into utilities. A utility is a personal assessment of how much a particular payoff is worth to an individual, not in terms of money, but in terms of a numerical scale from 0 to 1. Thus, *Subjective Expected Utility (SEU) Theory* came to include both subjective probabilities about the uncertainty of an outcome and a decision maker's propensity for risk for that outcome. Each decision maker has a unique function that assigns a utility to each possible outcome of the decision for every decision he faces. Combining this function with a subjective probability of an outcome yields an SEU value:

$$SEU[A_i] = \sum_k P_{ik} U(C_k) \tag{1}$$

where $[A_i]$ is a particular alternative and P_{ik} is the subjective probability of encountering consequence C_k given alternative A_i. Using the example of Figure 1, stock market and savings are the two alternatives. If the stock market alternative A_1 is chosen, then there are two possible consequences: getting \$5000 (C_1), or losing all money (C_2). The probability of receiving \$5000 given that the stock market was chosen (P_{11}) is 0.8. A similar statement can be made for the failure event. The SEU function is very similar to the one used in calculating expected value. They are equivalent if the utility function and the value function are identical.

The shape of an individual's utility function describes his propensity for risk for a given decision. For any point on the function, a person's attitude toward risk is formally defined by the coefficient of risk aversion [16]:

$$C_{RA} = \frac{U''(C_k)}{U'(C_k)} \tag{2}$$

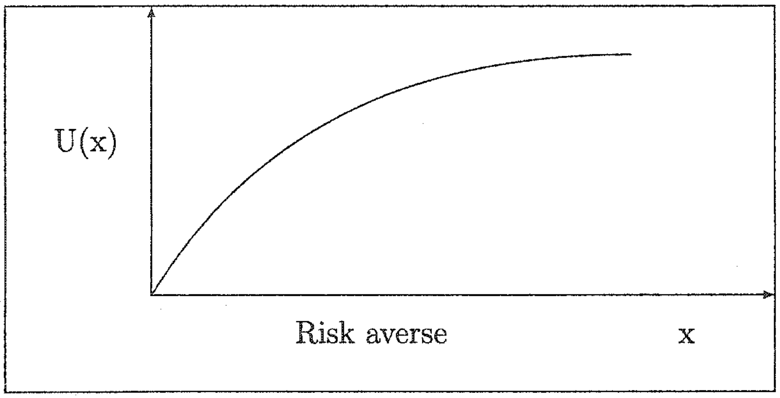

Figure 2. Utility function

Table 1. Example utility values

Choices	Probability(P_{ik})	Payoff(C_k)	Utility($U(C_k)$)
Stock Market	0.8	\$5000	0.90
Savings	1.0	\$2200	0.75

where $U'(C_k)$ and $U''(C_k)$ are the first and second derivatives of the utility function. If $C_{RA} < 0$ then a person is risk averse; if $C_{RA} > 0$, a person is said to be risk seeking. Figure 2 depicts a risk averse utility function. To illustrate the effect of personal risk bias, the monetary outcomes from the above example will be replaced by the decision maker's utility value for each of those outcomes.

Table 1 contains these values for this decision. Using equation (1) to calculate SEU for the stock market choice verses the savings choice yields:

$$\begin{aligned} SEU(stock\ market) &= (0.8)(0.9) + (0.2)(0) = 0.72 \\ SEU(savings) &= (1.0)(0.75) = 0.75 \end{aligned}$$

with the decision maker being risk averse, even though the expected value indicates the stock market is the appropriate choice, he is not willing to risk the loss of a sure \$2200. Other decision makers may have different utility functions and thus can arrive at different conclusions. Under utility theory, the payoffs or consequences need not be monetary. One can just as easily map qualitative results to utility values and calculate an SEU.

Multiattribute Utility Theory (MAUT) is an extension of SEU that takes into account multiple objectives of a decision maker [17]. In the above stock market example, the decision maker was only concerned with one payoff or consequence value. The utility function had only one independent variable to map to a utility. With MAUT, the utility function can accept multiple variables to calculate a utility value. For example, a decision maker may be concerned with soldier safety, mission accomplishment, and equipment losses. In the simplest case, the utility function would be a weighted addition of individual utility values given by:

$$u(x_1 \ldots x_n) = \sum_n k_n u_n(x_n) \tag{3}$$

where each constant k_n is a weighting factor for each u_n. More complex utility functions can be readily constructed. They are useful when two or more utility variables are interdependent.

Classical decision theory assumes that decisions are made in a prescriptive manner. By *prescriptive* it is meant that a decision maker always makes decisions in a rational way. Assumed in this concept is that classical decision theory is descriptive of how humans actually make decisions. However, as shown by Kahneman and Tversky [18], decision makers rarely behave in a prescriptive manner. They conducted a controlled set of experiments where subjects were given several problems requiring them to make a decision between two payoffs. For example:

In the first problem, the majority of the subjects chose option B (82%). From SEU, this choice implies the following inequality:

$$u(2400) > .33u(2500) + .66u(2400) \; or \; .34u(2400) > .33u(2500)$$

Table 2. Kahneman decision experiment

Problem 1

Choice A	Choice B
\$2500 with probability .33 \$2400 with probability .66 \$0 with probability .01 [18%]	\$2400 with certainty [82%]

Problem 2

Choice C	Choice D
\$2500 with probability .33 \$0 with probability .67 [83%]	\$2400 with probability .34 \$0 with probability .66 [17%]

In the second problem, the utility calculation is as follows:

$$.33u(2500) > .34u(2400)$$

Behaving prescriptively, a decision maker would have made a decision consistent with the utility of the given payoff. However, as shown by this example and several others in Kahneman and Tversky's study, decisions made by humans do not usually match the decisions calculated by the formulas. Klein reported similar results in his study of decision makers who were experts in their fields [19]. If this is the case, then classical decision theory does not completely describe how humans make the majority of their decisions.

Subjective probabilities play a significant role in SEU and MAUT calculations. Each decision maker assigns his or her own estimated probabilities to the outcomes of a decision problem in a manner similar to the way they assign their own utilities to those outcomes. These probabilities are based on the person's belief of the likelihood of the outcome relative to the other outcomes. Tversky and Kahneman [20] showed that people employ a small set of heuristics, which help reduce the complex task of assessing probabilities to simpler judgmental processes. Unfortunately, these heuristics often reflect biases that subconsciously enter into the estimates and render them less than optimal.

The first heuristic they described is called *representativeness*, which helps estimate the probability that an event or object A belongs to group B. Here, people have a tendency to estimate membership based on a comparison to a stereotype representation of a group. They ignore prior probabilities of outcomes, disregard the effect of sample size, do not take into account the underlying random processes, base results on irrelevant favorable of unfavorable descriptions, rely on illusions of validity rather than on verifiable facts, and do not understand the concept of regression to the mean.

The second heuristic employed to simplify probability estimation is *availability*, which Tversky and Kahneman defined as "...the ease with which instances or occurrences can be brought to mind." The easier it is for a person to imagine representative cases, the easier it is for him to estimate a probability of occurrence. But, this heuristic can also lead to biases. The biases may be due to how easily an instance my be retrieved, the effectiveness of a search set, the decision maker's ability to imagine solution sets, and illusionary correlation or overestimation of the frequency of occurrence of naturally associated objects or processes.

The final heuristic is *adjustment from the anchor* or estimating an outcome based on its deviation from an initial state called the *anchor*. Biases here include insufficient adjustment and biases in the evaluation of conjunctive and disjunctive events. Studies have shown that people have a tendency to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events.

So while decision makers employ heuristics to help generate subjective probabilities associated with decision outcomes, the rules they follow have unsuspected biases that could lead to less than optimal decisions.

This section has reviewed the tenets of classical decision theory including expected value theory, SEU, and MAUT. These theories provided a normative and a prescriptive model for human decision-making. This theory assumed that all people made decisions in a logical and rational manner. However, decision makers more often than not behaved non-rationally. That is, they did not make decisions in the manner prescribed by this theory. There must be other underlying decision behaviors that affect the human decision process. Additionally, when estimating subjective probabilities associated with classical decision theory, one uses heuristics. Various factors can bias the probability estimates of these heuristics, leading to less than optimal decisions.

2.1.2 Naturalistic decision making

This section will introduce *Naturalistic Decision Making* (NDM) as a theory that describes the process used by experienced decision makers to arrive at satisfactory decisions. Unlike classical decision theory, it is not based on a mathematical process for computing optimal outcomes but on a psychological model of the intuitive steps a person follows in reaching a decision.

As was shown in the previous section, classical decision theory is centered on the decision event. The decision event included two or more courses of action (COAs) or choices and their associated subjective probabilities and utilities. It does not account for the decision maker's past experiences or how proficient he is at analyzing situations. In scenarios requiring rapid decisions, a person may not have time to evaluated multiple COAs, let alone generate them.

Indeed, evidence strongly suggests that experienced decision makers do not employ classical decision methods for the majority of their decisions [19, 21, 22, 23]. Instead, their approach to decision making differs from the classical method in at least three ways:

- Experienced decision makers expend a significant effort in assessing the situation presented.
- They evaluate only a single option but look at different aspects of that option

through mental simulation.

- A choice or option is accepted if it is satisfactory but not necessarily optimal.

The idea of satisficing vice optimizing decisions was first studied by Herbert Simon, a Nobel Prize winner in economics who observed how those in business made decisions [24, 25]. His work showed that most experienced business people chose alternatives that produced satisfactory, rather than optimal, outcomes because exact solutions to complex problems were most likely not attainable. He called the concept of simplifying problems to a level where one could obtain a solution *bounded rationality.* In addition, most decisions made by experienced decision makers are embedded in a series of tasks working towards a larger goal that is heavily dependent on the situation context. These tasks help define the situation and provide a framework in which a decision is made. The features of these tasks and a decision maker's knowledge and experience relative to the tasks govern decision performance [26].

As described above, decisions take place in naturalistic settings, i.e. situations that people face in daily life that cannot and should not be separated from the context that defines them. NDM is a theory that models a person's mental decision process in his natural environment. NDM has been formally defined as *the way people use their experience to make decisions in field settings* [27].

Researchers have identified eight factors that most often appear in naturalistic decision settings [26]. A decision maker is likely to employ the naturalistic process to arrive at a decision when one or more of these factors are present. These factors are:

- Ill-structured problems.
- Uncertain dynamic environments.
- Shifting, ill-defined, or competing goals.
- Action/feedback loops.

- Time stress.
- High stakes.
- Multiply players.
- Organizational goals and norms.

These factors help characterize a naturalistic decision situation and bear further explanation. The first three factors describe the ambiguity a person may face when confronted with a decision. A person may expend considerable thought just trying to understand the nature of the problem and gain insight into the context in which the problem exists. This is known as developing situational awareness[7] of the problem at hand. Understanding the decision situation may be complicated by an environment that is changing or one where the decision maker has incomplete or imperfect information. An end state or goal that is unclear or that is dynamically shifting may further complicate the decision problem.

The fourth factor attests to the idea that a decision is rarely just one event. There may be several decisions that are needed to reach a specific goal. Each one may influence the subsequent ones. Also, as a person gains situational awareness of a problem, the knowledge gained acts as feedback to help the decision maker to realize a satisfactory choice.

Time stress and high stakes are significant characteristics of naturalistic decision situations. Time pressure, in particular, forces a person to take what is known about a problem, match it with similar situations encountered in the past, and make a decision based on the outcome of a previous experience. This sequence is the heart of NDM.

[7]Situational awareness and situational assessment are sometimes used interchangeably. However, in this manuscript, situational awareness is defined as a state of knowledge while situational assessment is the process by which that knowledge is achieved [2].

The last two factors indicate the NDM encompasses group decision processes where organizational rather than personal goals influence the decision outcome. Individual team members may bring unique insight to a problem, which adds to the group situational awareness. The collective experience of the group can then lead to a decision that satisfies the situation.

The NDM theory can be characterized as a *decision cycle* where the decision maker assesses the situation, formulates a single COA, and tests the COA through a mental simulation process to check its outcome. If modifications to the COA are necessary, he makes them and rechecks the outcome. The cycle continues until the decision maker is satisfied that his chosen COA will solve the problem at hand. This decision cycle relies on the decision maker's ability to use his past experiences to recognize what action to take.

2.1.3 Recognition-Primed Decision Model

A naturalistic decision model that encapsulates this recognition principle is the *Recognition-Primed Decision Model* (RPD) put forth by Klein [21]. RPD elaborates on the naturalistic decision cycle to describe the cognitive process decision makers go through to arrive at a COA. There are seven features that set the RPD model apart from classical decision models [22]. They are:

- RPD focuses on situational assessment rather than comparing several decision options.
- RPD describes how people use their experience[8] to arrive at a decision.
- RPD asserts that an experienced decision maker can identify a satisfactory COA as the first one he considers rather than treating option generation as a random process.

[8]Experience includes the periodic situational encounters that reinforce a person's knowledge and any training that he may receive to improve his expertise.

- RPD relies on satisficing rather than optimizing—finding the first COA that works rather than the optimal one.

- RPD focuses on sequential evaluation of COAs rather than on the simultaneous comparison of several options.

- RPD asserts that experienced decision makers use mental simulation to assess a COA rather than comparing the strengths and weaknesses of several COAs.

- RPD allows the decision maker to be more quickly prepared to initiate action by committing to a COA being evaluated rather than waiting until all COAs are compared.

Decision makers tend to employ RPD in the following situations [19]:

- When time pressure for a decision is great, because only one COA is analyzed at a time and an optimum solution is not necessarily sought.

- When the decision maker is experienced in the decision domain. He has more life experiences to match against to recognize the situation and to choose a satisfactory COA.

- When the decision situation is more dynamic and changes before an analytical decision analysis can be performed.

- When goals are ill-defined, which makes it difficult for the decision maker to determine solution evaluation criteria.

These four situations have a direct relationship to the eight factors that characterize NDM, indicating that the RPD process is a valid example of NDM.

Figure 3 depicts Klein's model [19] of the RPD process. The process begins with the decision maker experiencing the situation and determining if it is familiar. If the situation is not familiar, he seeks clarification of the situation (improved situational

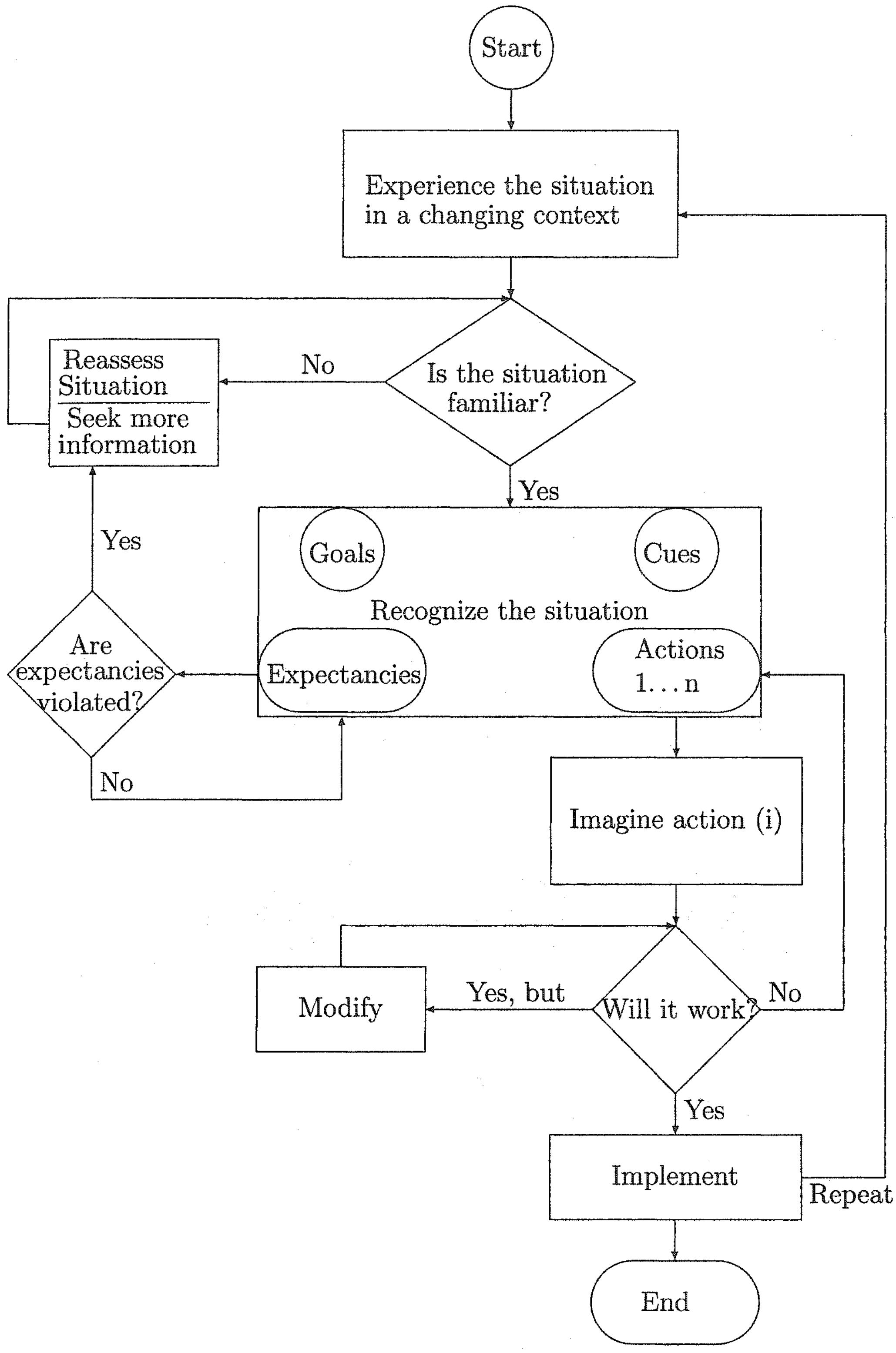

Figure 3. Recognition-Primed Decision Model

awareness) until he is able to match it with a similar experience. Once he recognizes the situation, he will be aware of four byproducts of this recognition: goals, cues, expectancies, and actions. He will be able to visualize an end state. If events contradict expectancies, the decision maker may reexamine his understanding of the situation. Once expectancies are consistent with the unfolding events, he will examine possible actions one by one. This is another key point of RPD. These options are not compared against one another but are evaluated on their own merits. Klein observed that experienced decision makers handled approximately 50 to 80 percent of all decisions in this manner [21]. As each action is examined, the decision maker mentally imagines (mentally simulates) how the action will achieve the goal. If he decides that the action will work, he accepts it as his decision and implements it. If, during his mental simulation, he decides that the action will work with modification, he mentally makes the modification, mentally simulates the modified action, and continues until the action is either accepted or rejected. If rejected, the decision maker must then choose another action and repeat this process. Since he is examining each action one by one rather than comparing actions against each other, he may not achieve an optimal decision, but will select one that he believes provides at least a satisfactory solution.

There are three key decision maker attributes that influence the use of the RPD model. The first is experience or expertise with the decision situation. The more experienced or familiar a decision maker is with the problem domain, the more likely he is to employ RPD to arrive at a decision [19, 21, 22]. An Army general CJTF is likely to have significant experience with land warfare and thus would have the background to formulate a decision in this domain using RPD. Conversely, a Navy admiral CJTF would feel less comfortable making a decision about land warfare without first gathering as much background information as feasible before deciding on a certain COA since he does not have the career experience in this area. He would be more likely to compare COAs using an analytical method to arrive at a decision than to recognize an appropriate COA based on his past experience. Or he would at least use the analytical method to gain insight into the problem before employing RPD to arrive at a decision [19].

The second key attribute is situational awareness (SA). In simple terms, SA is the decision maker's understanding of the context of the decision situation. A more complete definition was given by Endsley [28] as "...the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future." SA is directly coupled with experience[9] in that experienced decision makers expend more effort trying to understand the situation (gain SA) so that they can match the decision situation to previous experience as closely as possible [29]. Because they broader experience, the ability to pattern match between previous situations and the current situation sets experienced decision makers apart from novices [30].

Endsley [28] proposed a model of SA consisting of three levels:

- Level 1 SA—Perception of the elements in the environment.
- Level 2 SA—Comprehension of the current situation.
- Level 3 SA—Projection of future status.

These three levels bear further explanation. Level 1 is the first step in achieving SA. A decision maker must become aware of the status, attributes, and dynamics of key elements making up the decision situation. Once he understands these key elements, the decision maker is then able to synthesize disjoint elements into a holistic picture and relate it to his goals. This process constitutes Level 2. Level 3 SA occurs when a decision maker is able to take the current holistic picture and project the future actions of the elements based on the dynamics among the elements. Novice

[9]Experience includes both direct personal experience and indirect vicarious experience.

decision makers may be able to identify the key elements of a situation but it is usually only the experienced decision maker that can relate them to one another and to project a future outcome.

Endsley's view of SA is consistent with RPD. Level 1 SA directly relates to the first step in RPD, experiencing the situation in a changing context. It is through this experiencing of the situation that the decision maker begins to understand its context and its relation to past experiences. Level 2 SA is represented in RPD as the moment recognition occurs, i.e., the decision maker recognizes the situation and he becomes aware of the four byproducts of recognition mentioned earlier. Level 3 SA relates directly to RPD's expectancies and how the decision maker projects the situation will play out over the span of its relevancy.

SA can also be thought of as a bridge between perception and cognition [31]. Once a decision maker gains SA via the above three levels, he must translate it into reasoning, planning, and decision making (cognition), which reflect the action parts of the RPD model of Figure 3.

The recognition byproduct, cues, is an important part of experience and SA [30]. Cues are derived from both a decision maker's past experience and the context of the current decision situation gained through SA. Cues are the important factors of the current decision on which the decision maker is focusing. Cues act as a filter on the potentially vast amounts of data that may be reaching the decision maker and allow him to focus on only information that is critical to the decision. The use of cues by decision makers was noted many years earlier by Brunswick in his lens model of decision making [32] and extended by Brehmer and Hagafors in their study of staff decision-making [33] and Hollenbeck et al. in their study of team decision-making [34].

The third decision maker attribute, mental simulation, plays a significant role in RPD. Decision makers use mental simulation to help diagnose a situation. They imagine different aspects of a problem and form an explanation or mental picture of the problem. It also helps them decide whether the situation is familiar or not (pattern matching against previous experience) by mentally examining various aspects of the situation's elements. The end result of this portion of mental simulation is SA over the problem.

Mental simulation also helps generate and evaluate expectancies. It allows the decision maker to mentally examine events as they might occur so as to understand the end result of a particular option. He can also determine the accuracy of his mental simulation by checking how well his expectancies were satisfied. The fewer the number of expectancies satisfied, the less confident a decision maker would be about his mental simulation and diagnosis.

Once a decision maker has diagnosed the problem and generated expectancies, he uses mental simulation to sequentially evaluate solution options. Each option is mentally played out until one is found that satisfies the situation.

In summary, the RPD model is a naturalistic decision making model that explains how a decision maker uses his past experience and mental simulation to recognize a situation, develop expectancies about the situation, sequentially analyze COAs, and choose one that provides a satisfactory outcome.

