2001-06

Stochastic simulation of a Commander's decision cycle (SSIM CODE)

Posadas, Sergio.

Monterey, California. Naval Postgraduate School

http://hdl.handle.net/10945/2518

NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

STOCHASTIC SIMULATION OF A COMMANDER'S DECISION CYCLE (SSIM CODE)

by

Sergio Posadas

June 2001

Thesis Advisor:	Eugene P. Paulo
Second Reader:	Tom W. Lucas

Approved for public release; distribution is unlimited.

REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** June 2001	**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE: Stochastic Simulation of a Commander's Decision Cycle (SSIM CODE)			**5. FUNDING NUMBERS**
6. AUTHOR(S) Posadas, Sergio			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**. PERFORMING ORGANIZATION EPORT NUMBER**
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army TRADOC Analysis Center White Sands Missile Range, NM 88002			**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution unlimited			**12b. DISTRIBUTION CODE**

13. ABSTRACT *(maximum 200 words)*

This thesis develops a stochastic representation of a tactical commander's decision cycle and applies the model within the high-resolution combat simulation: Combined Arms Analysis Tool for the 21st Century (Combat XXI). Combat XXI is a Joint Army-Marine Corps effort to replace the Combined Arms and Support Evaluation Model (CASTFOREM)—a legacy combat simulation. Combat XXI is a non-interactive, high-resolution, analytical combat simulation focused on tactical combat. Combat XXI is being developed by the U.S. Army TRADOC Analysis Center-White Sands Missile Range (TRAC-WSMR) and the Marine Corps Combat Development Command (MCCDC). Combat XXI models land and amphibious warfare for applications in the research, development and acquisition, and the advanced concepts requirements domains. Stochastic decision-making enhances Command and Control (C2) decision processes in Combat XXI. The stochastic simulation of a commander's decision cycle (SSIM CODE) addresses variability in decision-making due to uncertainty, chance and the commander's attributes. A Bayesian Network representation of a conditional probability model for a commander's decision cycle is implemented in SSIM CODE. This thesis develops, applies and evaluates the effectiveness of SSIM CODE.

14. SUBJECT TERMS Combat Models, Simulation, Decision-making, Decision Cycle			**15. NUMBER OF PAGES**
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UL

NSN 7540-01-280-5500 Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

STOCHASTIC SIMULATION OF A COMMANDER'S DECISION CYCLE (SSIM CODE)

Sergio Posadas
Major, United States Marine Corps
B.S., University of Texas at Austin, 1988

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 2001

Author: ____________________________________
Sergio Posadas

Approved by: ____________________________________
Eugene P. Paulo, Thesis Advisor

____
Allen S. Olson, Co-Advisor

____
Tom W. Lucas, Second Reader

____
James N. Eagle, Chairman
Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

This thesis develops a stochastic representation of a tactical commander's decision cycle and applies the model within the high-resolution combat simulation: Combined Arms Analysis Tool for the 21st Century (Combat XXI). Combat XXI is a Joint Army-Marine Corps effort to replace the Combined Arms and Support Evaluation Model (CASTFOREM)—a legacy combat simulation. Combat XXI is a non-interactive, high-resolution, analytical combat simulation focused on tactical combat. Combat XXI is being developed by the U.S. Army TRADOC Analysis Center-White Sands Missile Range (TRAC-WSMR) and the Marine Corps Combat Development Command (MCCDC). Combat XXI models land and amphibious warfare for applications in the research, development and acquisition, and the advanced concepts requirements domains. Stochastic decision-making enhances Command and Control (C2) decision processes in Combat XXI. The stochastic simulation of a commander's decision cycle (SSIM CODE) addresses variability in decision-making due to uncertainty, chance and the commander's attributes. A Bayesian Network representation of a conditional probability model for a commander's decision cycle is implemented in SSIM CODE. This thesis develops, applies and evaluates the effectiveness of SSIM CODE.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF FIGURES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF SYMBOLS, ACRONYMS AND/OR ABBREVIATIONS