2.2 Military decision making

The types of decisions that a CJTF makes can be summed up in two general categories. The first are decisions for selecting and executing military actions to achieve joint force objectives. The second are decisions regarding the allocation of resources to those actions [4]. To aid him in making these decisions, the Department of Defense (DoD) has adopted a set of steps known as the *estimate process* to help guide military commanders in COA analysis and selection [4]. The estimate process steps are as follows:

- Determination of the mission. This includes mission analysis where the National Command Authority's (NCA) guidance and objectives are taken into account and the generation of a mission statement that describes the essential tasks to be accomplished and the purpose to be achieved.

- Situational assessment and COA generation. COAs should outline an ordered set of operational tasks to be accomplished, the forces required, a logistics concept, a deployment concept, an estimate of time to achieve the objectives, and a concept for reserve contingencies.

- Analysis of opposing COAs. Determine the possible impact of enemy COAs on the success of each friendly COA. Develop a list of advantages and disadvantages for each friendly COA.

- Comparison of friendly COAs. Evaluate the advantages and disadvantages of each. Refine COAs as necessary.

- Decision. The CJTF chooses the best COA and implements it.

The estimate process provides a framework upon which more detailed planning steps are built. Specifically, the *Deliberate Planning* process and the *Crisis Action Planning* (CAP) process follow the outline of the estimate process. They are the formal processes the CJTF uses in his planning [35].

Deliberate planning is, as its name implies, a methodical procedure to assess and prepare for probable warfare contingencies that a CJTF faces in his theater of responsibility. Steps include initiation, concept development, plan development, plan review, and supporting plans. This type of planning takes place over several months and results in a general operational plan for the relevant contingencies.

CAP, on the other hand, spans a much shorter time, usually over hours or days, and addresses a specific problem that requires a military solution almost immedi-

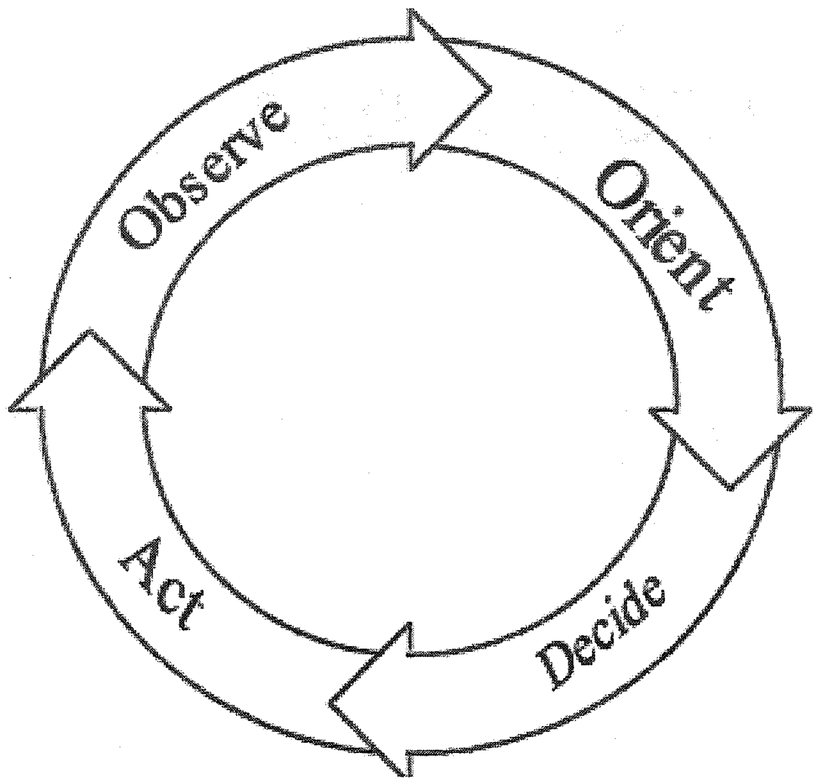

Figure 4. The decision-making cycle in the OODA model [36].

ately. It has 6 steps that include: situation development, crisis assessment, COA development, COA selection, execution planning, and execution.

While deliberate planning involves the CJTF, most of the operational decisions that he encounters occur under the CAP process. CAP requires the CJTF and his staff to gain SA on the mission, to develop and analyze COAs, and for the commander to decide on the best COA to follow. This process is the essence of joint operational planning. It provides the necessary information for a CJTF to make operational decisions.

Rather than CAP being a finite process with a specific beginning and end, one can think of it as a continuous process following the pattern of observe, orient, decide, act or "OODA loop." The OODA loop is depicted in Figure 4. The OODA model was introduced in 1987 [37] as a way to describe military decision-making and has been accepted by the Joint Chiefs of Staff (JCS) as a valid representation of the military

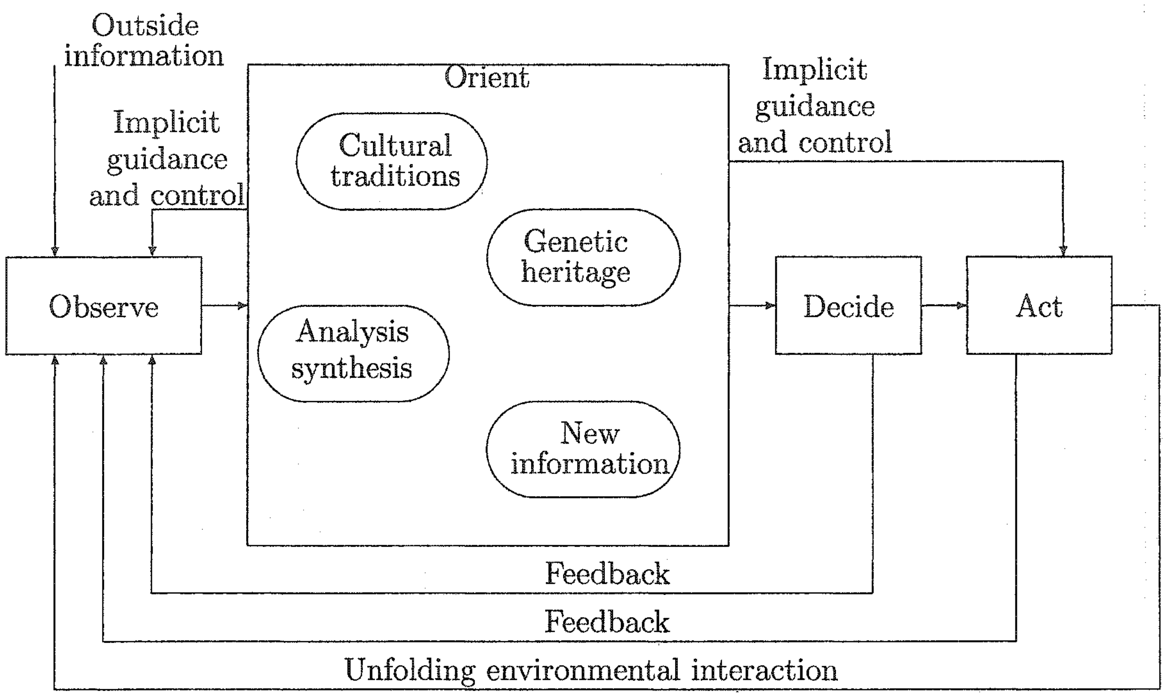

Figure 5. Processes, data flows, and feedback loops in the OODA model [38].

decision process [36].

The CJTF observes the results of his decision and these results are fed back into the loop for analysis, more decisions, and further actions. The cycle continues until the crisis is resolved.

Figure 5 represents a more detailed depiction of the OODA model. There are several parallels between it and the RPD model. They both begin with observing the situation at hand. Once observed, both models have the decision maker going through an orient phase where he tries to relate the situation to past experiences. The RPD model goes one step further at this point. It includes mental simulation; a process that an experienced decision maker uses to refine a COA that he intuitively feels is the best. The OODA model is not clear on how a decision maker examines COAs, only that an analysis is done (a weakness in thoroughly explaining the human decision process). Also, the OODA model does not limit the decision maker to examining one

COA only, which is what most experienced decision makers do [19]. Following this step, both models indicate a decision is made and action is taken to implement that decision.

Both models rely heavily on feedback. In the OODA model, a decision maker uses feedback from his decision and resulting action to modify experience and thus influence future decisions. Decision maker actions in the RPD model are much the same, using feedback to refine an intuitive COA choice, observing the results of a decision, and using those results as input to future decisions.

While the estimate process, deliberate planning, and CAP describe methods a military decision maker should follow to make decisions, they do not account for the psychological aspects of how an expert, in this case a CJTF, cognitively makes decisions. They follow along the path of how decisions are described in classical decision theory. The RPD model, on the other hand, was derived from observation of expert decision makers [19] and depicts the cognitive processes they use to arrive at decisions. This model has been shown to be valid in the military domain [21, 23, 39, 40, 41] where military decision makers employed RPD in at least 60% of the decision situations presented to them. This fact is not surprising since most CAP decisions are made under time pressure by experienced decision makers in dynamic situations with often ill-defined goals.

As an illustration, Kaempf et al. [40] observed how naval officers aboard an AEGIS cruiser made decisions in the complex, time-pressured environment of the ship's Combat Information Center. They found that the officers employed RPD in about 95% of their decision situations.

This section has described the doctrine guiding joint service military decision-making. As shown, a structured process of COA development and analysis officially characterize it. However, generating multiple COAs for selection is not the method employed by most experienced military commanders when arriving at a decision.

They may use the COAs to gain insight into the problem at hand. But, when it comes to making a decision, a CJTF will rely on his assessment of the situation, his past experiences that have made him a military expert, and his ability to intuitively recognize a satisfactory COA that will ultimately lead him to a decision. This decision-making procedure is captured in the RPD model.

2.3 Computational techniques for implementing the CJTF decision process

> *"The modeling of cognition and action by individuals and groups is quite possibly the most difficult task humans have yet undertaken [2]."*

It is one thing to develop a conceptual or mathematical model of how experienced individuals make decisions. It is quite another to implement that model on a computer through a set of algorithms. In essence, one must attempt to emulate the human brain's intricate processes of gathering, storing, and assessing information, setting goals, developing expectancies, performing mental simulation, and arriving at a decision. This section will review the techniques that have been developed and applied to implement computational models of human decision-making. It will compare them to the human decision processes described in RPD to determine how well they model decision-making. It will look at past methods used to implement a CJTF decision process and it will also look at ways in which others have attempted to implement the RPD model.

2.3.1 Finite state machines and Markov Chains

Finite state machines (FSMs) are computational models that can be used to simulate human decision-making.[10] They consist of a set of states linked together by transition

[10] In this context, FSMs are a specific implementation of the more generalized system called finite state automata (FSA). FSAs are studied in the context of formal computing systems.

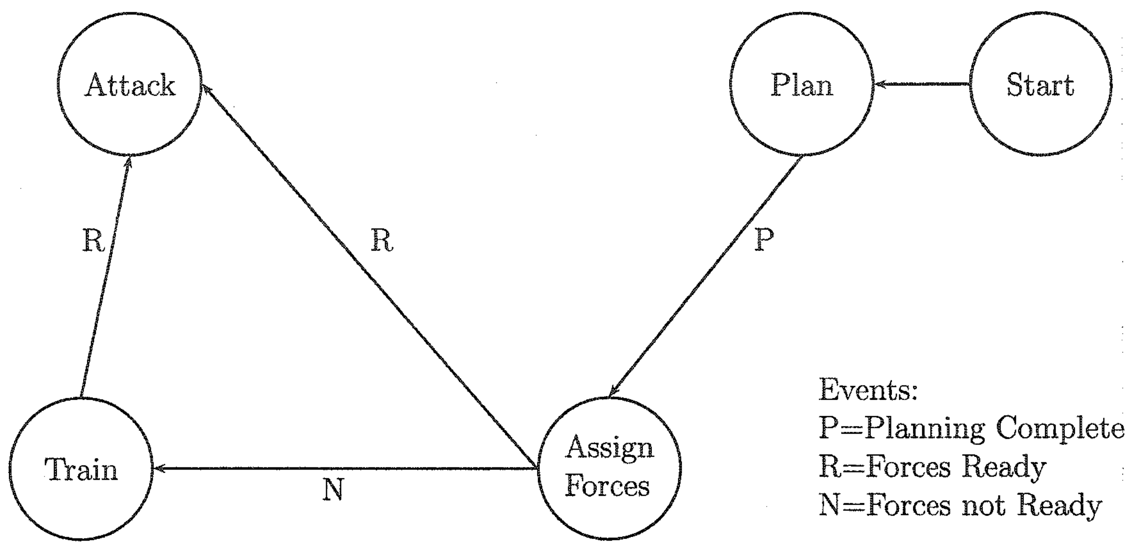

Figure 6. Finite State Machine structure

functions. Each state represents a condition of a FSM's environment. States can have associated with them one or more actions to be accomplished once that state is reached. The transition functions govern what state is visited next based on the occurrence of a particular event within the previous state [42].

In the context of decision models, finite state machines can be thought of as a means of abstracting a decision into a set of states with each state representing one element leading to a decision. Figure 6 depicts a simple FSM where the circles represent the states and the arrows connecting the circles represent the events that cause a transition from one state to another. In this example, the FSM represents a CJTF's decision on when to order an attack. Planning occurs first. Once the planning event is complete, forces are assigned. If the forces are ready, then they are ordered to attack. If not properly trained, they transition to a training state until they are trained and then they are ordered to attack. This simple example illustrates the concept of how a FSM is used to model a set of elements leading up to the decision to attack.

A Markov chain is an adaptation of a FSM where the transitions among states are probabilistic in nature. Instead of transitioning from one specific state to another in a deterministic manner, variability is added through a stochastic method of determining the next state.

Modular Semi-Automated Forces (ModSAF) is one military simulation that uses FSMs to simulate human behavior and decision-making [2, 43]. ModSAF's design is centered on the concept of tasks. In general, one can break complex military operations up into a series of individual or group tasks. These tasks represent behaviors and decisions of the simulated forces. Each task within ModSAF is implemented using a FSM. The actions necessary to accomplish the task correspond to the states within the FSM.

To date, no researchers have produced a model of the human decision process using FSMs. One disadvantage that hampers using FSMs to simulate complex human decisions is that the number of states can grow exponentially with every new event that is considered. This may hamper FSM's ability to scale to a size where realistic behavior modeling is possible [44].

2.3.2 Rule-based Models (Expert Systems)

Rule-based models replicate intelligent behavior by executing a base of knowledge containing *If-Then* logical constructs. These rules represent the sum total of conditions and actions to which the model can respond. Expert systems are the most common form of a rule-based model. Figure 7 depicts a typical expert system structure. The heart of the system is the knowledge base. The *If-Then* rules reside there. The inference engine is software that searches the knowledge base and locates the appropriate rules to follow for the decision at hand based on the data that is input to the model. It also provides a means of tracing the logic so that one can see exactly how the system arrived at the decision.

One of the difficulties in using a rule-based system to model human decision-

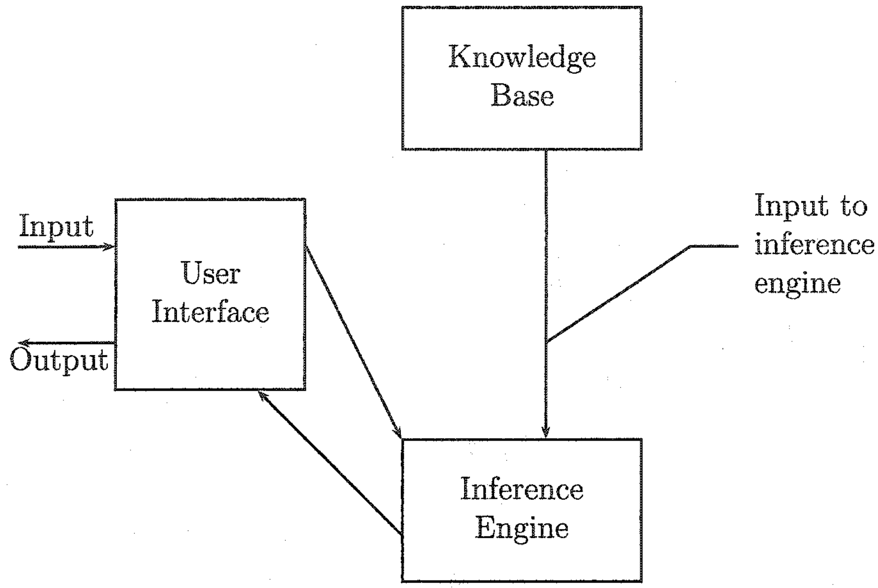

Figure 7. Expert system structure

making is in the ability to generate the knowledge base. It is difficult to get human experts to express their expertise in a series of *If-Then* rules. Once the rules are extracted, it is likely that they will be incomplete and inconsistent [45].

Another difficulty is the inflexibility of the system to adapt to a changing context. If the model encounters a decision situation that does not exactly match what has been captured by the *If-Then* rules, no rule will "fire" i.e. be chosen. This may lead to no decision or a default decision that is inappropriate for the situation [2].

SOAR is a rule-based model that attempts to overcome a rule-based system's inability to account for a changing situation by adding a learning capability [46]. SOAR is goal-oriented much like human decision makers. When presented with a decision situation, SOAR identifies a goal and searches through its knowledge base of *If-Then* rules for a set of rules to achieve that goal. If it is unable to find a sequence of existing rules to achieve that goal, it will set up subgoals that generate actions that can be executed to see if the ultimate goal can be reached. In this manner, SOAR overcomes the limitation of having all its knowledge captured before the start of the decision process. The subgoal logic that leads to achieving the final goal is added to the knowledge base as another set of *If-Then* rules, thus achieving a learning capability. The technique used to combine existing rules into new ones is called *chunking.*

SOAR has the ability to model a type of erroneous human decision-making. When a decision maker misperceives the decision environment, it often leads him to make the correct decision about the wrong problem. That is, if his SA of the situation is not consistent with reality, he may make a decision that is correct for the perceived situation but incorrect for the real situation. This type of error has been termed *sensation error* [47].

To recognize the decision situation, SOAR has a module that attempts to perceive and assess its environment [2]. It then uses this perceived state as the starting point for its decision search. A misperceived state could propagate through the model, thus providing a realistic representation of sensation error.

SOAR has been used in many instances to implement decision-making in military simulations. One example is TacAir-SOAR, which uses the SOAR decision-making scheme to model tactical military pilot decisions in various combat situations [48].

2.3.3 Case based reasoning

Case based reasoning (CBR) is a technique in which knowledge is represented as a compilation of individual cases. One can think of this library as a storehouse of solutions to previous problems that can be used as a starting point to solve new problems.

A case is a set of features containing three major parts: the *problem-situation description* that describes the state of the situation at the time of the case, the *solution* that specifies what was decided and in some cases how it was decided, and the *outcome*, which contains the state of the situation after the solution was implemented [49, 50].

Proper indexing is critical to retrieving the right set of cases to help solve a new decision problem. In her work on CBR, Kolodner [49] proposed four characteristics for choosing indexes:

1. Indexes should be predictive.

2. Indexes should be abstract enough to make a case useful in a variety of future situations.

3. Indexes should be concrete enough to be recognizable in future cases.

4. Predictions that can be made should be useful.

To be predictive, an index should contain problem descriptors that are responsible for part of the outcome of a case. For example, if having a particular weapon for a battle helped ensure a victory, then that weapon should be a predictive index for success in similar battles.

Achieving the proper level of abstraction is critical to having a useful index. In the above example, having a particular class of weapon may have been just as successful in achieving victory thus broadening the number of cases for which it could provide a satisfactory solution. One must be careful, however, to ensure that the index is not too abstract, which could lead to false selection of cases.

It is unlikely that the closest-matching retrieved case will perfectly match the target case. At this point, the CBR model applies built-in rules to try and adapt the retrieved case to its target. These rules are generally domain specific. CBR models can only tailor themselves to the domain space bounded by these rules.

CBR models have two appealing properties. They contain explicit references to past decision maker experiences which, as pointed out earlier, is a key aspect of human decision-making [19]. CBR models can also be used when no valid domain model exists, i.e., when the only information about a decision domain rests in the known cases. Since CBR essentially constructs its domain space dynamically through its adaption rules, CBR can be used to model complex systems where it is extremely difficult to generate a valid domain model beforehand.

While there haven't been any implementations of decision models in military simulations using CBR, other domains have employed it to develop decision models. One example is the construction industry. They used CBR to predict the outcome of construction litigation based on features of previous litigation cases. Their prediction rate reached 83%, which led to better construction planning before the fact, thus saving significant money for the construction companies [51].

Gilboa and Schmeidler [52] have proposed a new decision theory based on the CBR technique called *Case-Based Decision Theory (CBT)*. Their theory takes the concepts of CBR and expands them to cover all aspects of human decision-making. CBT is similar to RPD in that it relies on past experience as the basis of decisions and it argues that most human decisions are not optimal but most likely satisficing in nature since a person may not possess the experience to recognize the optimal decision but can recognize one that will work.

2.3.4 Neural networks

Neural networks (NNs) are algorithmic models of the human brain that are based on fundamental neuroscience principles of how the brain functions. They are composed of elements called *neurons*, which take as input the summed signals from other interconnected neurons. Once the summed signals reach a specific threshold, the neuron "fires" and passes its output on to other neurons connected to it. *Connection weights* are numbers that represent the connection strength between neurons and serve as the collective memory of the network [53].

The network consists of multiple layers of neurons with one input layer that accepts data from the environment, zero or more hidden layers, and an output layer (Figure 8).

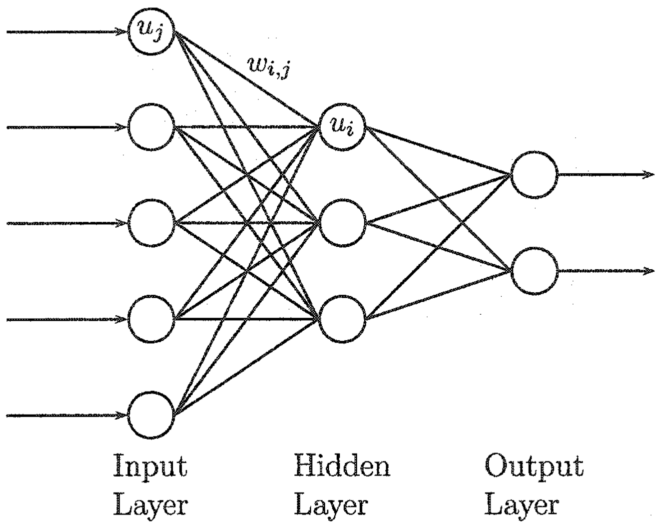

Figure 8. Neural Network Architecture

The number and the configuration of these layers determine the processing capability of the network.

Each neuron receives input values that are either continuous, falling in the interval [0,1] or [-1,1], or discrete, taking on values {0,1} or {-1,0,1}. An activation function associated with each neuron acts on these inputs to produce a single output value for that neuron. Typical activation functions are:

$$f(x) = \frac{1}{1+e^{-x}}$$

or

$$f(x) = \tanh(x)$$

Each connection has a numerical weight $w_{i,j}$ that specifies the influence of neuron u_j on neuron u_i. If the weight is positive, there is a positive influence and vice versa. Each neuron computes its activation value a_i by taking as input to its activation function the weighted sum of all other neurons that are inputs to it:

$$\begin{aligned} S_i &= \sum_{j=0}^{n} w_{i,j} u_j \\ a_i &= f(S_i) \end{aligned}$$

Once a neural network is constructed, it must be trained to make proper decisions (provide proper output) for a given set of inputs. This training is typically accomplished through training data consisting of inputs and their associated outputs. Inputs are supplied to the network. They are propagated through the network resulting in an output. That output is compared to the expected output and an error is calculated based on their difference. This error is propagated back through the network via a gradient descent algorithm and the interconnection weights are adjusted to minimize the error. The input is once again applied. The output is again compared to the expected output and the minimization cycle continues until the error is reduced to some acceptable value. This error correction process is known as back propagation.

Once the network is trained with sufficient data to cover the plausible set of expected inputs, it should theoretically provide a proper output (decision) when input data is presented to it. A significant advantage to a neural network is its ability to take incomplete or distorted (noisy) data and still produce an output that is similar to one that would have resulted from perfect input data. In this manner, it can provide satisfactory decisions based on the uncertain and highly dynamic conditions that exist in a complex warfare scenario [40].

A NN is very good at recognizing underlying patterns in data [53]. Therefore, it could be a useful tool to implement the recognition part of RPD. However, a significant amount of training data would be required to properly prepare the network to recognize situations over the entire domain of joint warfare. NNs would also have to be enhanced with other techniques to allow them to learn new situations. Additionally, after the NN recognized the situation, further processing would be required to determine a satisfactory COA. This step could be accomplished through another NN or through other logical techniques such as rule-based reasoning discussed earlier, or by using a fuzzy inference system [40] to be discussed in the next section.

One effort attempted to implement RPD using a NN approach [54]. Here, the NN performed the RPD tasks of situational awareness and COA selection. To train the network, 12 military experts were each shown 12 different scenarios and were asked to devise plans to achieve the goals of each scenario. The scenario starting data and the resulting plans generated by the experts were then digitized to form the training data. Once the network was trained, the researchers input new scenarios to it and had the military experts analyze the network's solutions. Results from these tests showed that the NN was a viable tool to implement RPD. However, it had certain shortcomings. Mental simulation, a key factor in RPD, was not implemented in this work. Therefore, there was no mechanism to take a marginal solution and refine it to one that was more acceptable. Also, perfect scenario data was used as an input to the NN. In reality, a military commander would rarely have perfect data on which to recognize the situation. The NN did not take into account individual commander personalities and preferences. These factors must be addressed to have a more accurate and complete model of a commander's decision-making process.

2.3.5 Fuzzy logic and fuzzy inference systems

Fuzzy logic is a revision to classical set theory. It is based on the thought that humans don't necessarily categorize information in a crisp manner. Rather, they describe conditions in terms of fuzzy conditions [55]. For example, if you asked a person how he decides when to turn up the thermostat on the heater, he most likely will say, "When I feel cold." He probably will not say, "Oh, I do it when I think it is

68°F." If asked the same question, a second person would give a similar answer but his idea of what cold is will probably differ from the first person. In this case, cold is a fuzzy value that has some degree of membership in a set, unlike in classical set theory where an object is either in or not in the set. The degree of membership is based on a defined membership function on the interval [0,1] with zero representing fully not in the set and one representing fully in the set. A value in between would specify the degree of membership, e.g. 68°F is 40% cold.

Once fuzzy variables have been designed, one can set up fuzzy inference rules that can be used as a logic structure for decision-making. This technique is similar to a rule-based system except that different rules may fire based on how a fuzzy variable value is chosen. The following is an example of a possible fuzzy rule that may be modeled for an operational decision by a CJTF:

> *If the weather is acceptable and troop strength is high and supplies are adequate,*
> *then authorize the attack,*
> *else wait to satisfy the conditions.*

Because of the fuzziness in the variables(weather, troop strength, supplies), multiple rules may fire for a given decision. In that case, a method to combine rule outputs must be devised so that the simulation can choose a single action representing the commander's decision.

One other concept, defuzzification, must be explained. At times, discrete values may be required to control some action. While humans understand vague terms such as "Turn the handle to the right a little," a computer must have a discrete value to execute that action. Defuzzification employs an algorithm to convert a fuzzy value to a discrete value to be executed by the computer. This algorithm can significantly affect how actions are carried out and must be chosen carefully to achieve the desired decision-making realism.

Clearly, fuzzy inference can be used as an enhancement to a rule-based decision model to provide more human-like characteristics. It could also be used to help generate a human perception of a decision situation. Instead of dealing with discrete, digitized data, fuzzy variables could be used to describe the situation (situational awareness) in terms of how a human perceives it. This perception could then form the basis of an input to a NN to generate a COA. Robichaud [56] did just that by extending the NN with fuzzy inference rules in [54] with favorable results. However, his decision model still did not account for mental simulation or commander personality.

While not a specific implementation of RPD, Vakas et al. [57] used fuzzy rule sets to implement decision-making in the Commander Model (CM) and the Commander Behavior Model (CBM) of the Joint Warfare System (JWARS). These rule sets were used in CM to assess situations, to determine doctrinal reactions to situations, and to determine the likelihood of achieving an objective in a given situation. The CBM added four other fuzzy rule sets concerned with commander personality and the rating of intermediate actions used to achieve a goal. Their decision-making model essentially accounts for all parts of RPD with one exception. It considers multiple COAs all at once and tries to optimize the selected action rather than using mental simulation on a single COA to achieve a satisfactory set of actions to achieve the stated goal. Also, all portions of the fuzzy rule sets mentioned above have not been completely implemented so complete performance results of their model are not available.

Combining fuzzy logic with neural networks shows promise as a decision-modeling tool. It uses the strengths of these two concepts to form a neuro-fuzzy system for decision-making. George and Cardullo [58] used this technique to model the decisions pilots made to position their aircraft to track other aircraft. NNs were used to learn the responses pilots made to various tracking situations. The NN then categorized these responses into seven fuzzy responses that were used to decide how the control model would respond. They achieved results comparable to the human decision responses except when only small error adjustments needed to be made. They surmised that using smaller fuzzy sets near the zero point as well as more fuzzy inference rules would correct the problem.

2.3.6 Multi-agent system simulation

> *I'll call "Society of Mind" this scheme in which each mind is made of many smaller processes. These we'll call agents. Each mental agent by itself can only do some simple thing that needs no mind or thought at all. Yet when we join these agents in societies—in certain very special ways—this leads to true intelligence [59].*

The above quote is from Marvin Minsky, a mathematician and computer scientist who developed a theory about how the human mind actually works. His research lends credibility to the hypothesis that human decision-making can be modeled using multi-agent system technology. He theorized that the human mind is made of many thought processes or agents. When combined together, these agents form an intelligent being. Modeling the human decision process using MAS is based on this premise.

To ensure a common understanding of MAS, the following definitions are provided:

Agent. An autonomous, computational entity that perceives its environment through sensors and acts upon that environment through effectors to achieve goals.

Multi-agent system. A system in which several interacting, intelligent agents pursue some set of goals or perform some set of tasks [60].

MAS simulation. A bottom-up modeling technique that uses diverse, multiple agents to imitate selected aspects of the real world system's active components [61].

MAS is a relatively new field that has its origin in several disciplines, the two most important ones being distributed artificial intelligence (DAI) and artificial life (A-

Life) [62]. DAI is a sub-field of artificial intelligence (AI) dealing with defining and constructing multiple intelligent systems that interact. A-Life can best be described as "abstracting the underlying principles of the organization of living things and implementing them in a computer so as to be able to study and test them [63]."

MAS simulations can be used as a bottom-up approach to modeling complex and ill-defined problems. The appeal of MAS simulations for modeling the human decision process lies in their ability to leverage the emergent behavior[11] of several individual agents to discover a new path to a solution not previously envisioned by the simulation designer. This is possible due to the many interactions that can take place among multiple agents. The result of these interactions are not explicitly defined at the start of the simulation but evolve as the agents encounter one another and their environment. Human decisions are based on past experiences and understanding of the current decision situation, i.e. they are unique to the person and could be as numerous as the number of people faced with the decision. A MAS simulation can enhance the ability to produce a human decision model because it can generate many unique options that rival the ones humans are capable of generating. MAS simulations promote adaptive behavior in a rapidly changing world much the way humans adapt their decisions based on the context of the situation they are experiencing.

In keeping with Minsky's concept of many agents acting together to define the human mind, researchers at Naval Postgraduate School have developed the concept of a *Composite Agent* (CA) [64]. A CA is composed of a combination of cognitive *Symbolic Constructor Agents* (SCA) and *Reactive Agents* (RA) that work together to define a complex agent entity. A CA can be programmed to simulate an individual decision maker with specific goals to achieve, actions to take, and a personality to influence decisions.

A description of the CA architecture is in order. As depicted in Figure 9, a CA

[11]One can think of emergent behavior as a complex pattern of actions that are generated at run time from the simple behaviors possessed by the individual agents.

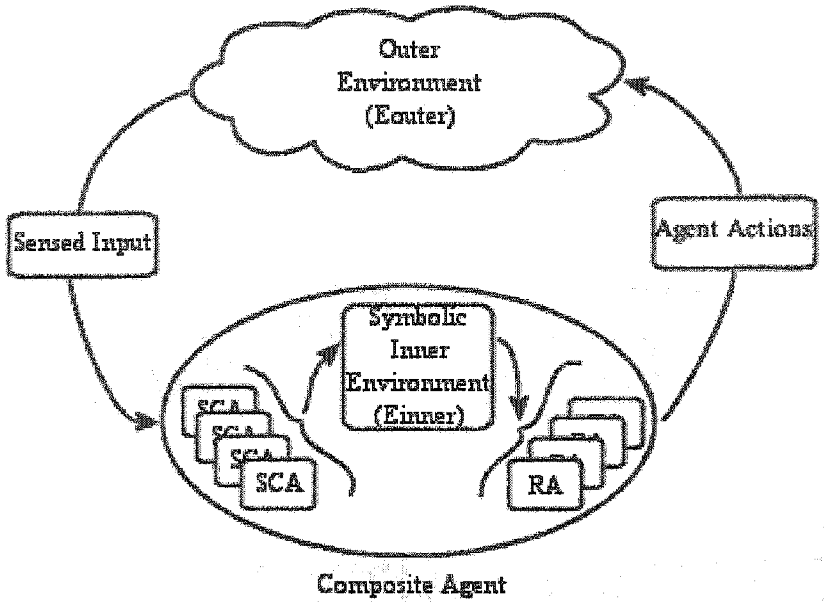

Figure 9. Composite Agent [64].

has one or more SCAs and RAs. SCAs perform the role of sensing and interpreting the CA's environment. They gather sensory input from the CA's environment, E_{outer}, and build a symbolic inner environment, E_{inner}, that represents how the CA perceives its surroundings much the same way humans use their senses to experience their surroundings and form a perception of them. The SCAs also act as a filter so as not to overload the CA in a sensory-rich environment. E_{inner} can be controlled to represent only the information normally available to a decision maker through his information gathering process. It is most likely not a one-for-one mapping of E_{outer} to E_{inner}. This realistically portrays how decisions are made based on the perceived environment. This internalization can lead, as in reality, to incorrect decisions when the perceived situation does not closely match the actual situation. This perceived environment is a key attribute to have in a model of human decision-making [47].

RAs use E_{inner} generated by the SCAs to select actions for the CA to perform. CAs include multiple RAs, each one responsible for a particular CA behavior. RAs have one or more goals that drive the selection of a particular action. With multiple

RAs, CAs can have many goals vying for attention just as human decision makers must contend with competing goals. These goals constantly shift in priority based on the dynamic nature of the perceived situation. The CA contains a variable goal management process contained within the RAs that closely mimics a human's flexibility and adaptability in dealing with changing situations [64]. This structure allows a CA to rapidly adjust its selected COA based upon how quickly a given decision situation is changing.

Goals consist of four components: state, measurement method, weight, and actions for achieving the goal. The goal's state indicates if it is active, dormant, or in some other domain-specific state. The measurement method uses the sensory input from the SCAs to calculate the strength of a goal and how well it is being satisfied. This is the mechanism that allows the agent to prioritize its goals and adjust them to the situational context. Goal weight is a measure of priority and importance. It can be updated based on agent experience to replicate reinforced learning. The action set are those steps the agent must accomplish to attain the goal. CA goals directly relate to RPD goals. In the RPD model, a decision maker has specific goals that are byproducts of the recognition process. The goals are what he is trying to achieve and govern the actions he selects to achieve them. CAs perform the same way. Goals guide the CA by influencing its choice of actions to achieve the desired end state.

The action steps necessary to achieve a goal must be related to the context of the situation that the agent is experiencing. To accomplish this, a data structure called *tickets* was developed. It encodes the procedural knowledge necessary to accomplish the actions associated with each goal. It ensures that these procedures have some doctrinal structure to prevent agents from adapting so radically that they take actions not consistent with plausible military operations.

For any given goal, there may be several COAs to follow to achieve it. Selecting the most appropriate COA to fit the particular context of the situation is the job of devices called *connectors*. As Hiles et al. state [64]: "Connectors are a way to associate impressions, ideas, and actions with a given context and achieve a logical sequence of behavior." Their main function is to ensure the most appropriate action is chosen to satisfy a goal given the specific context of the decision situation. In RPD, this replicates how an experienced decision maker distinguishes among subtle nuances of similar situations and "knows" which set of actions to take that are appropriate to those subtle differences.

CAs also have a built in learning process. By associating a weight value with actions used to achieve a goal, they can ignore actions that do not further their goals and more frequently employ those actions that do. This simple reactive learning process is similar to a human using his experience about what works and what does not work in a situation to know what to do when a similar problem presents itself.

The CA's design closely matches components of the RPD model and appears to be a viable tool with which to implement RPD. The following paragraphs compare the previously defined characteristics of the RPD model to those of a CA. The numbers in parenthesis after the paragraph headings refer to the seven RPD features mentioned in Section 2.1.3.

Adapts to changing situation (1,7). The RPD model is context sensitive. It has feedback mechanisms that continually monitor the situation and refine a decision maker's response based on the changes. CAs do the same by constantly evaluating the inner environment sensed by the SCAs and shifting their goal priorities to respond to the perceived situational changes.

Based on experiences (2). The foundation of RPD is that human decisions are greatly influenced by their direct and vicarious experiences, which provide a knowledge base for recalling or recognizing past decisions and their contexts. In a similar manner, CAs contain data structures that encode individual experiences along with representation of the doctrinal procedures that help to balance an agent's actions.

Accounts for personality (2). Because RPD is based on a decision maker's personal experience, it incorporates his tolerance for risk, his mental state, and possibly his physical state. CAs are able, through data structures, to encode these individual personality traits and have them influence the outcome of a decision.

Sensory data filtered by cues (2). A realization of relevant cues is a byproduct of situational recognition in the RPD model. These queues help focus the decision maker on the important information necessary to monitor the situation. Similarly, one can program SCAs to focus on specific aspects of the sensed environment to prevent sensory overload of the RAs.

Satisfies vice optimizes decisions (3,4,5,7). Another key tenet of RPD is that experienced decision makers look for satisfactory vice optimal decisions. They tend to use the first set of actions that adequately solve a problem without conducting an exhaustive search for better alternatives. CAs act the same way because their goal management process does not perform a complete search for an optimal solution, but will choose one based on some base set of criteria.

Employs mental simulation (6). RPD regards mental simulation as the process used by decision makers to modify previous experiences into a COA to meet the particular requirements of an existing situation. While CAs don't perform mental simulation explicitly, they do have data structures that allow them to recall past experience, and through their inherent capability to discover unique sequences of action, they could be thought of as performing mental simulation. Further modification of RA behavior would more fully implement this concept.

2.3.7 Other RPD implementations

The above sections have reviewed the computational techniques that can be used to model the human decision process. This section specifically addresses how these techniques have been used to implement the RPD model.

Researchers from Micro Analysis and Design and Klein Associates have implemented parts of RPD using a data structure to encode a decision-maker's long-term memory (LTM). LTM holds the person's experience and is the basis for situational recognition in the model [65]. Their approach to simulating LTM is based on Hintzman's *multiple-trace memory model* [66]. As an agent experiences its environment, it leaves behind a trace of the experience. These traces are stored in the LTM database and represent the sum total of the agent's experience. As a new situation is encountered, it is compared with each experience in LTM. A similarity value is computed and is used to "recognize" a closely related experience and its associated COA. This modeling approach has been implemented in a test bed environment, and while not a complete model of the RPD process, it shows promise in forming part of a computational representation of RPD.

Researchers at NASA Ames Research Center developed MOCOG1 [56]. This simulation implemented RPD using heuristic rules written in the declarative logic programming language Prolog. While their effort appears to have successfully implemented RPD in an algorithmic form, since it was rule-based, it was limited in its decisions by the explicit rule set programmed into the model. It was employed in a static environment and therefore not suitable to simulate the complex dynamic environment of operational level warfare.

Scientists from the University of Melbourne [67] have begun an implementation of RPD using a form of MAS simulation called a *Belief-Desire-Intent* (BDI) agent. BDI agents evolved from the theory of practical reasoning developed by Michael Bratman [68]. His theory focuses on how human intentions influence reasoning and action. One can describe the BDI model as follows. Belief is analogous to situational awareness and represents the agent's interpretation of its environment. Desire can be thought of as an agent's goal structure. Finally, intent is the plan currently in place to achieve the active goal. Similar to this author's contention, Norling et al. believe BDI agents have characteristics of the RPD model (goal driven, action oriented). Their current work revolves around an agent's ability to recognize subtle differences between situations so that the first step in the RPD model (proper diagnosis of the situation) can be realized. Their model has not yet successfully implemented this process.

As noted above, the BDI implementation of the RPD model is focused on accurate modeling of situational awareness and goal achievement. It does not include other aspects of RPD such as personality and mental simulation as will the CA implementation. Additionally, CAs handle the cue and expectancy parts of the RPD model. These parts of the model are not addressed by BDI.

2.4 Summary of the state-of-the-art

This section presented an overview of the relevant theories that have emerged to describe human decision-making. Until the late 1980's, human decision characterization was dominated by classical decision theory, a theory that stated humans always made decisions in a logical manner that maximized the decision outcome value. It provided a means to calculate decision outcomes in terms of probabilities of risk and uncertainty. It focused on the decision outcome itself rather than on the context that described the decision situation. Utility theory was incorporated to account for tolerances of individual risk preferences since each person has a unique threshold for accepting a particular decision outcome.

Classical decision theory came into question when research showed that humans do not necessarily make decisions in a logical manner. Few people spend time performing decision optimization calculations and many decisions can not be formulated in mathematical terms. Personal biases also influence decisions and tend to drive humans away from the purely optimal choice because of many competing factors. This led researchers to investigate more thoroughly how humans actually make decisions. As a result, the theory of Naturalistic Decision Making was developed.

NDM is based on the intuitive steps a person follows in reaching a decision rather than on a mathematical process for computing optimal outcomes. Decision makers tend to make decisions under the NDM paradigm rather than using analytical means when problems are ill-structured; the decision environment is rapidly changing; and when decisions must be made under time stress and involve high stakes. The more experience a decision maker has in a particular decision domain, the more likely he is to employ NDM since his experience provides for a significant intuitive feel of which COA should be chosen. The RPD model was formulated to instantiate NDM in a formal manner and represents the decision process of an experienced decision maker. Since senior military commanders, e.g., CJTFs, are considered expert in the art and science of warfare, RPD is a valid model for describing their decision process. RPD has been validated in the military domain.

Several computational methods exist for implementing the human decision process. Rule-based models have been used in the past for the majority of military simulation decision modeling. Since it is very difficult to define a set of rules that account for all decisions that s simulated military commander must make, models based on this approach tended to be too predictable and inflexible. Neural networks, fuzzy logic, and case based reasoning are techniques that have been employed to increase the robustness of military simulation decision models and have succeeded in varying degrees.

Multi-agent system simulation has just begun to be used to implement decision-making in the military simulation domain. The concept of a composite agent was derived from MAS and has characteristics that closely match the RPD model. It appears to be a viable computational model with which to implement RPD.

3 RESEARCH PROJECT

From review of the background material in Section 2, RPD was chosen as the most appropriate cognitive model to represent a senior military commander's decision process. MAS simulation, including composite agents, was chosen to implement RPD because of the close match between MAS simulation characteristics and the concepts of RPD. RPDAgent is the MAS simulation that resulted from this implementation.

This section describes RPDAgent from its design process through its implementation. It also details the validation approach taken to ensure an accurate model. It concludes with an analysis of the research data and the associated statistical results.

3.1 RPDAgent design and implementation

RPDAgent design was focused on implementing the various portions of RPD in a computational form. These parts included modeling human experience, capturing the recognition process including its byproducts of goals, cues, expectancies, and actions, and implementing the action evaluation and selection process. Model design started with a formal MAS simulation engineering process to develop the architecture needed to describe the RPD model. This architecture formed the basis for writing the software code necessary to implement the cognitive behavior described by RPD. A decision scenario was also developed to provide for a limited scope experience base on which to test the model.

3.1.1 RPDAgent Architecture Design

When designing a complex software system, it is important to follow a formal design process to ensure that system design goals are met. This is especially true when designing MAS simulations with their complex interactions and their numerous agent states. One such process, and the one used for RPDAgent, is that of DeLoach [69, 70]. DeLoach's MAS engineering approach consists of a project analysis phase and a project design phase. The analysis phase includes: identifying system goals, applying use cases, and refining roles. The design phase maps the analysis products to agents by creating agent classes, constructing agent communication, assembling agent classes, and defining system deployment.

The first step under the analysis phase, capturing goals, takes the system specification (RPD model) and maps it into a set of goals, which the MAS must achieve. This step is crucial to ensuring that the overall system design goals are met. For RPDAgent, system goals consisted of:

- Controlling system initialization and execution.
- Recognizing the decision situation facing the model.
- Constructing an internal representation of an external environment.
- Constructing a representation of the current decision and coordinating a decision action.
- Evaluating potential decisions against agent goals.

Once system goals were identified, *use cases*[12] were developed. They define how the system should behave in a given situation and help define the role agents must play to produce the desired model performance[13]. RPDAgent's use cases consisted of:

- Producing a decision from a given set of inputs.
- Reevaluating a decision when the initial inputs change or when new inputs are presented.

Use cases also represent a sequence of events between roles. This event representation defines the minimum set of communications that must take place among the agents.

[12]Use cases are a sequence of events that define desired system behavior.

[13]A role is an abstraction of an entity's function. The concept of a role is similar to that of an actor in a play.