AA	Avenue of Approach
ACR	Advanced Concepts Requirements
ANOVA	Analysis of Variance
BFR	Battle Force Ratio
BP	Blocking Position
C2	Command and Control
C4I	Command, Control, Communications, Computers and Intelligence
C4ISR	C4I, Surveillance, and Reconnaissance
CAS	Close Air Support
CASTFOREM	Combined Arms and Support Evaluation Model
CCIR	Commander's Critical Information Requirement
CINC	Commander-in-Chief
COA	Course of Action
Combat XXI	Combined Arms Analysis Tool for the 21^{st} Century
DISA	Defense Information Systems Agency
HLA	High Level Architecture
i.i.d.	Independent, Identically Distributed
MCCDC	Marine Corps Combat Development Command
MCDP	Marine Corps Doctrinal Publication
METT-T	Mission, Enemy, Troops, Terrain and Time Available
MOE	Measure of Effectiveness
MSE	Mean Squared for Error
MST_r	Mean Squared for Treatment
NAI	Named Area of Interest
OODA	Observe Orient Decide Act
RDA	Research, Development and Acquisition
SA	Situational Awareness
SSIM CODE	Stochastic Simulation of a Commander's Decision Cycle
SSE	Sum of Squares for Error
SST	Sum of Squares Total
SST_r	Sum of Squares for Treatment
TAI	Targeted Area of Interest
TRAC	TRADOC Analysis Center
TRADOC	Training and Doctrine Command
UOR	Unit Of Resolution
WSMR	White Sands Missile Range
y_{ijk}	Response Observation for i^{th} treatment, j^{th} replication, and k^{th} run
μ	True Mean
τ_i	Treatment Effect for i^{th} treatment
δ_{ij}	Interaction Variable for i^{th} treatment and j^{th} replication
ε_{ijk}	Error Term for i^{th} treatment, j^{th} replication, and k^{th} run
σ^2	Variance
H_o	Null Hypothesis
H_a	Alternative Hypothesis

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

First, I would like to express my sincere appreciation to my wife, Sylvia, for her unwavering support during this endeavor.

The Combat XXI team members spent many hours describing the details of their combat simulation. LtCol Al Olson, the assistant Combat XXI team leader, Maj Gary Harless, the creator of the Combat XXI SA module, and Maj Simon Goerger, the keeper of the Combat XXI code, all helped develop my understanding of the simulation. LtCol Olson also provided essential Java tutoring and continued guidance as a co-advisor. Dave Durda, the head of the Combat XXI team, made the experience tour possible with TRAC-WSMR funding, and was a great host at White Sands.

LtCol Eugene Paulo, the thesis advisor, was a consistent source of motivation and new ideas. His mission C2 philosophy is very much appreciated. Professor Tom Lucas provided inspired guidance from the inception of this thesis to its completion. I would also like to thank Professor Patricia Jacobs for devoting class time to examine the stochastic models used in this thesis.

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

This thesis develops a representation of a tactical commander's decision cycle and implements it in a computer simulation. A stochastic decision cycle model is applied within the high-resolution combat simulation: Combined Arms Analysis Tool for the 21st Century (Combat XXI).

The thesis objectives include:

- *Model tactical commander decision cycles (battalion and below).*
- *Apply command and control (C2) doctrine.*
- *Develop a functionality module for Combat XXI.*
- *Exercise the stochastic simulation of a commander's decision cycle (SSIM CODE) as a stand-alone simulation.*
- *Evaluate the effectiveness of SSIM CODE's decision-making.*

Combat XXI is a Joint Army-Marine Corps effort to replace the Combined Arms and Support Evaluation Model (CASTFOREM)—a legacy combat simulation. Combat XXI's charter includes meeting or exceeding CASTFOREM's capabilities. Combat XXI is a non-interactive, high-resolution, analytical combat simulation focused on tactical combat. Combat XXI models land and amphibious warfare for applications in the research, development and acquisition, and the advanced concepts requirements domains. Combat XXI is being developed by the U.S. Army TRADOC Analysis Center-White Sands Missile Range (TRAC-WSMR) and the Marine Corps Combat Development Command (MCCDC). These agencies seek to incorporate C2 decision-making with an appropriate degree of realism in Combat XXI.

C2 in CASTFOREM is accomplished using an expert system that refers to a knowledge base. The knowledge base is a set of decision tables that prescribe decision outcomes according to expert judgment. One of the major assumptions in CASTFOREM's C2 module is that tactical "Decision processing takes no [simulation] time." (TRAC-WSMR, 1999)

The analysis requirements driving Combat XXI's development call for an enhanced representation of the commander and the his decision process. The C2 component in Combat XXI can be enhanced by a decision-making model implemented as a functionality module (an interface by which Combat XXI accesses services and specific combat processes such as movement, communications, and engagement). SSIM CODE (a Combat XXI functionality module for stochastic, tactical decision-making) addresses variability in decision-making due to uncertainty, chance and a commander's attributes.

The key facets of simulating decision-making in C2 include: representing the complete commander's decision cycle, portraying the evolving nature of the commander's awareness, and capturing the stochastic nature of decision-making due to uncertainty and chance. These attributes are included in SSIM CODE.