Table 3. Roles and associated agent classes

Role	**Agent Class**
System management	MainAgent
Recognition functions	RecognitionAgent
Internalization of Environment	SymbolicConstructorAgent
Decision coordination	DecisionAgent
Decision evaluation	ReactiveAgent

Roles for RPDAgent include: system management, recognition functions, internalization of the external environment in a way that mimics human internalization, decision coordination, and decision evaluation.

Role refinement consisted of developing tasks that defined role behavior. These tasks represent high level agent behavior that will be transformed into detailed agent functionality once specific agents are defined. Tasks for RPDAgent included:

- Providing an interface with the RPDAgent program.
- Initializing RPDAgent experience.
- Performing situation recognition and matching it to previous experience.
- Generating a sequence of preferred actions.
- Evaluating an action against agent goals.
- Selecting a satisfactory decision.
- Handling interagent communication.

With the project analysis phase complete, the above results were used as the basis for the design phase. Agent classes were defined based on the identified roles with one agent class representing each specified role. Table 3 shows the relationship of the identified roles to the agent classes.

Since an agent is an autonomous entity, it must have a means of communicating and interacting with other agents and its environment. These functions are handled via an agent communication mechanism, which was defined next. Message type and content were developed to allow the agents to carry out their assigned tasks in support of the use cases that they were required to execute.

Agent assembly and system deployment were combined into one step. Here, agent methods and variables were developed to give each agent its required functionality. This functionality will be explained in detail below. RPDAgent was implemented using the Java programming language [71] because of its object oriented nature and its powerful interface and data base capabilities.

In addition to the main agent classes, several other software classes were developed to help with various tasks that the agents must perform and to act as custom data structures for RPDAgent's long term memory (experience) and internalization of its environment. The functionality of these classes will be included in the detailed RPDAgent description to follow.

3.1.2 RPDAgent Experience Representation

To understand RPDAgent's architecture, one must first comprehend how RPDAgent represents human experience. This section will provide a detailed discussion on the methodology used to represent experience.

RPDAgent's experience structure consists of a set of frames and a negotiation function. The model's experience in a specific situation is defined by the following structure:

$$E = (F, \eta) \tag{4}$$

where E is a single situation experience with $E \in E^*$ the total model experience, F is a frame, and η is a negotiation function.

The first of these variables is a data structure called a frame, which is a framework for representing knowledge. Minsky [72], who conceptualized the idea of frames, describes them as follows.

> "When one encounters a new situation (or makes a substantial change in one's view of the present problem), one selects from memory a structure called a frame. This is a remembered framework to be adapted to fit reality by changing details as necessary. A frame is a data structure for representing a stereotyped situation... Attached to each frame are several kinds of information. Some of this information is about how to use the frame. Some is about what one can expect to happen next. Some is about what to do if these expectations are not confirmed."

Frames embody many RPD concepts. A frame is a convenient structure for capturing discrete pieces of information about a situation. For this architecture, each frame will hold the set of all cues, goals, and actions associated with a decision experience. Formally:

$$F = (SN, C^*, G^*, A^*) \tag{5}$$

where SN is the situation name, C^* is the set of all cues for an experience and C is a single cue with $C \in C^*$, G^* is the set of all goals for an experience and G is a single goal with $G \in G^*$, and A^* is the set of all actions for an experience and A is a single action with $A \in A^*$.

Frames are indexed by their situation name. These indices represent the sum total of all experiences contained within RPDAgent. When RPDAgent is started, the experience database situation indices are loaded into computer memory for easy lookup. The actual frame data is not loaded until its associated situation is matched with the situation currently being experienced. The following describes each element that makes up a frame.

A cue is a data structure represented by an object class. Cues are defined as follows:

$$C = (CN, CV^*, CF^*, E^*, rn, cw) \tag{6}$$

where CN is the cue name, CV^* is the set of cue values for each action A, CF^* is the set of cue fuzzy values for each action A, E^* is the set of environmental variable values associated with each cue, rn is a saved random number, and cw is the cue weighting factor.

CV^* is a set of integer values. Each cv of CV^* represents a cue value derived from the set of associated environmental variable values E^*, corresponding to a specified action A. Since this model architecture is focused around decisions made by operational military commanders, the cues represent higher level abstractions of data that a senior commander would use rather than lower level environmental variables that one can physically measure. Two or more environmental variables that embody a cue are aggregated to form the cue value. For example, in deciding the location for an amphibious landing, a military commander may consider landing zone hydrography as a cue. The commander would want to know if the hydrography of each potential landing zone (each landing zone corresponds to a potential action or decision) satisfactorily supports the amphibious landing. Making up the evaluation of hydrography may be many environmental factors such as water depth, tides, and currents. However, a commander would tend to aggregate and internalize these lower level variables into the higher level abstraction of hydrography. The model architecture takes this aspect into account by providing a function that calculates cue values from their associated environmental variable values for a given action. This function is defined as:

$$cv_j = \sum_{i=1}^{n} e_{i,j} \tag{7}$$

where $e_{i,j}$ is the ith environmental variable value associated with the jth cue value cv_j, cv_j is a cue value, $cv_j \in CV^*$, and n is the number of environmental variables associated with the cue. Environmental variable values are integers that represent qualitative descriptions of these variables. For RPDAgent, the minimum value for cv_j is zero if all environmental variable values are zero. This situation could occur if all

$e_{i,j}$ were unfavorable. Its max value is $\sum_{i=1}^{n}(\max e_{i,j})$ if all associated environmental variable values are at their maximum value, i.e., if all were favorable.

Once the appropriate environmental variable values have been mapped to their respective cues, the discrete cue values generated from the environmental variables must be converted to a value more representative of how humans perceive cues. Humans tend to think of physical parameters in terms of imprecise values rather than discrete numbers. When asked to comment on the temperature, a person will most likely say that it is cold or warm or hot rather than give a discrete temperature such as 78.4 degrees F. This human representation of physical values is captured in a form of mathematics called *fuzzy logic*. Fuzzy logic provides a means of determining the degree of membership a discrete value has to a *fuzzy set* that represents the human interpretation of the physical value. See Section 2.3.5 for a further discussion of fuzzy logic. RPDAgent places cue values in one of three fuzzy categories (fuzzy sets): unsat, marginal, or sat, based on how past experience interpreted the influence of this cue on the situation. Most military personnel tend to evaluate conditions in this three part manner [5, 73] where unsat is military shorthand for unsatisfactory and sat represents satisfactory. The function, *cuefuzzyvalue*, maps cue values to fuzzy interpretations of the cues.

$$cuefuzzyvalue : CV^* \rightarrow CF^* \tag{8}$$

The *cuefuzzyvalue* function plays an essential role in quantifying the model's experience. The shape of the fuzzy sets will determine how the model interprets a specific cue. For example, the model could evaluate the hydrography cue for a given action as either unsat, marginal, or sat. This evaluation will depend on the specific fuzzy sets that are picked to represent the cue categories. The specific fuzzy sets are picked based on how a decision maker intuitively views the value of this cue. The intuitive view is based on his past experience.

For RPDAgent, triangular fuzzy sets were used to represent the fuzzy values as-

Table 4. Hydrography cue structure

Cue	**Environmental variables**	**Description**	**Value**
Hydrography	Reef	none	2
		partial	1
		full	0
	Water Depth	shallow	2
		moderate	1
		deep	0
	Anchorage	none	0
		yes	2
	Tides	small	2
		moderate	1
		large	0
	Currents	light	2
		moderate	1
		severe	0

sociated with each cue. Triangles capture a maximum fuzzy set value corresponding to a human's ideal value for the fuzzy parameter and the tailing off of that value as one moves further away from it on an absolute scale. RPDAgent's *cuefuzzyvalue* algorithm, used to calculate fuzzy values from triangular fuzzy sets, was adapted from Rao and Rao [74].

The following example illustrates how RPDAgent calculates cv and its corresponding fuzzy value (cf). It is based on the hydrography cue of the amphibious landing location decision mentioned earlier. Table 4 depicts one possible structure of the hydrography cue. Hydrography has five environmental variables associated with it. Each environmental variable has two or three descriptive values and corresponding numeric values (E^*). The descriptive values represent how the decision maker perceives these environmental variables based on past experience. The numeric values are assigned to facilitate computation of cv.

When presented with a decision situation involving an amphibious landing location, some or all of the environmental variable values will be available. RPDAgent will then compute cv for the hydrography cue using Equation 7. In this example, the

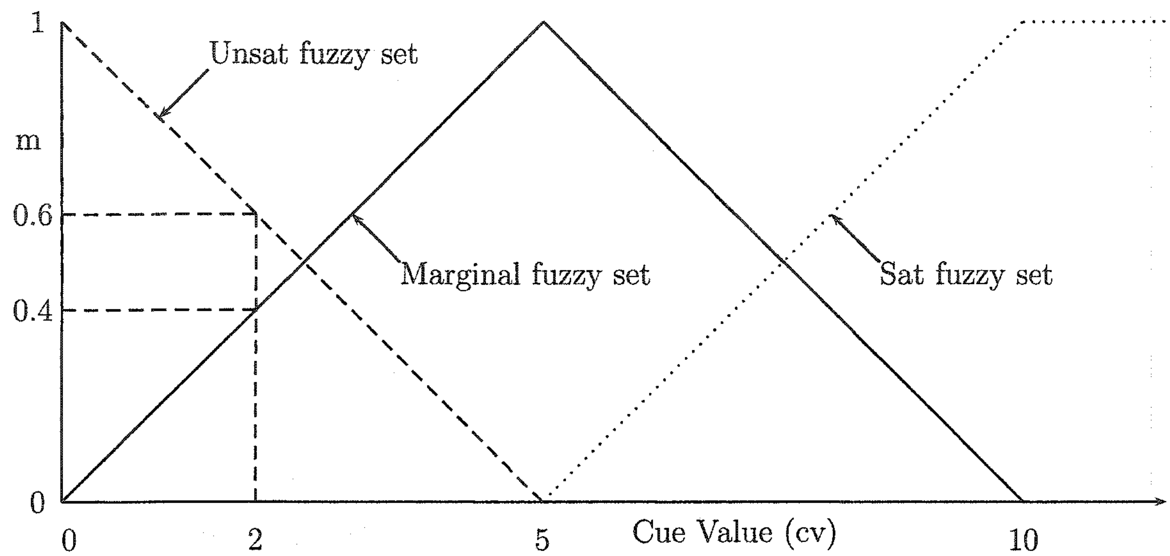

Figure 10. Hydrography fuzzy sets

hydrography cue will have an integer value between zero and ten depending on the value of each environmental variable for the given situation. Missing information is assigned a default value chosen by the user.

RPDAgent then computes the hydrography fuzzy value (cf), which represents the decision maker's evaluation of this cue based on his past experience and the current situation data. This evaluation is performed via the fuzzy sets that describe the decision maker's "intuitive assessment" of hydrography from his past experience. Figure 10 depicts the fuzzy sets associated with hydrography. The vertical axis (m) represents the percentage probability of membership. Because there is more than one fuzzy set, there is a finite probability that the cue fuzzy value (cf) will belong to more than one set. To calculate the cue fuzzy value for a given cv, one must compute the percentage probability of membership of that cv to the fuzzy sets. This is accomplished through the *cuefuzzyvalue* function derived from the fuzzifier algorithm of Rao and Rao [74]. To illustrate this algorithm using Figure 10, suppose $cv = 2$. At 2, the *unsat* fuzzy set height is 0.6 and the *marginal* set height is 0.4. The sum of these two heights provides a normalized value on which to base the percentage probability of membership. The subjective probability of being unsat is therefore 0.6/1.0 and the subjective probability of being marginal is 0.4/1.0. A random number, rn, is then generated to make the selection. For this example, any $rn < 0.6$ would produce a cf of unsat. Any $rn \geq 0.6$ would indicate a cf of marginal. The value, rn, is saved for future reference in case RPDAgent must reevaluate this cue based on new or updated information. Saving rn ensures that this cue's evaluation is consistent across the current decision context.

The next set that makes up a frame is G^*. Each goal in the set is an object class data structure that stores RPDAgent's goal information for a given experience. This goal structure is defined as follows:

$$G = (GN, GV, GF, C_g^*) \tag{9}$$

where GN is goal name, GV is goal value, GF is goal fuzzy value, and C_g^* is the set of cues that influence the goal. The computation of GV and GF will be discussed below with the *DecisionAgent* description.

The final set making up a frame is the set of all actions, A^*. Each $A \in A^*$ is also an object class data structure with the following definition:

$$A = (AN, A_e^*, AV, AF) \tag{10}$$

where AN is the action name, A_e^* is the set of environmental variable values associated with this action, AV is the computed action value, and AF is the computed action fuzzy value.

Actions can represent both past decisions for a given type of situation and the available actions that may be taken in a constrained decision environment. Associated with each action is a set of environmental variables that influence it and provide its context when given specific values. The action evaluation and selection process of

RPDAgent will be discussed in the *DecisionAgent* section below.

The final factor associated with defining experience in RPDAgent is the negotiation function, η. A decision maker may have many goals that he is trying to achieve. Some of these goals may conflict with one another. For example, a military commander may have goals of achieving the mission and minimizing casualties. These goals could be in direct conflict. The commander must evaluate a given action and decide if all goals can be satisfied to some threshold level for which he is willing to accept the risk. If all goals can be satisfied, the decision is relatively easy. If not, the decision maker must weigh the relative value of each goal and decide if he can compromise on one or more goals to achieve the overall goal. The negotiation function η allows the model to assess competing goals, similar to how a human uses mental simulation to weigh one goal against another. It does this by mapping goal fuzzy values, GF, to revised goal fuzzy values, based on RPDAgent's characterization of a decision maker's personality traits. RPDAgent encodes personality through a *risk value* that represents a decision maker's risk tolerance. Risk tolerance is the primary personality trait influencing a senior military commander's decisions [5]. The negotiation function is defined as follows:

$$gf_i^r = \eta(\rho, gf_i) \tag{11}$$

where gf_i^r is the revised goal fuzzy value for the *ith* goal, gf_i is the goal fuzzy value for the *ith* goal, and ρ is a real value, $1 \leq \rho \leq 2$, that quantifies risk tolerance with 1.0 being risk averse, 1.5 being risk neutral, and 2.0 being risk tolerant. The negotiation function algorithm will be examined in the *ReactiveAgent* material presented below.

3.1.3 RPDAgent Implementation

The Concept of MAS simulation discussed in Section 2 will now be extended to provide a formal definition of the RPDAgent architecture. This section describes the functionality of the various classes that make up RPDAgent including the interac-

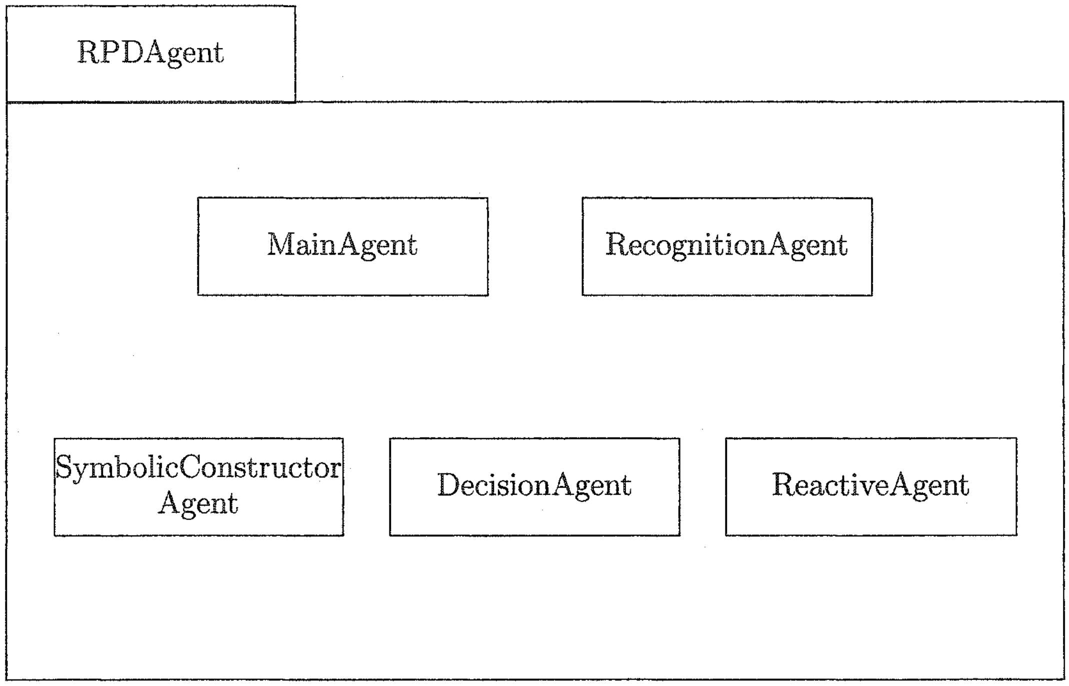

Figure 11. RPDAgent UML class diagram

tions that must take place between the classes. Figure 11 depicts RPDAgent's class structure in the unified modeling language (UML) format [75] and represents the basic agent classes that will be discussed.

RPDAgent builds on the composite agent concept of Symbolic Constructor Agents and Reactive Agents working together to model the human cognitive process. However, a composite agent as defined by Hiles et al. [64] is not sufficient to capture all the processes necessary to model RPD. Additional agent types were added (Figure 11) to achieve the required role functionality. In addition to the UML definition, RPDAgent can also be defined in mathematical terms as:

$$RPDAgent = (A_{ma}, A_{recog}, A_{sca}, A^*_{da}, A^*_{ra}) \tag{12}$$

where A_{ma} is *MainAgent*, A_{recog} is *RecognitionAgent*, A_{sca} is *SymbolicConstructorAgent*, A^*_{da} is the set of *DecisionAgents*, and A^*_{ra} is the set of *ReactiveAgents*.

The *MainAgent* class performs the system management and user interface role. It is here that the user interface is created and model commands are input. However, MainAgent's most crucial role is the establishment and population of the experience database. For RPDAgent, experience data was gathered through a Cognitive Task Analysis process. This process is discussed in Section 3.1.4. When RPDAgent starts, the experience database is initialized by reading in all situation names (SN) representing all situational experiences of which RPDAgent is aware. The remaining data such as cues, actions, and goals are not input until a request for a particular decision is made. When such a request arrives, only the data pertinent to that situation is input to RPDAgent's frame structure. This procedure prevents unneeded data from being unnecessarily loaded.

With initialization of the experience database complete, *MainAgent* transitions to a wait state, waiting for a decision to be requested of it through its user interface. This emulates a CJTF's staff approaching a CJTF with a decision request. Once *MainAgent* receives a decision request, it informs *RecognitionAgent* of a pending decision through an agent communication protocol. RPDAgent implemented a subset of the *Knowledge Query and Manipulation Language (KQML)* [76] as its agent communication protocol. Message transmission between agents was accomplished by Java event handlers [77], with each message handled as an event.

When *RecognitionAgent* receives a decision request from *MainAgent*, it performs a lookup of the requested decision type in the experience data base. This lookup is in the form of a keyword search on the type of decision requested. If no match is found, RPDAgent notifies the user that it does not have the experience necessary to render this type of decision.

If a match is found, *RecognitionAgent* reads in to computer memory the experience data associated with this type of decision. It is here that the frame data structure is populated with the basic cues, goals, and actions pertinent to this decision. *RecognitionAgent* then informs *SymbolicConstructorAgent* of the decision request.

Recall from the discussion of composite agents in Section 2.3.6 that Symbolic Constructor Agents convert external environmental variables into an internal representation of the environment. This process represents how a human internalizes his external environment. *SymbolicConstructorAgent* accomplishes the same objective for this model architecture. It is here that each $cf \in CF^*$ is calculated as described in Section 3.1.2. Once these calculations are complete, the elements of CF^* represent the personal internalization of the external decision environment.

After the internal environment is generated, *SymbolicConstructorAgent* instantiates a *DecisionAgent.* One *DecisionAgent* is instantiated for every unique decision presented to RPDAgent. Each *DecisionAgent* is then responsible for coordinating its respective decision situation.

DecisionAgent performs several tasks. First, it surveys the available actions for the given situation and ranks those actions from most to least desirable. This process is analogous to the RPD notion of a human decision maker identifying the most intuitively desirable action and evaluating it first.

$$AV_i = \sum_{j=1}^{n} cv_{j,i} \tag{13}$$

Action value is computed by summing all cue values associated with that action. This computation is shown in Equation 13 where AV_i is the action value for the *ith* action and $\sum cv_{j,i}$ is the sum of all cv_j associated with the *ith* action. The action with the largest AV_i is considered the most favorable since it has the most positive cue values. If two or more actions have the same action value, they are sorted in the order they were evaluated. Cue values (cv) are used for this computation rather than cue fuzzy values (cf) because this calculation is meant only as an intuitive indicator of the most favorable action. Further evaluation must be carried out by RPDAgent before this action is chosen as the most suitable for the situation.

DecisionAgent's second task is to instantiate *ReactiveAgents.* One *ReactiveAgent* is instantiated for every goal associated with the current decision situation. Once the *ReactiveAgents* are activated, *DecisionAgent* informs them of the decision situation and requests that they evaluate the most favorable action against how well that action satisfies the goals for which they are responsible.

As noted in Section 2.3.6, Reactive Agents' role is to act on the symbolic representation of the environment generated by SCAs to select an action consistent with their assigned goals. In RPDAgent, *ReactiveAgents* perform the same function. They evaluate how well their assigned goal can be achieved for the given action under consideration.

$$goalfuzzyvalue : CF^* \rightarrow GF^* \tag{14}$$

This evaluation is performed by the $goalfuzzyvalue$ function, which maps cue fuzzy values to goal fuzzy values as noted in Equation 14. A goal fuzzy value is an evaluation of the potential for a specific action to achieve a specific goal. The potential is based on how well the cues associated with a specific action favor accomplishing the goal. Each decision situation has a set of goals associated with it that RPDAgent must try to satisfy. RPDAgent will use cues and their associated cue fuzzy values as a measure of how well a specific proposed action will satisfy the goals of the situation.

Just as with *cuefuzzyvalue, goalfuzzyvalue* has a direct link to quantifying the model's experience. Based on past experience, a decision maker associates specific cues with the evaluation of one or more goals. One can assess the degree to which a proposed action will achieve a goal by assessing the qualitative influence of that action's cues on a goal. That qualitative influence is described by goal fuzzy sets, which are derived from experience.

RPDAgent's *goalfuzzyvalue* method is described as follows. Recall from Equation 9 that each goal, G, has a set of cues, C_g^*, that influence or govern the achievement

Table 5. Goal evaluation example

Goal	Cues	cf	GV_c^i
Accomplish Mission	Beach Topography	marginal	1
	Beach Hydrography	sat	2
	Beach Obstructions	sat	2
	Beach Staging Area	marginal	1
	Route to Objective	sat	2
Goal Value			8

of it. This set of cues is used to calculate GV as follows.

$$GV = \sum_{i=1}^{n}(GV_c^i * cw_i) \tag{15}$$

where GV_c^i is the integer value that represents cf for this cue with $GV_c^i = 2$ if $cf =$ sat, $GV_c^i = 1$ if $cf =$ marginal, and $GV_c^i = 0$ if $cf =$ unsat, cw_i is its respective cue weight, and n is the number of cues associated with this goal. The cue weighting factor is applied here because humans often perceive that some cues influence goals more than others.

Once the goal value is computed, RPDAgent converts it to a fuzzy value representing more closely how a military commander perceives his goal evaluation. Goal fuzzy values (GF) are derived from triangular fuzzy sets representing an evaluation of sat, marginal, or unsat. The computation is similar to that described for *cuefuzzyvalue*.

The following example serves to illustrate the *goalfuzzyvalue* function. It is again based on the amphibious assault landing location decision. Suppose that one goal a CJTF has for this decision is to accomplish the mission. Associated with this goal are five cues that directly influence it. Table 5 lists the goal, its associated cues, their corresponding cue fuzzy values, and the assigned integer value for the cue fuzzy variables. For the computation of goal value in this example, all cue weights are assumed to equal one. GV could range anywhere from zero if all cue fuzzy values were unsat to $\sum_{i=1}^{n}((\max GV_c^i) * cw_i)$ if all cue fuzzy values were sat.

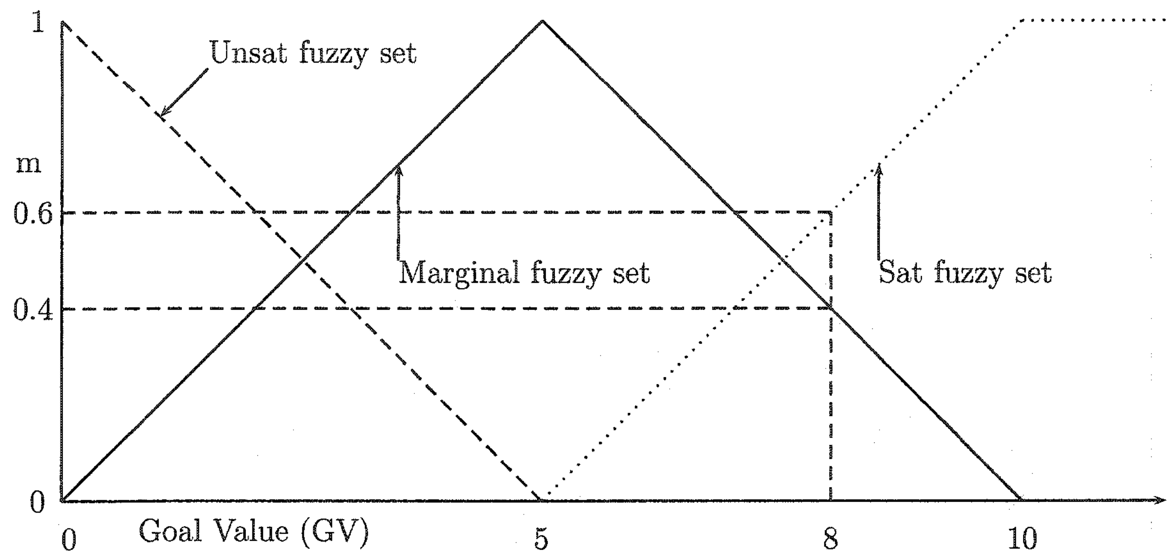

Figure 12. Goal: Accomplish Mission fuzzy sets

Once *GV* is computed, the *goalfuzzyvalue* function is used to compute *GF*. The function *goalfuzzyvalue* uses the same method to compute its fuzzy value as that described earlier for *cuefuzzyvalue.* As an example, suppose $GV = 8$. From Figure 12, the height of the *marginal* fuzzy set is 0.4 and the height of the *sat* fuzzy set is 0.6. The subjective probability of membership is 0.4/1.0 for the marginal set and 0.6/1.0 for the sat fuzzy set. A random number is then generated to determine the specific fuzzy membership result. This process is repeated by each *ReactiveAgent* for its respective goal. When *ReactiveAgents* complete their assigned goal evaluation, they inform the *DecisionAgent* of their evaluation of the action under consideration.

Once *DecisionAgent* receives all of its *ReactiveAgents'* goal assessments, it checks to see if all goals were fully satisfied.[14] If they were, RPDAgent accepts the current action as its decision and renders it to the user. If all goals were not fully satisfied, *DecisionAgent* requests that the *ReactiveAgents* negotiate to see if each is willing to compromise on its goal evaluation to achieve a satisfactory evaluation for all goals.

[14]Fully satisfied implies all goal fuzzy values were evaluated as sat.

Since agents are autonomous entities, they do not take orders from other agents. Instead, they communicate requests and information among one another. When they differ in their goal evaluations, they must have a means of resolving those differences. Many schemes have been devised including auctions and negotiations for resolving those differences [76]. Negotiation [78] was chosen as the resolution method for RPDAgent because it best represents how a human decision maker uses mental simulation to arrive at a compromise on multiple conflicting goals within his mind [59].

In the case of RPDAgent, compromise is handled within the *ReactiveAgents* by a multiplication factor applied to GV. This multiplication factor is based on a decision maker's risk tolerance. For RPDAgent, it is represented as a real value from 1.0 to 2.0 with 1.0 being risk averse, 1.5 being risk neutral, and 2.0 representing risk tolerant. Section 3.2.1 discusses the method for evaluating a decision maker's risk tolerance. Multiplication values from 1.0 to 2.0 were selected to provide reasonable compromise results based on the chosen goal fuzzy sets. This computation is represented in Equation 16:

$$GV^n = GV * \rho \tag{16}$$

where GV^n is the compromise goal value and ρ is the risk factor from Equation 11. A new GF is then calculated as above, based on GV^n. The result is then fuzzified in the same manner as the original goal value. This process represents the negotiation function, η that was defined in Equation 11. The result is reported back to *DecisionAgent.* Multiplying GV by ρ has the effect of increasing GV by some percentage. The larger ρ, the greater the increase. This indicates that a person with a higher risk tolerance will compromise to a larger extent on a particular goal up to some threshold set by the risk factor. Within RPDAgent, this calculation has the possible effect of moving the goal fuzzy value into the next higher fuzzy set, i.e., from unsat to marginal or marginal to sat, thus allowing for a more favorable goal evaluation by its associated *ReactiveAgent*.

At this point, if all goals are fully satisfied, *DecisionAgent* renders a decision based on the current proposed action. If all goals are not fully satisfied, no compromise could be reached. This situation is similar to a person having a certain goal threshold below which he will not go. The proposed action is discarded and the next best action is selected for evaluation. The goal evaluation process is repeated until a satisfactory action is found or until no satisfactory action is discovered. In this case, a default decision, supplied with the current decision situation, is rendered.

What was described above is the sequence of events RPDAgent follows to satisfy its first use case, producing a decision from a given set of inputs. The second use case is concerned with reevaluating a decision when the initial inputs change or when new inputs are presented. RPDAgent handles this use case in a similar manner except that the decision situation has already been identified and *SymbolicConstructorAgent* has already generated RPDAgent's initial interpretation of the external environment. When reevaluating a decision, RPDAgent starts from this point and recalculates cv and cf for each cue, reevaluates the available actions to determine if the order of most to least favorable actions has changed, and then evaluates the actions against the goals in the same manner as in the first use case.

In addition to the primary agent object classes discussed above, there are ten other object classes that support RPDAgent's functionality. They are shown in Figure 13. The *Agent class* is a superclass on which all other agents are based. It provides for basic agent data storage and for abstract methods to handle agent communication events.

AgentEvent and AgentEventListener supplement the Agent class by defining a general event structure for agents and by implementing the necessary event listeners that allow the agents to communicate with one another.

The *Frames class* provides the necessary data structures and methods to define

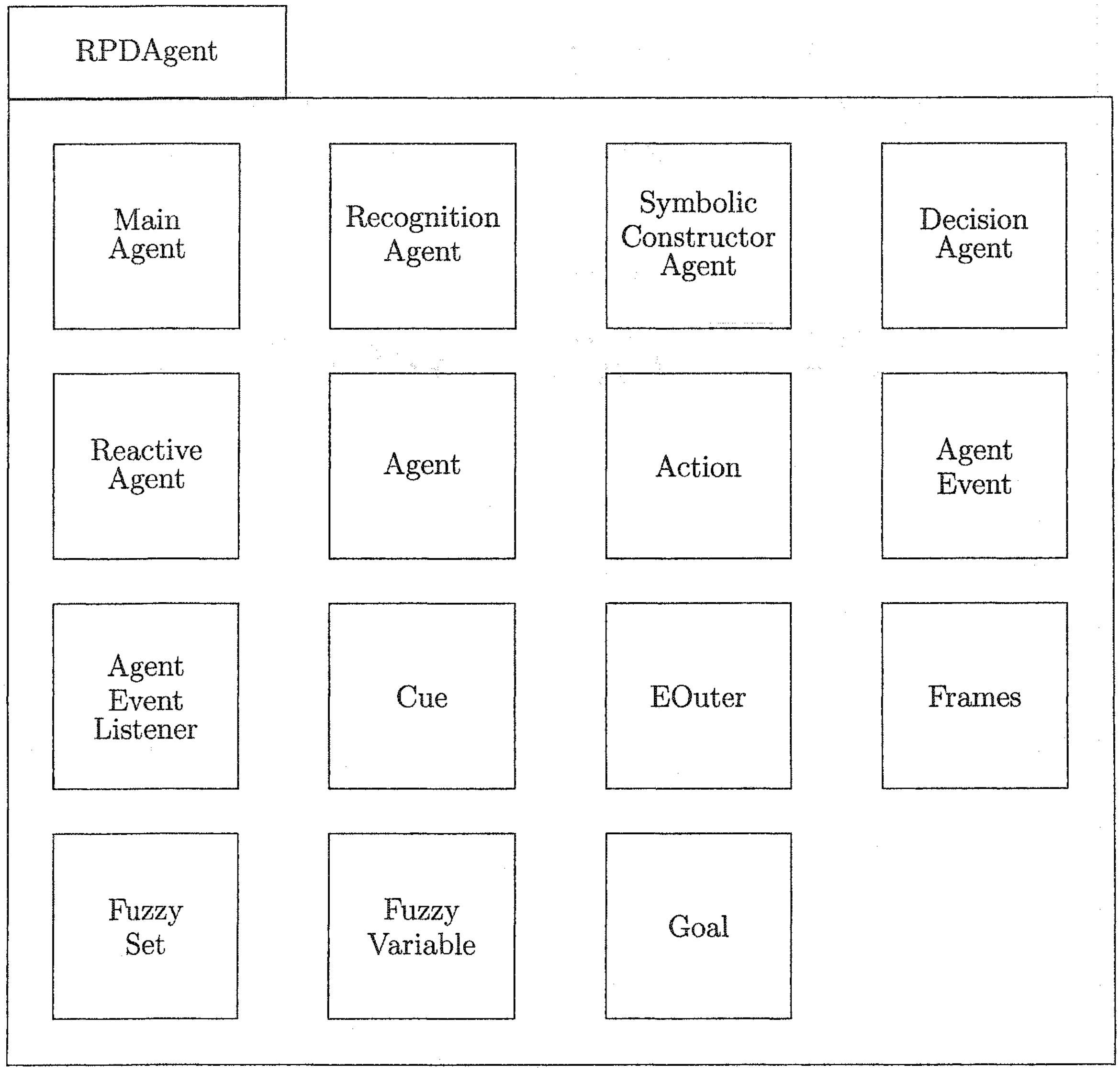

Figure 13. Complete RPDAgent UML class diagram

part of the agent's experience. It is supplemented by the *Action, Cue, and Goal classes*, which populate the Frames' data structures with their respective information. The *EOuter class* is closely aligned with Frames and provides data structures to hold the various environmental variables that define RPDAgent's outer environment.

FuzzySet and FuzzyVariable classes provide the ability to define their respective data structures and to provide the necessary methods to calculate fuzzy values given the fuzzy set definitions. They form the major input to the *cuefuzzyvalue and goalfuzzyvalue* functions that help complete the mechanism for defining RPDAgent's experience.

Of note, RPDAgent executes single decision requests on the order of milliseconds so model execution speed can support faster than real time simulation requirements.

3.1.4 Decision scenario design

Per the RPD model, cognitive decision-making relies on a person's past experience to recognize and to interpret a decision situation. Once recognition occurs, experience provides for the cues, goals, actions, and expectancies that guide the decision maker's response to the situation. For RPDAgent to respond in the same manner, it must have an experience base from which to draw. A decision scenario was devised to provide a limited scope experience base on which to test the model. This decision scenario was not meant to represent all decision situations that a CJTF could possibly face. Instead, it was developed to allow for testing of the model against an operational military decision that a CJTF could likely face. Further research is required to identify and populate an experience base that would allow RPDAgent to make all plausible decisions facing a CJTF.

Given the above, an amphibious assault was chosen as the decision scenario on which to test RPDAgent. The amphibious assault scenario provided for a wide variety of operational decisions that a CJTF could likely face. It allowed for both qualitative and quantitative environmental variables and cues on which to base the decisions. Having both types of these factors was required to ensure physical characteristics and mental assessments could be accounted for in the decision process. Aspects of an amphibious assault included skills from all warfare communities such as land, air, and sea components. This helped ensure that RPDAgent could represent military commanders from all Services since a CJTF is likely to come from any one of them.

To facilitate the scenario design, a cognitive task analysis (CTA) of amphibious assaults was performed. CTA encompasses formal methods to identify the steps a person uses to perform both physical and mental tasks [79, 80]. Most importantly, it attempts to discover a person's thought processes while he completes a task. Gott [81] suggested that CTA should be used when faced with gathering knowledge of a complex task that goes on in the head of the performer, that is not presequenced, and that is dynamic, unstable, and ill-structured. These are all characteristic of the thought process facing a CJTF when he makes an operational decision.

The CTA consisted of two portions. First, an historical review of amphibious assaults was conducted. Historical assaults have been well documented and analyzed [82, 83, 84] and provided the majority of information necessary for the CTA. The assaults that were analyzed occurred from World War II through the Persian Gulf War. As a result of this analysis, two major operational decisions and their associated cues and goals were identified. These decisions were: *assault location* (referred to as *location*) and *assault timing* (referred to as *timing*). To ensure current doctrine, tactics, techniques, and procedures were accounted for, the CTA results were reviewed by an amphibious subject matter expert. The CTA results were found to be consistent with current amphibious assault planning and decision-making [85].

The second portion of the CTA consisted of questionnaires provided to thirty military officers with joint operational military experience. The questionnaire was structured around the knowledge solicitation techniques found in Hoffman, Crandall, and Shadbolt [86]. This questionnaire can be found in Appendix B. These officers were part of the model validation process described in Section 3.2. Their CTA information was used to confirm the results of the historical review and to add additional cues that were not previously identified.

Location and timing provided two decision points for the scenario. Each decision point represents a single past experience. These two decision points were influenced mainly by physical cues. To ensure that decisions based on mental cues were also accounted for, two other decision points were added to the decision scenario. The third point was a decision on whether a change in assault timing was necessary based on unexpected enemy troop movement (referred to as *change*). The fourth point occurred after the amphibious landing was completed. It required a decision on whether to continue to fight or to retreat based on unexpectedly heavy enemy opposition and significant casualties once ashore (referred to as *continue*). CTA for the third and fourth decision points came from past history, the CTA questionnaires, and from the author's own operational military experience [5]. The fourth decision point was the only one that required extensive modification to the original cues based on the information provided in the questionnaires. Once the four decision points were determined, they were woven into a notional operational military scenario that a CJTF could typically face. That scenario is contained in Appendix B.

The CTA identified a portion of the data necessary to form RPDAgent's experience data base. This portion included the cues and goals associated with each decision point. The experience associated with the location decision consisted of the nine cues listed in Table 6 and the two goals listed in Table 7. Table 6 also lists each cue's associated environmental variables and their possible descriptive values.[15] RPDAgent represented these descriptive values with integers. Generally, the value 2 was used to encode the most favorable descriptive value, 1 was used to encode the mid descriptive

[15] The abbreviation CAS in Table 6 stands for Close Air Support

Table 6. Location cues and associated environmental variables

Cues	**Environmental Variables**	**Variable Values**
Beach Topography	Steepness	shallow, moderate, steep
	Sand type	coarse, fine
	Obstacles	none, walls, jungle, rocks
Beach Hydrography	Reefs	none, partial, full
	Water depth	shallow, moderate, deep
	Suitable anchorage	yes, none
	Tides	small, moderate, large
	Current	small, moderate, severe
Water obstructions	Mines	no, yes
	Barriers	no, yes
Staging Area	Staging area	adequate, marginal, none
Route to Objective	Route to objective	adequate, marginal, inadequate
Enemy Defenses	Level	company, battalion, brigade
	Equipment	light, moderate, heavy
	Enemy experience	novice, experienced, professional
	Experience change	decreasing, constant, increasing
	Enemy CAS	none, yes
	Enemy Naval Support	none, yes
Enemy Perception of Location	Perception	unimportant, important, vital
Quality of Intelligence	Quality	excellent, good, poor
Location of Landing Site	Location	near objective, away from objective

Table 7. Location goals and associated cues

Goals	Associated Cues
Achieve Mission	beach topography, beach hydrography, water obstructions, staging area, route to objective, location of landing site
Minimize Casualties	enemy defenses, enemy perception of location, quality of intelligence

value if it existed, and 0 represented the least favorable descriptive value relative to the environmental variable being described.

Two goals were identified by the CTA process for this decision scenario. These goals were: *accomplish mission* and *minimize own casualties.* These goals are typical of high level goals that an operational military commander takes into consideration when making a decision. In RPDAgent, cues are used to assess how well a specific proposed action will satisfy a particular goal. Table 7 identifies the cues that are associated with the goals for the location decision. Section 3.1.3 explains how these cues are used in the goal evaluation process.

Actions within RPDAgent can be a combination of previous actions learned from experience and current actions available to the decision maker. For the location decision, the decision scenario of Appendix B identified four possible landing locations frow which to choose. The location decision was restricted to these four sites because they were the only sites that could support an assault. The experience necessary for action selection was encoded within the fuzzy evaluation of goals as explained in Section 3.1.3. Table 8 characterizes each landing site identified in the scenario based on its associated environmental variables. Variable values for each location were selected at random from among the allowable values. Section 3.1.3 discusses the encoding of this information within RPDAgent.

CTA for the timing decision identified five cues used by military commanders for this decision. Table 9 lists these cues along with their associated environmental variables.

Table 8. Location actions and associated environmental variable values

Variables	Actions			
	Alpha	Bravo	Charlie	Delta
Steepness	shallow	moderate	moderate	shallow
Sand type	coarse	fine	coarse	fine
Obstacles	walls	jungle	jungle	rocks
Reef	none	none	none	full
Water depth	shallow	moderate	deep	moderate
Anchorage	none	yes	yes	yes
Tides	moderate	small	large	large
Current	severe	moderate	severe	moderate
Mines	yes	no	no	no
Water barriers	yes	no	no	no
Staging area	adequate	adequate	adequate	adequate
Route to objective	adequate	adequate	adequate	inadequate
Enemy strength	brigade	company	company	company
Enemy equipment	heavy	moderate	moderate	moderate
Enemy change	constant	increasing	constant	constant
Enemy experience	pro	experienced	experienced	novice
Experience change	constant	constant	increasing	decreasing
Enemy CAS	yes	no	no	no
Enemy naval	none	yes	none	none
Enemy perception	important	important	important	unimportant
Intel quality	excellent	excellent	poor	good
Location	away	near	near	near

Default decision: No suitable location exists. Do not conduct the assault.

Table 9. Timing cues and associated environmental variables

Cues	**Environmental Variables**	**Variable Values**
Resource Availability	Troop level	insufficient, marginal, sufficient
	Troop buildup rate	low, moderate, high
	Ship level	insufficient, marginal, sufficient
	Ship buildup rate	low, moderate, high
	Air support	insufficient, marginal, sufficient
	Supply level	insufficient, marginal, sufficient
	Resupply rate	low, moderate, high
Weather	Cloud cover	overcast, partly, clear
	Cloud cover change	increasing, constant, clearing
	Precipitation type	rain, snow, sleet, hail
	Precipitation rate	light, moderate, heavy
	Precipitation rate change	slowing, constant, increasing
	Visibility	clear, haze, fog, reduced
	Visibility change	clearing, constant, decreasing
	Wind level	light, moderate, strong
	Wind level change	decreasing, constant, increasing
	Wave height	low, moderate, rough
	Wave height change	decreasing, constant, increasing
	Forecast quality	poor, good, excellent
Troop training	Training	low, moderate, high
Enemy status	Enemy status	unaware, suspicious, alerted
Staff Recommendation	Recommendation	recommended, not recommended

Table 10. Timing goals and associated cues

Goals	**Associated cues**
Achieve mission	resources, weather, troop training, enemy status, staff recommendation
Minimize casualties	troop training, enemy status, staff recommendation

CTA identified the same goals for the timing decision as the ones for the location decision. The associated cues for these goals are listed in Table 10.

The decision scenario provided for four possible timing choices based on required coordination with other military forces. These choices were linked to other factors within the scenario and were the only ones available. Table 11 lists the four timing choices and their associated environmental variables.

CTA results for the third and fourth decision points are presented below in Tables 12 through 17. For these decision points, the environmental variables that make up the cues rely less on physical parameters that are easily measured or assessed and more on qualitative parameters that require human interpretation. Both of these types of parameters influence decision-making and were included in the model to ensure the cognitive decision process could be adequately represented within RPDAgent.

The information in these tables forms part of the experience data base necessary for RPDAgent to mimic the cognitive decision process represented by the RPD model. Section 3.1.3 discusses other elements needed to represent human experience.

3.2 Validation methodology

Balci defined modeling and simulation validation as comparing the model to the real world system to determine if the model matched the real world system to an acceptable level [87]. To determine if RPDAgent adequately mimicked the decision process of a CJTF, it also had to undergo validation. This section describes the validation plan and the tools used to measure the model's validity.

Table 11. Timing actions and associated environmental variable values

Variables	Actions			
	36 Hours	**48 Hours**	**72 Hours**	**96 Hours**
Troop level	marginal	sufficient	sufficient	sufficient
Troop buildup rate	high	low	low	low
Ship level	insufficient	insufficient	sufficient	sufficient
Ship buildup rate	moderate	moderate	low	low
Air support	marginal	marginal	marginal	high
Supply level	marginal	sufficient	sufficient	insufficient
Resupply rate	high	high	high	high
Cloud cover	overcast	partly	clear	overcast
Cloud cover change	constant	clearing	constant	constant
Precipitation type	rain	none	none	rain
Precipitation rate	heavy	none	none	moderate
Precipitation rate change	constant	clearing	clearing	constant
Visibility	fog	clear	clear	reduced
Visibility change	constant	constant	constant	constant
Wind level	moderate	strong	moderate	light
Wind level change	constant	constant	increasing	increasing
Wave height	moderate	low	moderate	moderate
Wave height change	constant	constant	increasing	increasing
Forecast quality	excellent	good	poor	poor
Troop training	moderate	moderate	high	high
Enemy status	unaware	unaware	suspicious	alerted
Staff recommendation	no	yes	possible	no

Default Decision: Available timing can not be supported. Assault will not be conducted.