The SSIM CODE model builds on three basic elements: an Observe-Orient-Decide-Act (OODA) loop-based decision cycle, dynamic situational awareness, and stochastic decision-making. The functionality of the SSIM CODE is based on the OODA loop. The Combat XXI situational awareness (SA) module structure is used by SSIM CODE for dynamic SA. A Bayesian C2 network provides stochastic decision-making in SSIM CODE.

SSIM CODE is programmed in Java. The use of Java allows the development of an object-oriented, event-driven model that meets Combat XXI requirements for a functionality module. To meet the Combat XXI functionality module requirements, SSIM CODE must implement the methods (subroutines or processes) specified by the Combat XXI functionality module interface. SSIM CODE development and testing includes over nine-thousand lines of Java code.

Combat XXI and SSIM CODE use Simkit as a simulation engine. Simkit is a Java class library (collection of Java programs) for event-driven, component-based simulation. Figure 1 depicts the Combat XXI/SSIM CODE relationship. Because SSIM CODE must interact with Combat XXI as the simulation runs, SSIM CODE must be capable of placing Simkit events (SimEvents) on the Simkit event list and monitoring state variable changes from the Combat XXI simulation.

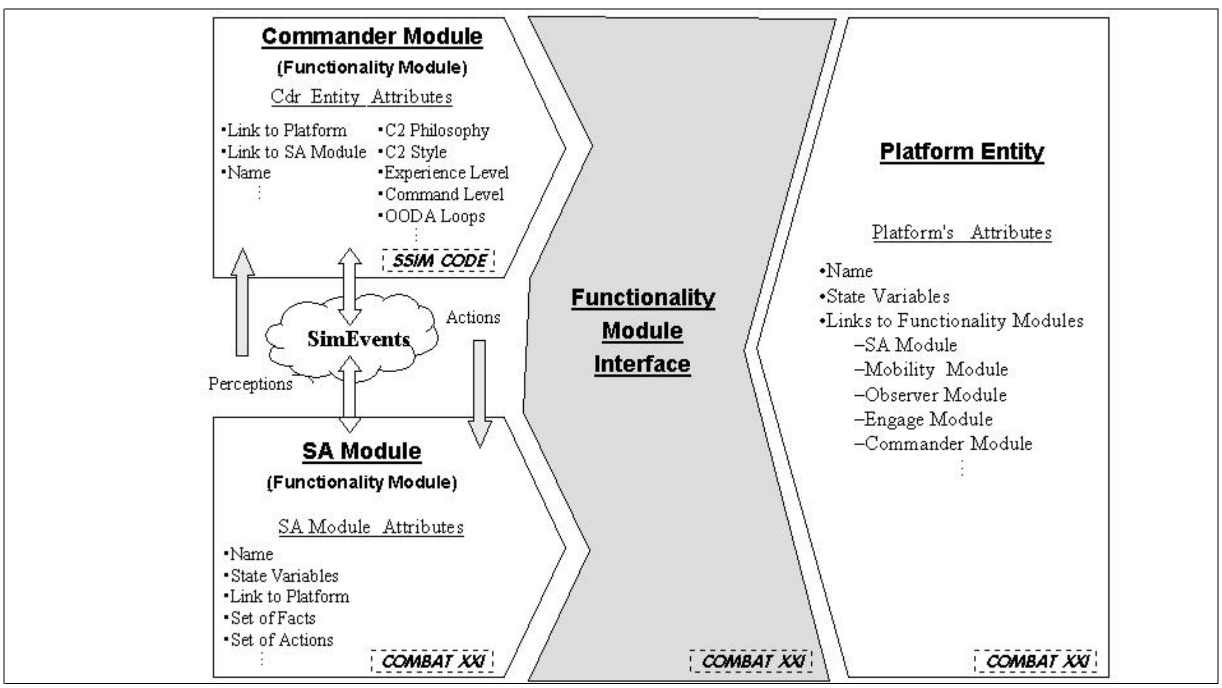


Figure 1. Combat XXI/SSIM CODE Relationship

SSIM CODE's commander entity is a Combat XXI functionality module that interfaces with the rest of the simulation through the SA module.

Decision factors are binary, discrete random variables computed as functions of varying states in the combat simulation. Decision factors are aggregated elements that influence tactical decision-making.

In practice, commanders make decisions based on reported estimates—not on perfect information. To model this concept, report nodes are used with decision factors in a Bayesian network. Three sets of nodes are used: the commander's decision, reports, and decision factors. The lack of perfect information in tactical decision-making is captured in the relationship between the three sets of nodes. The decision outcome is probabilistically dependent on report states, and it is independent of decision factor states. Figure 2 shows a Bayesian network with imperfect information.