Table 12. Change cues and associated environmental variables

Cues	Environmental Variables	Variable Values
Risk	Enemy force size	small, moderate, large
	Change of plan	low, moderate, high
Readiness	Reposition	high, moderate, low
	Earlier time	high, moderate, low
Recommendation	Recommendation	recommended, not, possible

Table 13. Change goals and associated cues

Goals	Associated Cues
Achieve mission	risk, readiness, recommendation
Minimize casualties	risk

Table 14. Change actions

Variables	Actions		
	Go Earlier	Change Location	Go On Time
Enemy force size	small	moderate	moderate
Change of plan	moderate	low	low
Reposition	high	moderate	high
Earlier time	high	high	high
Recommendation	recommended	possible	possible

Default Decision: Assault can not be supported under the new conditions.

Table 15. Continue cues and associated environmental variables

Cues	Environmental Variables	Variable Values
Opposition	Enemy forces	low, medium, high
	Casualties	low, medium, high
	Withdrawal risk	low, medium, high
	Threat to Terrier	low, medium, high
	Probability of success	low, medium, high
	Recommendation	recommended, possible, not
Force Effectiveness	Withdrawal ability	high, medium, low
	Air support	likely, possible, unlikely
	Force ration	high, medium, low
	Reenforcements	likely, possible, unlikely

Table 16. Continue goals and associated cues

Goals	Associated Cues
Achieve mission	opposition, force effectiveness
Minimize casualties	opposition

Table 17. Continue actions

Variables	Action Continue on
Enemy forces	high
Casualties	high
Withdrawal risk	moderate
Threat to Terrier	low
Probability of success	medium
Recommendation	not
Withdrawal ability	high
Air support	likely
Force ratio	high
Reenforcements	likely

Default Decision: Casualty risk is too great. Withdraw troops from landing zone.

3.2.1 Validation plan

There are several methods that one could employ to validate a model. RPDAgent was intended to improve upon the decision algorithms in military simulations so that they better replicated the decisions a human would make. One way to measure this improvement would be to compare the decisions made by RPDAgent against existing model decisions. However, this method posed problems. Incorporating RPDAgent into an existing model, so that the model decisions with and without RPDAgent could be compared, was technically problematic and beyond the scope of this research. Also, how to determine if the model with RPDAgent produced more human-like decisions is not easily done and could produce inconclusive results.

Instead, RPDAgent decisions would be compared against the decisions made by real human decision makers. This approach proved to be a better test of model validity. As noted in Section 1.2, a CJTF makes decisions at the operational level of warfare. Existing military simulations generally rely on expert role players to make these decisions and to input them into the model, rather than the model making them. So, a better test of RPDAgent would be to compare its decisions against the role players' decisions.

A CJTF role player is typically a mid to senior level military officer with joint operational experience who is taking the place of the CJTF for the purpose of model control and decision-making. For model validation, thirty such role players were solicited. They represented a population of surrogate CJTFs against which RPDAgent's decisions would be compared. The thirty role players ranged in military pay grade from O-4 to O-6. Twenty-one were U.S. military officers from all four Services. Nine were coalition officers from NATO-affiliated countries. This mixture of role players provided a cross section of military experience that represents the population of military officers from which a CJTF would come.

All role players were volunteers who were solicited from U.S. Joint Forces Command Joint Warfighting Center and Headquarters, Supreme Allied Commander Atlantic. These commands employ military officers with joint and coalition military experience. In addition, these officers typically participate in Joint Task Force exercises as role players. Since these role players are human subjects, they were solicited under the guidelines of Old Dominion University's Institutional Review Board (IRB). IRB approval was obtained prior to obtaining any information from the role players. Appendix C contains the IRB-approved informed consent document used to solicit role player data.

To collect the data necessary to compare the role players' decisions against RPDAgent, a decision scenario was devised. As noted in Section 3.1.4, this scenario (see Appendix B) represented four operational decisions that a CJTF would likely face when conducting an amphibious assault in support of a larger campaign. Each role player was asked to render four decisions, one for each decision point. Their decisions were only constrained by the scenario. They were also asked to complete the CTA questionnaire (Appendix B) for each decision to capture any task information not previously obtained from historical analysis. This provided 120 decisions (30 role players times 4 decisions) against which to compare RPDAgent.

In addition to the decision scenario, each role player was asked to complete a personality measurement questionnaire (Appendix D). This questionnaire was based on Goldberg's International Personality Item Pool (IPIP) [88], which measures personality traits identified by the Five Factor model [89]. This model has been shown to be an indicator of a person's risk tolerance [90]. As noted in Section 3.1.3, a person's risk tolerance was used as a factor in determining a decision. Risk tolerance is the personality factor that most influences a CJTF's decision-making [5, 73].

Results of this questionnaire showed that twenty-nine role players tended towards risk tolerant. One role player was assessed as risk neutral. However, he made decisions that were similar to those role players who were risk tolerant. Because of this, RPDAgent was run with its risk trait set at the risk tolerant level (2.0) for all data runs.

Once all role player data was collected, RPDAgent was provided with the same decision scenario, and the model was run to collect its decisions for comparison against those of the role players. Since RPDAgent is a stochastic model, two hundred replications were performed to obtain a distribution of RPDAgent's decisions. Each replication consisted of thirty decision sets representative of the thirty role player decision sets. Each RPDAgent decision set contained a distribution of model decisions for each decision point. It was this distribution of decisions for each point that was compared to the role player decision distribution for each point. Specifically, the mean for each decision from the two hundred replications was compared against the number of role players that made that decision. Comparison results are presented in Section 3.3.

3.2.2 Statistical analysis method

Standard statistical tests exist to compare a sample mean with a known population mean with unknown population variance [91]. These tests allow one to determine whether the absolute difference between the sample mean and the population mean is greater than zero. The statistical test would have the following hypotheses:

$$h_0 : |\overline{X} - \mu| = 0$$
$$h_a : |\overline{X} - \mu| > 0$$

where h_0 is the null hypothesis, h_a is the alternate hypothesis, $\overline{X}$ is the sample mean, and μ is the population mean. However, when performing statistical analysis involving the complexity and uncertainty of human decision-making, determining if the difference between model and human decisions is precisely zero is overly restrictive and unrealistic. Instead, psychologists have developed *significance tests* to measure if some pre-selected meaningful difference exits between a population mean and a sample mean [92].

Unlike the hypothesis noted above, the purpose of significance testing is to determine whether two values are sufficiently close to one another to be considered equivalent. Equivalency testing is appropriate if an investigator is able to specify some small, non-zero difference between two values that would define an "equivalence interval" around a difference of zero. Any difference that falls within this interval would be considered insignificant or acceptable.

Significance testing consists of two one-sided hypothesis tests. With the first test, one seeks to reject the null hypothesis that the difference between two values is less than or equal to some value δ_1. With the second test, one seeks to reject the null hypothesis that the difference between the two values is greater than or equal to some value δ_2. For these tests, $\delta_1 = -\delta_2$ and δ represents the pre-selected allowable equivalence difference.

If it can be shown that the difference between the two values comes from a distribution that is simultaneously to the right of δ_1 and to the left of δ_2, one can conclude

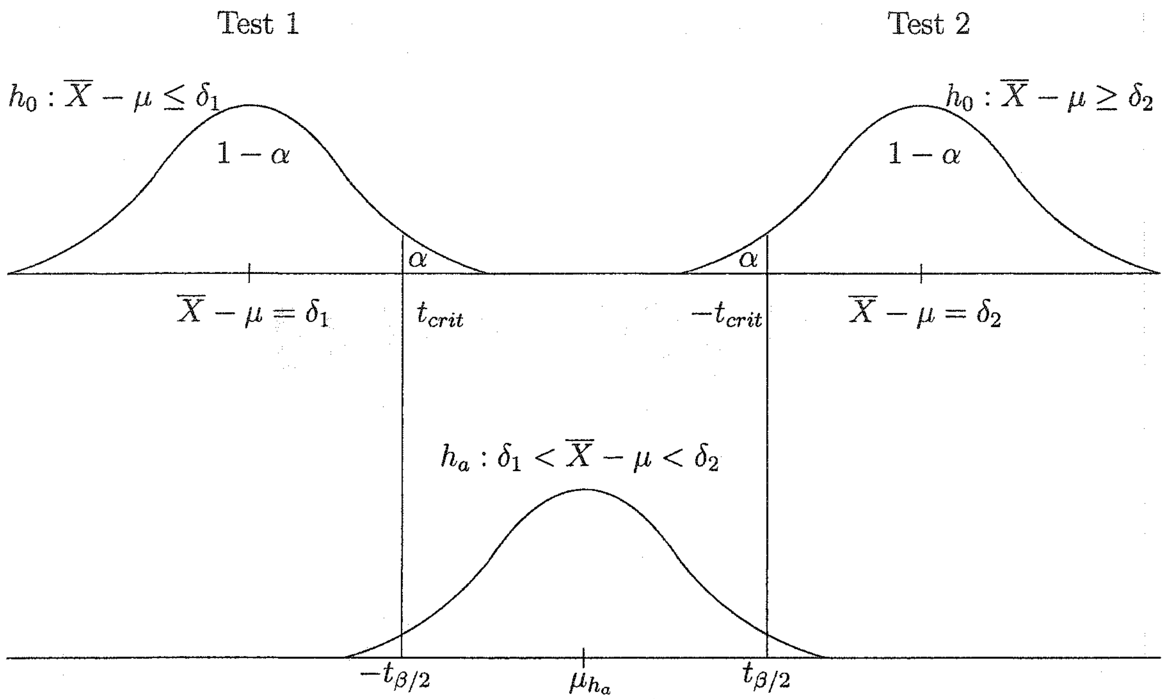

Figure 14. One-sided hypothesis tests for significance testing [92]

that the distribution it came from is somewhere in the middle with a true difference less than the minimum difference of importance that was pre-selected. Figure 14 depicts the two one-sided hypothesis tests. Table 18 lists the hypotheses for each test and its associated test statistic. $\overline{X}$ represents the sample mean. μ represents the population mean. The value, $s_{\overline{X}-\mu}$, is the standard error. The test statistic is the student t test with the critical test statistic given as t_α.

Table 18. Hypothesis and test statistics for significance testing

Hypothesis		Test statistic
Test 1	$\begin{cases} h_0 : \overline{X} - \mu \leq \delta_1 \\ h_a : \overline{X} - \mu > \delta_1 \end{cases}$	$t_1 = \dfrac{(\overline{X} - \mu) - \delta_1}{s_{\overline{X}-\mu}}$
Test 2	$\begin{cases} h_0 : \overline{X} - \mu \geq \delta_2 \\ h_a : \overline{X} - \mu < \delta_2 \end{cases}$	$t_2 = \dfrac{(\overline{X} - \mu) - \delta_2}{s_{\overline{X}-\mu}}$

To establish equivalency, one must reject the null hypothesis from both one-sided tests. However, to accomplish this, one need only perform the calculations for one test, provided that the investigator chooses the test with the smallest difference between $\overline{X}-\mu$ and δ_1 or δ_2. Choosing the smaller difference will yield the smallest test statistic and consequently the larger p value of the two possible tests. If the test with the larger p value is rejected, the second test with the smaller p value will always be rejected.

To perform the one-sided significance test, one must also choose the acceptable probability of a Type I error (α).[16] In some instances, when more than one statistical test is required, α must be adjusted to account for test independence. However, for significance testing, both tests are dependent. One test perfectly predicts the other so no adjustment to α is required. The α selected for one test will accurately represent the Type I error.

For the purpose of RPDAgent validation, equivalency between RPDAgent decisions and role player decisions was defined as having model results within twenty percent of role player results. For example, if ten role players chose location Bravo as the amphibious assault landing location, then the mean value of the number of times RPDAgent selected location Bravo for its two hundred replications, must fall within twenty percent of ten (8-12). Twenty percent was chosen because it is not too wide a band to be unreasonable and not too narrow a band to account for human variability. This was the criteria used to assess model validity and to determine if RPDAgent adequately mimicked the human decision process. Results of this assessment are presented in Section 3.3.

3.3 Data analysis and results

This section presents the decision data obtained from the role players and RPDAgent. It also presents the results of the significance tests between the two sets of data.

[16]In statistics, a Type I error is the probability of rejecting the null hypothesis when it is actually true. This probability is symbolized by α and is usually set to either 0.05 or 0.01.

Table 19. Role player location decision results

Location decision	Number of players who chose
Alpha	0
Bravo	21
Charlie	4
Delta	5

Table 20. Role player timing decision results

Timing decision	Number of players who chose
36 hours	2
48 hours	27
72 hours	1
96 hours	0

3.3.1 Role player decision results

Thirty military officers, playing the role of a CJTF, participated in this research. They were provided the decision scenario from Appendix B. Their decisions were recorded on decision data sheets. The first decision point of the scenario asked them to select a landing location for the amphibious assault based on the information provided. Table 19 shows the results of their decisions. One can see from the decision results that humans make different decisions given the same scenario information. The variability is a result of their past experience and how they interpret the information. RPDAgent must be able to mimic this variability to successfully replicate the human decision process.

The second decision point required the CJTF role players to decide on the timing of the amphibious assault. Table 20 presents the results of their timing decisions.

After making the timing decision, the CJTF role players were presented with unexpected troop movements that could affect the location and timing decisions. They were asked to render a new decision based on this updated information. From the thirty role players, three decisions emerged. Some decided to move the timing up and execute the landing earlier, some decided to change the landing location, and

Table 21. Role player change decision results

Change decision	Number of players who chose
On time	7
Go early	21
Change location	2

Table 22. Role player continue decision results

Continue decision	Number of players who chose
Continue	21
Withdraw	9

some decided to go as scheduled at the previously selected location. Their decision distribution is presented in Table 21.

Once the amphibious landing was completed, the scenario presented a situation where the landing force encountered unexpected enemy opposition and larger than expected casualty rates. Role players were asked for a decision on whether to continue the assault or to abort it. Table 22 presents the results of this decision.

3.3.2 Model decision results and analysis

This section will present the results of RPDAgent's mean decision values over the two hundred replications that were run. Equivalency was tested per the twenty percent equivalency level mentioned above. Additionally, results of ten percent equivalency tests will also be presented to help judge model performance. For all statistical tests, the α Type I error level chosen was 0.05 giving a critical test statistic $t_\alpha = 1.645$.

Table 23 provides basic statistical data for each location decision. This data is based on the two hundred replications. Table 24 provides the results of the model location decisions and the test statistic (t) for each decision. For all decisions, $|t| > t_\alpha$. These tests support the rejection of all null hypotheses, indicating that the model decisions are equivalent with the role player decisions within the twenty percent equivalency band. Test results from ten percent equivalency testing are also included.

Table 23. Location decision descriptive statistics

Action	Minimum	Maximum	Mean	Std. Deviation
Alpha	0	0	0	0
Bravo	13	27	21.745	2.4185
Charlie	0	12	3.955	1.8976
Delta	0	11	4.3	1.9257

Table 24. Model location decision results and analysis

				20% equivalence		10% equivalence	
Action	**Human**	**Model**	s	**20%** δ	t	**10%** δ	t
Alpha	0	0	0	0	na	0	na
Bravo	21	21.745	0.1710	4.2	-20.2047	2.1	-7.924
Charlie	4	3.955	0.1341	0.8	5.6301	0.4	2.6473
Delta	5	4.3	0.1361	1.0	2.2043	0.5	-1.4695

These results show that the *Bravo and Charlie* decisions fall within this equivalency band. Decision *Delta* is not equivalent at the ten percent difference level.

Presented next, in Tables 25 and 26, are the model results from the timing decision with its corresponding statistical analysis. Once again model results are equivalent with the role player results at the twenty percent equivalency level. The *48 hour* decision was equivalent at the ten percent level.

Results from the change decision are shown in Tables 27 and 28. Statistical tests again show that the model results are equivalent to the CJTF role player's decisions at the selected twenty percent level. Here, only the *change location* decision is not equivalent at the ten percent level.

The fourth and final decision point concerned the decision to withdraw from the landing zone because of unexpected enemy opposition and greater than expected friendly casualties. Tables 29 and 30 shows that all decisions are again equivalent at the twenty percent level. The *continue* decision was not equivalent at the narrower equivalency level.

Summarizing the above results, all model decisions were determined to be equivalent to the role player decision results when calculated using the twenty percent

Table 25. Timing decision descriptive statistics

Action	Minimum	Maximum	Mean	Std. Deviation
36 hours	0	6	1.87	1.4981
48 hours	22	30	27.04	1.7532
72 hours	0	4	1.09	0.9033
96 hours	0	0	0	0

Table 26. Model timing decision results and analysis

				20% equivalence		10% equivalence	
Action	Human	Model	s	20% δ	t	10% δ	t
36 hours	2	1.87	0.1059	0.4	2.5496	0.2	0.6610
48 hours	27	27.04	0.1239	5.4	-43.2607	2.7	-21.4689
72 hours	1	1.09	0.0638	0.2	-1.7241	0.1	-0.1567
96 hours	0	0	0	0	na	0	na

Table 27. Change decision descriptive statistics

Action	Minimum	Maximum	Mean	Std. Deviation
On time	3	14	7.2	2.0529
Go early	16	26	20.755	2.1395
Change location	0	6	1.825	1.2777

Table 28. Model change decision results and analysis

				20% equivalence		10% equivalence	
Action	Human	Model	s	20% δ	t	10% δ	t
On time	7	7.42	0.1451	1.4	-6.7540	0.7	-1.9297
Go early	21	20.755	0.1512	4.2	26.1574	2.1	-12.2685
Change location	2	1.825	0.0903	0.4	2.4917	0.2	0.2769

Table 29. Continue decision descriptive statistics

Action	Minimum	Maximum	Mean	Std. Deviation
Continue	12	28	22.09	2.3917
Withdraw	2	18	7.91	2.3917

Table 30. Model continue decision and analysis

				20% equivalence		10% equivalence	
Action	Human	Model	s	20% δ	t	10% δ	t
Continue	21	22.09	0.1691	4.2	-18.3915	2.1	-5.9728
Withdraw	9	7.91	0.1691	1.8	4.1987	0.9	-1.1236

Table 31. Equivalency test summary

Decision	Action	Equivalent at	
		20% level	10% level
Location	Alpha	na	na
	Bravo	yes	yes
	Charlie	yes	yes
	Delta	yes	no
Timing	36 hours	yes	no
	48 hours	yes	yes
	72 hours	yes	no
	96 hours	na	na
Change	On time	yes	yes
	Go early	yes	yes
	Change location	yes	no
Continue	Continue	yes	yes
	Withdraw	yes	no

equivalency difference that was specified during validation design. Six of the eleven model decisions were shown to be equivalent to the surrogate CJTF decisions when examined using the ten percent equivalency test. Table 31 summarizes these results.

3.3.3 A Turing test analysis of model results

The section above described the model results in terms of a statistical comparison between its decisions and human decisions. In a purely mathematical comparison, one could argue that there are subtleties between the model decisions and the decisions made by humans that statistics may not identify. To ensure that these subtleties are not overlooked, an additional test, patterned after the Turing test proposed by Alan Turing, was conducted.

Turing's original concept of the Turing test was a method to determine if a computer had achieved intelligence [93]. The test consisted of a human interrogator who could pose questions and receive answers from two hidden respondents; the respondents could be either human or a computer system. The questions and answers were transmitted in an impersonal manner such as a computer terminal. The interrogator's goal was to determine which of the respondents was a man and which was a woman. The computer system would pass the Turing Test if the interrogator was no more likely to identify the man from the woman if one of the respondents was a computer vice when both were humans. Since Turing originally posed this test, another form of the test has evolved. This test specifies that the goal of the interrogator is to determine if a single responder is a computer or a human. It is this form of the test that was used to measure RPDAgent's decision-mimicking ability. This test would determine whether human experts were able to identify a set of computer decisions from a set of human decisions through some pattern not identified by statistical equivalency testing. The Turing test has been previously used to assess computer generated behavior at the tactical level [94, 95]. The utility of the Turing test for such assessments has been widely asserted [96].

The test consisted of twenty sets of decisions. Each set represented the four decision points from the amphibious assault scenario. The twenty sets were selected at random from among the thirty human decision sets obtained from the role players and thirty computer decision sets generated by one replication run of RPDAgent. Selecting twenty decision sets from the sixty available sets allowed for a possible 4.19×10^{15} combinations of sets. Two such groups of twenty sets of decisions were generated and used in the test. The two groups are listed in Appendix E along with the test instructions provided to the subject matter experts. Test one contained eleven human decision sets and nine computer decision sets. Test two contained seven human and thirteen computer. Four subject matter experts responded to test number one and one responded to test number two. These assignments were made by one of the general officers. All responses were independent of one another.

The subject matter experts consisted of a total of five general officers from the U. S. Army and Air Force. Three of the five general officers were of the rank of General

Table 32. Turing test results

SME	Number of "can't tell" responses	Number of "human" or "computer" responses	Number of correct "human" or "computer" responses	Percentage correct
GEN. A	20	0	0	0
GEN. B	6	14	8	40%
GEN. C	13	7	3	15%
GEN. D	18	2	2	10%
GEN. E	17	3	2	10%

(four star). Two were of the rank of Lieutenant General (three star). All were retired officers with significant joint task force experience including command of a JTF or its equivalent. Per the test instructions, they were asked to attempt to identify the source of each decision set. They had three choices: "human", "computer", or "can't tell". Their selection results are presented in Table 32. Column one identifies each subject matter expert (SME). Column two lists the number of sets (out of twenty) that each SME said they could identify a computer decision from a human decision. The third column lists the number of correct assessments from the ones they could identify. The fourth column lists the percentage correct out of twenty sets.

To analyze the Turing test results of Table 32, one can compare the number of correct assessments to the expected number of successes by purely guessing the results. The expected number of successes (S)[17] from purely guessing can be represented by a Bernoulli calculation [97].

$$S = np \tag{17}$$

Equation 17 represents this calculation where S is the expected number of successes, n is the number of trials (20), and p is the probability of success. For all trials, it is assumed that each SME had a fifty percent probability of guessing correctly. Therefore, the expected number of successes from purely guessing is $(20) * (0.5) =$

[17]Success is defined as correctly identifying the source of the decision set.

10. The number of correct identifications produced by the SMEs is fewer than the number to be expected from random guessing. Even if the seventy-four SME "can't tell" responses are assumed to be replaced with guesses with $p = 0.5$, this produces $15 + (0.5)74 = 52$ assumed successes, a number not statistically greater than pure guessing. These results indicate that it is unlikely that a pattern of decisions exist that would allow human observers to distinguish the computer decisions from the human decisions.

4 CONCLUSION

The motivation for this research stemmed from the lack of adequate decision models within military simulations. Most of the existing simulations modeled decision-making in a very homogeneous and rigid manner. When provided with the same input, models produced the same output time after time. Human decision models also did not account for personality traits that influenced decisions.

The above shortcomings were especially true when looking at decision modeling at the operational level of warfare. Most decision models were centered around tactical decisions. Capturing the decision process of a senior military commander was almost non-existent.

Previous attempts at producing a computational model that mimicked the human decision process were centered around rule-based models with classical decision theory as the underlying cognitive process. In most decision situations facing operational military commanders, the decision process they employ is not characterized by classical concepts. Their decision process was centered more on Naturalistic Decision Theory of which RPD is the primary model. To adequately mimic their decision-making, a computational model of RPD was required.

Multiagent system simulation was evaluated as the best computational method with which to implement the RPD process. The autonomous, goal orientated nature of MAS, closely resembled the cognitive process described by RPD. MAS supported the use of an experience data base and mental simulation to closely capture how decision makers, experienced in their domain of expertise, drew on this experience to arrive at a decision that would satisfy the situation.

As a result, this research developed a computational model of RPD using multiagent system simulation techniques that was able to produce decisions equivalent to those made by CJTF role players. In doing so, the concepts of situational awareness, the recognition process, and the action selection process were captured in a mathematical form that accurately modeled RPD and CJTF decision-making at the operational level of warfare.

4.1 Future work

This research is significant in that it produced the contributions noted in Section 1.5. Additionally, it has opened the door and formed the basis for further research in many areas. These areas include:

1. **Incorporating RPDAgent into an existing simulation.** To assess the effectiveness of RPDAgent against existing decision methodologies, RPDAgent could be incorporated into an existing military simulation and its performance could be measured against the simulation without RPDAgent incorporated.

2. **Incorporating the influence of Joint Task Force Staff decisions into the CJTF decision model.** In some situations, a CJTF may not possess the domain expertise to render a satisfactory decision for a given situation. He must rely on his staff to provide him with recommendations on how to proceed. Yet, he has the experience to recognize what staff recommendations will produce satisfactory results. Capturing this group synergy could form the basis for modeling the entire JTF staff decision process.

3. **Creating an experience base that would allow the model to make all types of CJTF decisions.** This research was limited by a single decision scenario that represented the type of operational decision facing a CJTF. Expanding the experience base to allow for generalized CJTF decision-making would be necessary for employing this model in a broad military environment.

4. **Researching fuzzy set shape and its influence on experience representation.** The fuzzy sets chosen for RPDAgent were triangular in nature. Other

fuzzy set shapes, and the extent of those sets, may influence the embodiment of experience in different ways. Research is required to determine the nature of this influence and its effect on decisions.

5. **Better defining measures of risk tolerance and its relationship to military decisions.** While research exists that link specific personality traits to risk tolerance, no studies have been conducted that precisely measure one's tolerance for risk and its direct influence on the decisions they have made or are likely to make. Also, one could explore the sensitivity of decisions to the risk tolerance factor encoded in the model.

6. **Better defining the personality traits affecting senior military commander decisions.** Risk was a readily identifiable personality trait that influenced an operational military commander's decision process. Further research is required to determine if other traits have a significant influence in this type of decision-making.

7. **Incorporation of dynamic action generation.** RPDAgent currently has a fixed set of actions from which it may choose for a given decision experience. Providing the capability to dynamically generate potential actions would increase the sophistication of the model.

8. **Incorporation of learning.** RPDAgent has the potential to learn based on its decisions. Incorporating learning would help improve its decision quality. Learning could be incorporated through its goal satisfaction mechanism. Research is required to devise a methodology that could adequately perform this function.

5 REFERENCES

[1] Moore, S., 1999. Joint Warfighting Center Command Briefing. Presented to Congressional Staff Members, June.

[2] Pew, R. W. and A. S. Mavor. 1998. *Modeling Human and Organizational Behavior: Application to Military Simulations.* National Academy Press, Washington D. C.

[3] Joint Staff. 2000. Joint Pub 1-02: Department of Defense Dictionary of Military and Associated Terms. Government Printing Office, Washington D. C.

[4] Joint Staff. 1995. Joint Pub 3-0: Doctrine for Joint Operations. Government Printing Office, Washington D. C.

[5] Personal knowledge.

[6] Erwin, S. I. 2000. Simulation of Human Behavior Helps Military Training Models. *National Defense*, 85(564):32–35.

[7] United States Congress. 1986. National Defense Authorization Act for Fiscal Year 1987 (commonly: Goldwater-Nichols Department of Defense Reorganization Act of 1986), Public Law No. 433. GPO, Washington D. C.

[8] Cole, R. H. 1995. OPERATION JUST CAUSE: The Planning and Execution of Joint Operations in Panama February 1988 - January 1990. Government Printing Office, Washington D. C.

[9] Dorsey, J., 2003. Command in Norfolk Takes on Job of Innovation. The Virginian Pilot, January 2.

[10] Department of Defense. 1995. Modeling and Simulation Master Plan. Government Printing Office, Washington D. C.

[11] Erwin, S. I. 2001. Commanders Want Realistic Simulations. *National Defense*, 85(567):50–51.

[12] Coppieters, D. 2001. The Increasing Need for the Representation of Decision Making and Human Behaviour in Simulations used for Computer Assisted Exercises in NATO. Tech Report RTO-ENP-017, NATO Research and Technology Organization, Cedex, FR.

[13] Beach, L. R. and R. Lipshitz. 1993. Why Classical Decision Theory is an Inappropriate Standard for Evaluating and Aiding Most Human Decision Making.

In Klein, G., J. Orasanu, R. Calderwood, and C. E. Zsambok, editors, *Decision Making in Action: Models and Methods.* Ablex Publishing Corporation, Norwood, NJ, pp 21–35.

[14] von Neumann, J. and O. Morgenstern. 1953. *Theory of Games and Economic Behavior.* Princeton University Press, Princeton, NJ.

[15] Clemen, R. T. 1996. *Making Hard Decisions: An Introduction to Decision Analysis.* Duxbury Press, Pacific Grove, CA.

[16] Lehto, M. R. 1997. Decision Making. In Salvendy, G., editor, *Handbook of Human Factors and Ergonomics.* John Wiley and Sons, Inc, New York, pp 1201–1248.

[17] Keeney, R. L. and H. Raiffa. 1976. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs.* John Wiley and Sons, Inc, New York.

[18] Kahneman, D. and A. Tversky. 1979. Prospect Theory: An Analysis of Decision Under Risk. *Econometrica*, 47(2):263–291.

[19] Klein, G. 1998. *Sources of Power: How People Make Decisions.* The MIT Press, Cambridge, MA.

[20] Tversky, A. and D. Kahneman. 1974. Judgment Under Uncertainty: Heuristics and Biases. *Science*, 185:1124–1131.

[21] Klein, G. 1989. Strategies of Decision Making. *Military Review*, 69(5):56–64.

[22] Klein, G. 1993. A Recognition-Primed Decision (RPD) Model of Rapid Decision Making. In Klein, G., J. Orasanu, R. Calderwood, and C. E. Zsambok, editors, *Decision Making in Action: Models and Methods.* Ablex Publishing Corporation, Norwood, NJ, pp 138–147.

[23] Pascual, R. and S. Henderson. 1997. Evidence of Naturalistic Decision Making in Military Command and Control. In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 217–226.

[24] Simon, H. A. 1957. *Models of man: social and rational mathematical essays on rational human behavior in a social setting.* John Wiley and Sons, Inc, New York.

[25] Simon, H. A. 1981. *The Sciences of the Artificial.* John Wiley and Sons, Inc, New York.

[26] Orasanu, J. and T. Connolly. 1993. The Reinvention of Decision Making. In Klein, G., J. Orasanu, R. Calderwood, and C. E. Zsambok, editors, *Decision Making in Action: Models and Methods.* Ablex Publishing Corporation, Norwood, NJ, pp 3–20.

[27] Zsambok, C. E. 1997. Naturalistic Decision Making: Where are We now? In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 3–16.

[28] Endsley, M. R. 1997. The Role of Situational Awareness in Naturalistic Decision Making. In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 269–284.

[29] Randel, J. M. and H. L. Pugh. 1996. Differences in Expert and Novice Situation Awareness in Naturalistic Decision Making. *International Journal of Human-Computer Studies*, 45:579–597.

[30] Kurzweil, R. 1999. *The Age of Spiritual Machines.* Penguin Books, New York, NY.

[31] Zhang, W. and R. W. Ford, Jr. 2000. Situation Awareness and Assessment - An Integrated Approach and Applications. In *Proceedings of the Ninth Conference on Computer Generated Forces and Behavioral Representation*, May 16-18, Orlando, FL, pp 365–376.

[32] Brunswick, E. 1955. Representative Design and Probabilistic Theory In a Functional Psychology. *Psychological Review*, 62:193–217.

[33] Brehmer, B. and R. Hagafors. 1986. Use of Experts in Complex Decision Making: A Paradigm for the Study of Staff Work. *Organizational Behavior and Human Decision Processes*, 38:181–195.

[34] Hollenbeck, J. R., D. R. Ilgen, D. J. Sego, J. Hedlund, D. A. Major, and J. Phillips. 1995. Multilevel Theory of Team Decision Making: Decision Performance in Teams Incorporating Distributed Expertise. *Journal of Applied Psychology*, 80(2):292–316.

[35] Joint Staff. 1995. Joint Pub 5-0: Doctrine for Planning Joint Operations. Government Printing Office, Washington D. C.

[36] Joint Staff. 1996. Joint Pub 3-13.1: Joint Doctrine for Command and Control Warfare (C2W). Government Printing Office, Washington D. C.

[37] Boyd, J. R. 1987. A Discourse on Winning and Losing. Tech Report MU 43947, Air University Library.

[38] Rinaldi, S. M. 1997. Complexity Theory and Airpower: A New Paradigm for Airpower in the 21st Century. In *Complexity, Global Politics, and National Security.* National Defense University Command and Control Research Program, pp 247–302.

[39] Drillings, M. and D. Serfaty. 1997. Naturalistic Decision Making in Command and Control. In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 71–80.

[40] Kaempf, G. L., G. Klein, M. L. Thorsden, and S. Wolfe. 1996. Decision Making in Complex Naval Command-and-Control Environments. *Human Factors*, 38(2):220–231.

[41] Serfaty, D., J. MacMillan, E. E. Enton, and E. B. Enton. 1997. The Decision-Making Expertise of Battle Commanders. In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 233–246.

[42] Gill, A. 1962. *Introduction to the theory of finite-state machines.* McGraw-Hill, New York.

[43] Calder, R. B., A. J. Courtemanche, A. M. F. Mar, and A. Z. Ceranowicz. 1993. ModSAF Behavior Simulation and Control. In *Proceedings of the Third Conference on Computer Generated Forces and Behavioral Representation*, March 17-19, Orlando, FL, pp 347–356.

[44] Downes-Martin, S., 1995. A Survey of Human Behavior Representation Activities for Distributed Interactive Simulations: Final Report. http://www.msiac.dmso.mil/hobm_documents/!FINALE.WRD.doc.

[45] Gallant, S. I. 1995. *Neural Network Learning and Expert Systems.* The MIT Press, Cambridge, MA.

[46] Laird, J. E., A. Newell, and P. S. Rosenbloom. 1987. SOAR: An Architecture for General Intelligence. *Artificial Intelligence*, 33:1–64.

[47] Burns, K., 2001. Mental Models and Normal Errors in Naturalistic Decision Making. Presented at the Workshop on Computerized Representation of RPD, Boulder, CO, October 23.

[48] Jones, R. M., J. E. Laird, P. E. Neilson, K. J. Coulter, P. Kenny, and F. V. Koss. Automated Intelligent Pilots for Combat Flight Simulations. *AI Magazine*, 20(1):27.

[49] Kolodner, J. L. 1991. Improving Human Decision Making through Case-Based Decision Aiding. *AI Magazine*, 12(2):52–68.

[50] Kolodner, J. L. 1993. *Case-based reasoning.* Morgan Kaufmann Publishers, San Mateo, CA.

[51] Arditi, D. and O. B. Tokdemir. 1999. Comparison of Case-Based Reasoning and Artificial Neural Networks. *Journal of Computing in Civil Engineering*, 13(3):162–169.

[52] Gilboa, I. and D. Schmeidler. 1995. Case-Based Decision Theory. *The Quarterly Journal of Economics*, 110(3):605–639.

[53] Mitchell, T. M. 1997. *Machine Learning.* McGraw-Hill, Boston, MA.

[54] Liang, Y., F. Robichaud, B. J. Fugere, and K. N. Ackles. 2001. Implementing a Naturalistic Command Agent Design. In *Proceedings of the Tenth Conference on Computer Generated Forces*, May 15-17, Norfolk, VA, pp 379–386.

[55] Zadeh, L. A. 1975. *Fuzzy sets and their applications to cognitive and decision processes.* Academic Press, New York.

[56] Robichaud, F., 2001. Implementing a Naturalistic Command Agent Design. Presented at the Workshop on Computerized Representation of RPD, Boulder, CO, October 23.

[57] Vakas, D., J. Prince, H. R. Blacksten, and C. Burdick. 2001. Commander Behavior and Course of Action Selection in JWARS. In *Proceedings of the Tenth Conference on Computer Generated Forces*, May 15-17, Norfolk, VA, pp 387–398.

[58] George, G. R. and F. Cardullo. 1999. Application of Neuro-Fuzzy Systems to Behavioral Representation in Computer Generated Forces. In *Proceedings of the Eighth Conference on Computer Generated Forces and Behavioral Representation*, May 11-13, Orlando, FL, pp 575–585.

[59] Minsky, M. L. 1986. *The Society of Mind.* Simon and Schuster, New York.

[60] Weiss, G. 1999. *Multiagent systems: A modern approach to distributed artificial intelligence.* The MIT Press, Cambridge, MA.

[61] Roddy, K. and M. Dickson. 2000. Modeling Human and Organizational Behavior Using a Relation-Centric Multi-Agent System Design Paradigm. Masters thesis, Naval Postgraduate School, Monterey, CA.

[62] Ferber, J. 1998. *Multi-agent systems: An introduction to distributed artificial intelligence.* Addison-Wesley, Harlow.

[63] Langton, C. G. 1991. *Artificial life II: The proceedings of the workshop on artificial life held February 1990 in Santa Fe, New Mexico.* Addison-Wesley, Redwood City, CA.

[64] Hiles, J., M. VanPutte, B. Osborn, and M. J. Zyda. 2001. Innovations in Computer Generated Autonomy. Tech Report NPS-MV-02-002, Naval Postgraduate School, Monterey, CA.

[65] Warwick, W., S. McIlwaine, R. Hutton, and P. McDermott. 2001. Developing Computational Models of Recognition-Primed Decision Making. In *Proceedings of the Tenth Conference on Computer Generated Forces*, May 15-17, Norfolk, VA, pp 323–331.

[66] Hintzman, D. L. 1984. MINERVA 2: A Simulation Model of Human Memory. *Behavior Research Methods, Instruments and Computers*, 16:96–101.

[67] Norling, E., L. Sonenberg, and R. Rönnquist. 2000. Enhancing Multi-Agent Based Simulation with Human-Like Decision Making Strategies. In *Multi-Agent Based Simulation: Proceedings of the Second International Workshop, MABS 2000*, Boston, MA, Springer, pp 214–228.

[68] Bratman, M. E. 1987. *Intentions, Plans, and Practical Reason.* Harvard University Press, Cambridge, MA.

[69] DeLoach, S. A., 2001. Analysis and Design using MaSE and agentTool. Presented at the 12th Midwest Artificial Intelligence and Cognitive Science Conference (MAICS 2001), Mar 31-April 1.

[70] DeLoach, S. A., M. F. Wood, and C. H. Sparkman. 2001. Multiagent Systems Engineering. *International Journal of Software Engineering and Knowledge Engineering*, 11(3):231–258.

[71] Deitel, H. M. and P. J. Deitel. 2002. *Java: How to Program.* Prentice Hall, Upper Saddle River, NJ, 4th edition.

[72] Minsky, M. L. 1995. A Framework for Representing Knowledge. In Luger, G. F., editor, *Computation and Intelligence.* AAAI Press, Menlo Park, CA, pp 163–189.

[73] Page, M. 1987. Risk in Defence. In Singleton, W. T. and J. Hovden, editors, *Risk and Decisions.* John Wiley and Sons, Ltd., London, UK, pp 191–205.

[74] Rao, V. B. and H. V. Rao. 1995. *C++ Neural Networks and Fuzzy Logic.* MIS Press, New York, NY.

[75] Raumbaugh, J., I. Jacobson, and G. Booch. 1999. *The Unified Modeling Language Reference Manual.* Addison-Wesley, Reading, MA.

[76] Wooldridge, M. 2002. *An Introduction to MultiAgent Systems.* John Wiley and Sons, LTD., West Sussex, England.

[77] Bigus, J. P. and J. Bigus. 2001. *Constructing Intelligent Agents Using Java.* John Wiley and Sons, Inc., New York, NY.

[78] Sprinkle, J., C. vanBuskirk, and G. Karsai. 2000. Modeling Agent Negotiation. In *IEEE International Conference on Systems, Man, and Cybernetics*, Oct 8, Nashville, TN, pp 454–459.

[79] Randel, J. M., H. L. Pugh, and B. G. Wyman. January 1996. Methods for Conducting Cognitive Task Analysis for a Decision Making Task. Tech Report TN-96-10, Naval Personnel Research and Development Center, San Diego, CA.

[80] Gorgon, S. E. and R. T. Gill. 1997. Cognitive Task Analysis. In Zsambok, C. E. and G. Klein, editors, *Naturalistic Decision Making.* Lawrence Erlbaum Associates, Publishers, Mahwah, NJ, pp 131–140.

[81] Gott, S., 1994. Cognitive Task Analysis. Panel discussion at the Second Conference on Naturalistic Decision Making, Dayton, OH, June.

[82] Fuquea, D. C. Winter 1997. Bougainville: The Amphibious Assault Enters Maturity. *Naval War College Review*, L(1).

[83] Alexancer, J. H. and M. L. Bartlett. 1995. *Sea Soldiers in the Cold War.* Naval Institute Press, Annapolis, MD.

[84] Alexancer, J. H. 1997. *Storm Landings.* Naval Institute Press, Annapolis, MD.

[85] Ferguson, M., 2002. Personal communication, May.

[86] Hoffman, R. R., B. Crandall, and N. Shadbolt. 1998. Use of the Critical Decision Method to Elicit Expert Knowledge: A Case Study in the Methodology of Cognitive Task Analysis. *Human Factors: The Journal of the Human Factors Society*, 40(2):254–277.

[87] Balci, O. 1998. Verification, Validation, and Testing. In Banks, J., editor, *Handbook of Simulation.* John Wiley and Sons, New York, NY, chapter 10, pp 335–393.

[88] International Personality Item Pool, 2001. A Scientific Colaboratory for the Development of Advanced Measures of Personality Traits and Other Individual Differences. http://ipip.ori.org/, September.

[89] Goldberg, L. R. 1999. A Broad-Bandwidth, Public Domain, Personality Inventory Measuring the Lower-Level Facets of Several Five-Factor Models. In Mervielde, I., I. Deary, F. DeFruyt, and F. Ostendorf, editors, *Personality Psychology in Europe*, volume 7. Tilburg University Press, Tilburg, The Netherlands, pp 7–28.

[90] Lauriola, M. and I. P. Levin. 2001. Personality Traits and Risky Decision-Making in a Controlled Experimental Task: An Exploratory Study. *Personality and Individual Differences*, 31:215–226.

[91] Bruning, J. L. and B. L. Kintz. 1996. *Computational Handbook of Statistics.* Addison Wesley, New York, NY, 4th edition.

[92] Rogers, J. L., K. I. Howard, and J. T. Vessey. 1993. Using Significance Tests to Evaluate Equivalence Between Two Experimental Groups. *Psychological Bulletin*, 113(3):553–565.

[93] Turing, A. 1950. Computing Machinery and Intelligence. *Mind*, 59(236):433–460.

[94] Potomac. 1990. Report of the Evaluation of the Representation of Semi-Automated Forces (SAF) in the SIMNET Model. Technical report, Potomac Systems Engineering, Inc., Annandale, VA.

[95] Wise, B. P., D. Miller, and A. Z. Ceranowicz. 1991. A Framework for Evaluating Computer Generated Forces. In *Proceedings of the Second Behavioral Representation and Computer Generated Forces Symposium*, May 6-7, Orlando, FL, pp H1–H7.

[96] Petty, M. D. 1994. The Turing Test as an Evaluation Criterion for Computer Generated Forces. In *Proceedings of the Fourth Conference on Computer Generated Forces and Behavioral Representation*, May 4-6, Orlando, FL, pp 107–116.

[97] Roberts, F. S. 1984. *Applied Combinatorics*. Prentice-Hall, Inc., Englewood Cliffs, NJ.

A RPDAGENT COMPUTER DISK

B DECISION SCENARIO AND ASSOCIATED DATA

Road to War

The country of Cain has had a border dispute with the country of Abel for the past 50 years. Cain leaders believed that the Abel leaders deceived their forefathers when the borders were drawn. The deception consisted of not telling the Cains about the vast oil reserves that existed near the border region. The Cains have tried to peacefully renegotiate the border with little success.

Two years ago, a militant faction of the Cains came into power. They immediately began planning an invasion of Abel to claim an area of the disputed border region, which Cain felt was an equitable division of the oil reserves. Coincidentally, the disputed region also contained Abel's main port for oil distribution to other countries. Three months ago, Cain launched a military campaign. The Cain army forcibly invaded Abel and took possession of the disputed territory, including the port of Willing.

Cain's military strength exceeded Abel's by a factor of 5:1. Despite courageous fighting by Abel's military, they could not force the Cains from their occupied land. Abel appealed to the international community for military assistance. The international community agreed to assist Abel and has formed a coalition joint task force to provide military assistance to them. In addition to the illegal seizure of Abel land, the international community also felt that the disruption of oil production and distribution, caused by the invasion, would adversely affect the world's oil supply, and thus would not be tolerated.

As Commander Joint Task Force (CJTF) Echo, your mission is to regain control of the illegally seized territory and to restore the use of the port of Willing. To accomplish this mission, you have divided your assigned forces into two separate task forces. The main force, Task Force Terrier (Corps size ground element), will conduct a land campaign to drive the Cains from the occupied land. They will be staged in Abel and approach the occupied territory from the south and west. The other task force, Task Force Gator, (Marine Expeditionary Brigade size Marine unit with two supporting Amphibious Ready Groups) will conduct a supporting amphibious assault as a diversion and to cut off the Cain's lines of communication and resupply. The focus of this experiment will be on the decisions related to operational command of the amphibious assault.

Task Force Gator Commander's Intent

Mission Conduct an amphibious assault along the southern border of Cain or eastern border of Abel to interdict their lines of communication and to prevent resupply of their ground forces.

Intent We will use the surprise and mobility of our amphibious assault capability to overwhelm the enemy's shore defenses, seize control of the landing area, and deploy forces inland to sever communications and interdict resupply of Cain forces in the occupied territory while minimizing damage to the country's infrastructure. Air Force assets will augment the organic amphibious air combat element in a close air support role. The landing will be synchronized with Task Force Terrier to ensure proper support of that effort.

End state Complete disruption of communication, all land-based resupply efforts stopped, enemy resistance neutralized.

Decision Points

Decision situation no. 1—The first decision facing you as the coalition CJTF is approving the choice of the amphibious assault landing area. There are 4 possible landing sites that exist along the coasts of Abel and Cain. All are approachable from the Bay of Willing (see Figure 15).

Location Alpha is situated along the coast of Abel within the territory occupied by the Cains. It has a shallow beach slope with a 3 ft. wall that separates the beach from the adjoining road. The water adjacent to the beach is shallow with moderate tides and a severe rip current. There is no suitable anchorage near the beach. The beach has reportedly been mined; concrete barriers have been placed in the surf near the beach. The beach has adequate staging area for landing troops and supplies and adequate routes to access the Cains' lines of communication (5 miles to the main land supply route and communication lines, 7 miles to the main supply staging area, 113 miles to the supply depot and communication center.) A brigade-size force consisting of infantry, artillery, and tanks defends the landing zone. These troops are some of the most skilled in the Cain military and are backed up by close air support (CAS). No significant naval threat exists in this area. Coalition intelligence believes the Cains consider this area a likely assault site. They rate the above landing zone assessment as excellent.

Location Bravo is situated along the coast of Cain and is the closest landing zone outside the occupied territory. It has a moderate beach slope, fine-grained sand, and jungle growth on the shore side of the beach. The water adjacent to the beach is of moderate depth with a small tide range and a moderate rip current. A suitable anchorage is available near the beach. There are no known mines or barriers either on the beach or in its adjacent water. The beach has adequate staging area for landing troops and supplies and adequate routes to access the Cains' lines of communication (8 miles to the main land supply route and communication lines, 20 miles to the main supply staging area, 100 miles to the supply depot and communication center.) A company-sized force of experienced soldiers defends the beach with infantry and artillery. Troop strength is expected to increase in this area. CAS does not support them. A small naval force consisting of 4 patrol boats is operating in the area. Coalition intelligence believes the Cains consider this area a likely assault site. They rate the above landing zone assessment as excellent.

Location Charlie is situated along the coast of Cain. It has a moderate beach slope, coarse-grained sand, and jungle growth on the shore side of the beach. The water adjacent to the beach is deep with a large tide range and a severe undertow. A suitable anchorage is available near the beach. The beach and surf are not believed to be mined but there are concrete barriers in the surf near the beach. The beach has adequate staging area for landing troops and supplies and adequate routes to access the Cains' lines of communication (10 miles to the main land supply route and communication lines, 60 miles to the main supply staging area, 60 miles to the supply depot and communication center.) A company-sized force of experienced soldiers defends the beach with infantry and artillery. They are not expected to be numerically reinforced but their experience level is assessed as increasing due to one-for-one replacement with more experienced soldiers. CAS does not support them. There are no known naval forces in the area. Coalition intelligence believes the Cains consider this area a likely assault site. They rate the above landing zone assessment as poor because of the inability to directly observe the area.

Location Delta is situated along the coast of Cain. It has a shallow beach slope, fine-grained sand, and rocks on the shore side of the beach. The water adjacent to the beach is of moderate depth with a large tide range and a moderate undertow. A coral reef extends the length of the surf zone. There are no known mines or obstructions on the beach or in the water. The beach has adequate staging area for landing troops and supplies. However, there are no adequate routes to access the Cains' lines of communication. Routes would have to be forged through the jungle area. (12 miles to the main land supply route and communication lines, 100 miles to the main supply staging area, 20 miles to the supply depot and communication center.) A company-sized force of novice soldiers defends the beach with infantry and artillery. They are not expected to be reinforced and their experience level is assessed as decreasing due to one-for-one replacement with less experienced soldiers. CAS does not support them. There are no known naval forces in the area. Coalition intelligence believes the Cains consider this area an unlikely assault site. They rate the above landing zone assessment as good.

Based on the above assessments, your staff has recommended *location Delta* because it is lightly defended, it has an adequate landing zone, and it has an element of surprise. These outweigh the task of having to forge a path to the lines of communication. You must either concur or order another course of action (COA).

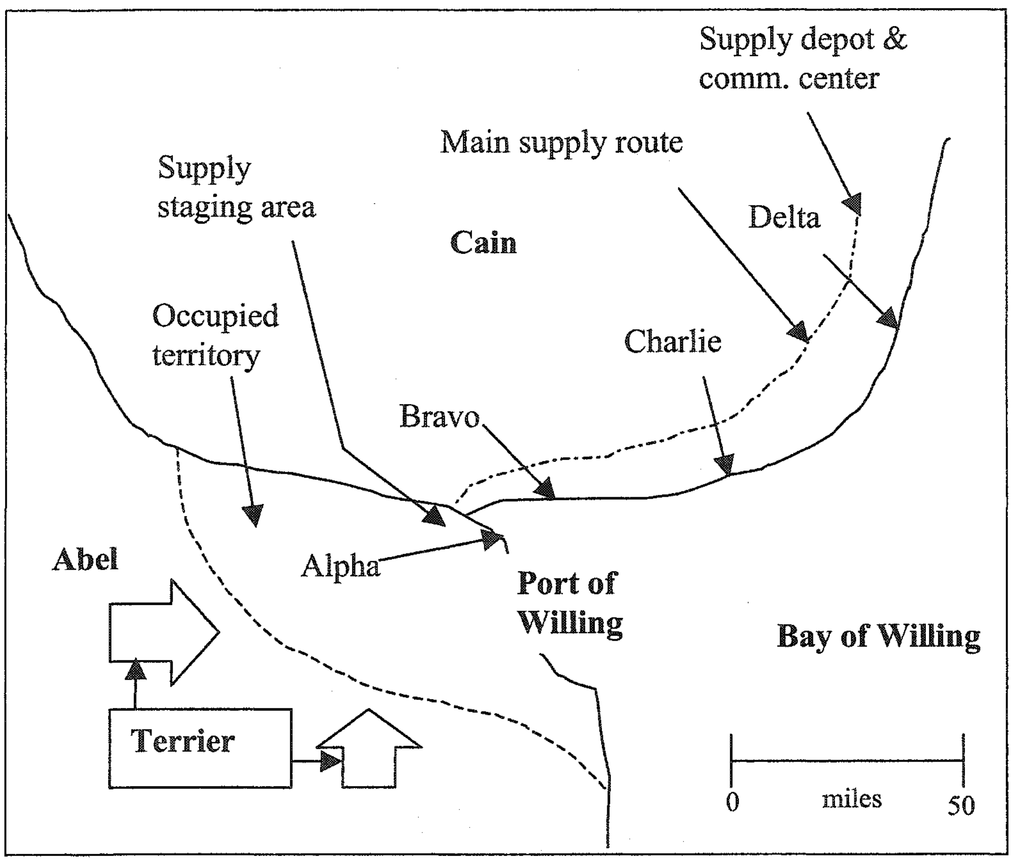

Figure 15. Map of Joint Operations Area (JOA)

Decision situation no. 2—The second decision facing you as the coalition CJTF is approving the timing of the amphibious assault. There are four choices that will support the efforts of the land campaign, which will be ready to start in 36 hours and must commence within 96 hours to remain on their timetable. They are summarized below.

36 Hours—The following is the expected level of readiness at this point. Troop level will be at a marginal level with the minimum number of troops available for a successful assault. Landing ship support is insufficient and will require twice the number of reloads to land the required number of troops, equipment, and supplies. Air support is sufficient. There are enough supplies to sustain the force for 30 days. Weather forecast is for an overcast sky with light rain and fog. Wind and wave height in the bay are moderate. The forces will have rehearsed the assault once and are considered at a moderate state of training. There are no significant enemy troop movements in the area. Coalition intelligence has no indication that Cain is alerted to the assault. You have both air and maritime superiority.

48 Hours—At this point, troop level will be at a sufficient level to easily assure mission success. Landing ship support is still insufficient and will require about one and a half times the number of reloads to land the required troops, equipment, and supplies. Air support is sufficient. There are enough supplies to sustain the force for 30 days. Weather forecast is for partly cloudy conditions with no precipitation and good visibility. Wind and wave height are low. The forces will have rehearsed the assault once and will be at a moderate state of training. There are no significant enemy troop movements in the area. Coalition intelligence does not predict that Cain will be alerted to the assault. You have both air and maritime superiority.

72 Hours—At this point, troops remain at a sufficient level. Landing ship support will be sufficient to land troops, equipment, and supplies in the desired time frame. Supply levels are still rated as marginal with enough to sustain the force for 45 days. Weather forecast is for clear skies with moderate wind and wave height but with conditions expected to worsen over the course of the landing. This forecast is rated poor because of a complex weather pattern that may affect the area. The forces will have rehearsed the assault twice and will be at a high state of training. There are no significant enemy troop movements in the area. Coalition intelligence estimates that the Cains will have a 25% probability of detecting the assault before it commences. You have both air and maritime superiority.

96 Hours—At this point, troops, ships, and supplies will be at sufficient levels to provide adequate support for the assault. Weather is expected to be overcast with moderate rain, reduced visibility, strong winds, and moderate but increasing waves. This forecast is rated poor because of a complex weather pattern that may affect the area. The forces will have rehearsed the assault three times and will be at a high state of training. There are no significant enemy troop movements in the area. Coalition intelligence estimates that the Cains will have a 50% probability of detecting the assault at this point. You have both air and maritime superiority.

Based on the above assessments, your staff recommends conducting the assault *48 hours* from now based on maintaining the element of surprise, which is a sufficient advantage to offset the insufficient ship level and marginal supply level. You must either concur or order a different COA.

Decision situation no. 3—You have decided on the timing of the amphibious assault and are within 24 hours of execution when your intelligence staff informs you that they have picked up indications of large Cain troop movements into the area of the landing zone you have chosen. They estimate that Cain troop strength will reach a brigade plus level within 48 hours. The intelligence staff is unable to tell if the Cains have been alerted to the assault or are moving the troops for further staging elsewhere. All subordinate commanders indicate they can support an earlier execution. A location change can also be supported with some risk of enemy alertment and not completing the relocation in the allotted time. Your staff recommends moving the start of the assault up by 12 hours and to continue on with the chosen landing site. There is urgency in this decision because it must be coordinated with the land campaign force plans and with air force air support for the landing. You must either concur with your staff's recommendation or order a different COA.

Decision situation no. 4—Your troops have successfully landed on the beach with only minor personnel and equipment casualties. As Task Force Gator begins to move towards its objective, it comes under intense fire. It appears that intelligence underestimated the enemy troop strength, which now is at least two brigades. The enemy seems to have waited until you were ashore to fully engage. The task force's forward progress is stopped and they begin taking heavy casualties with the casualty rate increasing. Air strikes have not improved the situation. For the moment, the task force is holding its position, but it is unclear if it will be able to overcome the opposition. Enemy casualties have also been high. Naval forces are still in place to affect a rapid withdrawal of personnel with no estimated increase in casualty rate. Your staff recommends abandoning the assault and withdrawing the troops back to their ships. You must either concur with your staff's recommendation or order a different COA.

Decision Situation Data Sheet

Decision: ______________________

1. What information (scenario variables or conditions) did you use in making this decision?
2. Based on this information, what were your expectations?
3. What were your specific goals and objectives for this decision?
4. Did you consider any other COAs than were provided by your staff? If so, what were they and why did you consider them?
5. How was this decision selected/other options rejected? Did you follow a rule for selection?
6. Did you imagine the possible consequences of this action? If so, what were those consequences? Did you imagine the events that would unfold? If so, what were those events?
7. What knowledge or information might have helped make this decision easier?
8. Were you reminded of any previous experience? If so, please describe how it was similar to this scenario.
9. Does this case fit a standard or typical scenario? Does it fit a scenario you were trained to deal with?

C ODU IRB INFORMED CONSENT DOCUMENT

INFORMED CONSENT DOCUMENT
OLD DOMINION UNIVERSITY

PROJECT TITLE: Modeling the Decision Process of a Joint Taskforce Commander

INTRODUCTION The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. This project is concerned with modeling the decision process of a Joint Taskforce Commander. To validate the model's performance, we must compare the model's results against decisions made by human role players. Because of your military background, you have been asked to make a series of decisions that will be used for comparison against the model's output.

RESEARCHERS This research is being conducted by John Sokolowski, a PhD candidate in the Modeling and Simulation program of Old Dominion University's College of Engineering and Technology.

DESCRIPTION OF RESEARCH STUDY Many military simulations exist. However, they are lacking in their ability to accurately model human decision-making. This is especially true for the operational level of warfare. This research hopes to produce an accurate model of the decision process that experienced decision makers employ to arrive at decisions in time constrained and volatile environments.

If you decide to participate, then you will join a study involving research into modeling military decisions at the operational level of warfare made by senior military commanders. If you say YES, then your participation will last for approximately 2 hours at the location designated by your command. Approximately 30 military officers in the ranks of O4 to O6 will be participating in this study. You will be given a decision scenario, which will ask you to make 4 decisions based on the information presented in the scenario. You will also be asked to explain your reasoning behind the decisions you chose and the factors that influenced that decision. In addition to the decision scenario, you will also be given a personality questionnaire that will help measure your risk tolerance. This measurement will be used as an input to the model to help capture your risk personality trait.

EXCLUSIONARY CRITERIA Only those military officers in the ranks of O4 to O6 with operational military experience have been asked to participate in this study.

RISKS AND BENEFITS RISKS: There are no known risks involved with participation in this study. However, as with any research, there may be risks that have not yet been identified.

BENEFITS: There are no direct benefits to you, however your participation in this study will help provide for a more accurate model of decision-making that may be incorporated into military simulations to improve training, analysis, and experimentation at all levels of warfare.

COSTS AND PAYMENTS The researchers are unable to give you any payment for participating in this study.

NEW INFORMATION If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY The researchers will take reasonable steps to keep private information, such as personality traits confidential. No personal identifying data will be linked to any results of this study. Only a tracking number will be used to correlate data. The results of this study may be used in reports, presentations, and publications but the researcher will not identify you.

WITHDRAWAL PRIVILEGE It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study at any time. Your decision will not affect your relationship with Old Dominion University or your parent command.

COMPENSATION FOR ILLNESS AND INJURY If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of problems arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact John Sokolowski at 686-6215 or Dr. David Swain the current IRB chair at 683-6028 at Old Dominion University, who will be glad to review the matter with you.

VOLUNTARY CONSENT By signing this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them: John Sokolowski at 757-686-6215

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. David Swain, the current IRB chair, at 757-683-6028, or the Old Dominion University Office of Research and Graduate Studies, at 757-683-3460.

And importantly, by signing below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Subject's Printed Name & Signature	**Date**

INVESTIGATOR'S STATEMENT I certify that I have explained to this subject the nature and purpose of this research, including benefits, risks, costs, and any experimental procedures. I have described the rights and protections afforded to human subjects and have done nothing to pressure, coerce, or falsely entice this subject into participating. I am aware of my obligations under state and federal laws, and promise compliance. I have answered the subject's questions and have encouraged him/her to ask additional questions at any time during the course of this study. I have witnessed the above signature(s) on this consent form.

Investigator's Printed Name & Signature	**Date**

D PERSONALITY MEASUREMENT QUESTIONNAIRE

Instructions for Completing the IPIP-NEO Short Form

On the following pages, there are phrases describing people's behaviors. Please use the rating scale below to describe how accurately each statement describes **you**. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence. Please read each statement carefully, and then circle the number that corresponds to the number on the scale below.

Response Options Very Inaccurate Moderately Inaccurate Neither Inaccurate nor Accurate Moderately Accurate Very Accurate

Am the life of the party.	1 2 3 4 5
Feel little concern for others.	1 2 3 4 5
Am always prepared.	1 2 3 4 5
Get stressed out easily.	1 2 3 4 5
Have a rich vocabulary.	1 2 3 4 5
Don't talk a lot.	1 2 3 4 5
Am interested in people.	1 2 3 4 5
Leave my belongings around.	1 2 3 4 5
Am relaxed most of the time.	1 2 3 4 5
Have difficulty understanding abstract ideas.	1 2 3 4 5
Feel comfortable around people.	1 2 3 4 5
Insult people.	1 2 3 4 5
Pay attention to details.	1 2 3 4 5
Worry about things.	1 2 3 4 5
Have a vivid imagination.	1 2 3 4 5
Keep in the background.	1 2 3 4 5
Sympathize with others' feelings.	1 2 3 4 5
Make a mess of things.	1 2 3 4 5
Seldom feel blue.	1 2 3 4 5
Am not interested in abstract ideas.	1 2 3 4 5
Start conversations.	1 2 3 4 5
Am not interested in other people's problems.	1 2 3 4 5
Get chores done right away.	1 2 3 4 5
Am easily disturbed.	1 2 3 4 5
Have excellent ideas.	1 2 3 4 5
Have little to say.	1 2 3 4 5
Have a soft heart.	1 2 3 4 5
Often forget to put things back in their proper place.	1 2 3 4 5
Get upset easily.	1 2 3 4 5

Do not have a good imagination.	1 2 3 4 5
Talk to a lot of different people at parties.	1 2 3 4 5
Am not really interested in others.	1 2 3 4 5
Like order.	1 2 3 4 5
Change my mood a lot.	1 2 3 4 5
Am quick to understand things.	1 2 3 4 5
Don't like to draw attention to myself.	1 2 3 4 5
Take time out for others.	1 2 3 4 5
Shirk my duties.	1 2 3 4 5
Have frequent mood swings.	1 2 3 4 5
Use difficult words.	1 2 3 4 5
Don't mind being the center of attention.	1 2 3 4 5
Feel others' emotions.	1 2 3 4 5
Follow a schedule.	1 2 3 4 5
Get irritated easily.	1 2 3 4 5
Spend time reflecting on things.	1 2 3 4 5
Am quiet around strangers.	1 2 3 4 5
Make people feel at ease.	1 2 3 4 5
Am exacting in my work.	1 2 3 4 5
Often feel blue.	1 2 3 4 5
Am full of ideas.	1 2 3 4 5

E TURING TEST INSTRUCTIONS

Modeling the Decision Process of a Joint Task Force Commander

The U.S. military is relying more and more on large scale simulation systems as a tool to provide for force training, war plan analysis, and new concept experimentation. An important element within these systems is their ability to simulate military decision-making. Legacy simulations have modeled decisions at the tactical level of warfare but very little decision-making has been modeled at the operational level.

To improve on operational decision modeling, a research effort was undertaken to develop a computer model that would mimic the cognitive decision process of senior military commanders in an operational setting. Specifically, a system was created to model the decision process of a Joint Task Force Commander (CJTF). The model was tested by comparing decisions it produced against decisions produced by military officers playing the role of a CJTF using a typical operational decision scenario.

As a final step in the validation process, you are being asked to further evaluate if one can tell the difference between a set of decisions made by human role players and a set of decisions made by a computer simulation. The following pages contain an operational decision scenario consisting of four decision points. This scenario was provided to thirty military officers in the grades of O-4 to O-6, each with joint operational experience. They were asked to make a decision on each decision point as if they were the CJTF. Their decisions had to be based only on the information provided in the scenario and their past experience as military officers.

The computer model was provided with the same decision scenario and was asked to generate its decisions as if it were these thirty role players. Note, the model was not programmed to produce optimal decisions but to mimic the human decision process that is influenced by a person's experience and the unclear and incomplete data that is often present in real world military operations.

The last page of this document contains a scoring sheet with twenty sets of decisions. This set of decisions was chosen from among the thirty role player decision sets and thirty model decision sets. Each decision set represents the sequence of decisions required by the enclosed scenario. Next to each decision set is a block to indicate your evaluation of that decision set. Clicking on the block next to your choice will place an x in it, indicating your evaluation. Please ensure that only one block is checked for each decision set.

Following the decision table is a block for comments. If you felt you were able to identify human vs. computer decisions, please explain in the comment block what indicators you used to make this differentiation. Once complete, please save this document back to its original file. This will save your responses. Thank you for your time in completing this evaluation. Your effort will help improve joint force training, analysis, and experimentation.

Decision set number one

Location	Timing	Change	Withdraw	Evaluation
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	on time	withdraw	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	on time	withdraw	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Delta	36 hours	another site	withdraw	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell

Comments:

Decision set number two

Location	Timing	Change	Withdraw	Evaluation
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	on time	withdraw	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	on time	withdraw	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	go early	continue	human computer can't tell
Charlie	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Delta	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	go early	withdraw	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Delta	36 hours	another site	withdraw	human computer can't tell
Bravo	48 hours	on time	continue	human computer can't tell
Bravo	48 hours	go early	continue	human computer can't tell

Comments:

CURRICULUM VITA
for
JOHN ANTHONY SOKOLOWSKI

DEGREES:

Doctor of Philosophy (Engineering with a Concentration in Modeling and Simulation), Old Dominion University, Norfolk, VA, May 2003

Master (Engineering Management), Old Dominion University, Norfolk, VA, May 1998

Bachelor of Science (Computer Science), Purdue University, West Lafayette, IN, December 1974

PROFESSIONAL CHRONOLOGY:

Virginia Modeling, Analysis and Simulation Center, Old Dominion University, Norfolk, VA
Project Scientist, December 2001-Present

Joint Warfighting Center, U. S. Joint Forces Command, Norfolk, VA
Head, Modeling and Simulation Division, March 1999-November 2001

Naval Safety Center, Norfolk, VA
Head, Afloat Safety Directorate, October 1995-February 1999

Commander, Submarine Squadron Eight, Norfolk, VA
Deputy Commander, January 1994-September 1995

USS Benjamin Franklin (SSBN 640), Charleston, SC
Commanding Officer, July 1991-December 1993

SCIENTIFIC AND PROFESSIONAL SOCIETIES MEMBERSHIP:

Society for Modeling and Simulation International, American Association for Artificial Intelligence, Association for Computing Machinery, Phi Beta Kappa

GRANTS AND CONTRACTS AWARDED:

Decision Modeling, Sponsor: Joint Warfighting Center/Defense Modeling and Simulation Office, $146,000

SCHOLARLY ACTIVITIES COMPLETED:

Sokolowski, J. A. Enhanced Military Decision Modeling Using a MultiAgent System Approach. In *Proceedings of the 12th Conference on Behavior Representation in Modeling and Simulation (BRIMS)*. May 12-15, 2003, Scottsdale, AZ, (accepted for publication).

Sokolowski, J. A. Representing Knowledge and Experience in RPDAgent. In *Proceedings of the 12th Conference on Behavior Representation in Modeling and Simulation (BRIMS)*. May 12-15, 2003, Scottsdale, AZ, (accepted for publication).

Sokolowski, J. A. Can a Composite Agent be Used to Implement a Recognition-Primed Decision Model? In *Proceedings of the Eleventh Conference on Computer Generated Forces and Behavioral Representation.* May 7-9, 2002, Orlando, FL, pp. 473-478.

Sokolowski, J. A. Using Neural Networks to Model Decision Making. In *Proceedings of the Advanced Simulation Technology Conference.* April 16-20, 2000, Washington D. C., pp. 131-135.