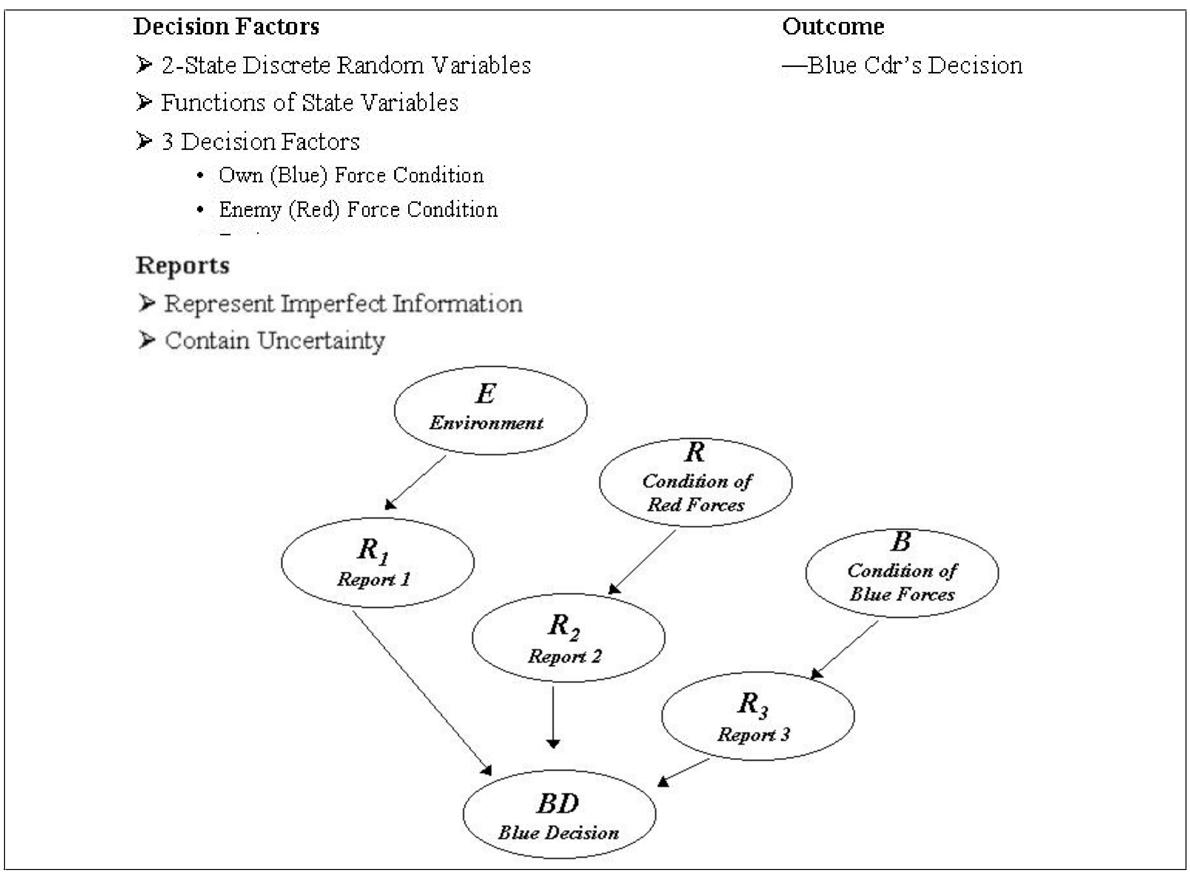


Figure 2. Bayesian Decision-Making Network (After Stephens, 1998)

The report nodes represent uncertainty inherent to the commander's information. Based on the Bayesian network in Figure 2, the commander's decision is conditionally independent of E, R and B, given R_1, R_2 and R_3. SSIM CODE is capable of collecting information from the Combat XXI simulation to develop reports for the commander.

The SSIM CODE model is centered on the commander entity. A commander's individual characteristics are considered in the SSIM CODE's decision-making process. The SSIM CODE commander entity possesses an SA module, a C2 style, a C2 philosophy, an experience level, and a set of decision cycles (OODA loops).

SimEvents from within Combat XXI trigger changes in the SA module's facts. The commander entity in SSIM CODE monitors these changes. When a decision is required, the appropriate type of OODA loop is started. Reports on decision factors are received and a perception of the current situation is developed. The Bayesian network is used to determine a decision outcome. The decision is then implemented with a set of actions. The SA module's facts are updated, and subsequent decisions are scheduled.

Two stages of fractional factorial design experiments are used in evaluating SSIM CODE. SSIM CODE is deemed to make tactical sense through a face validation. The evaluation concludes that the first steps in developing a decision-making model for Combat XXI and the purpose of this thesis are accomplished.

SSIM CODE has applications within Combat XXI and other Department of Defense simulations. The Australian armed forces will also be replacing CASTFOREM with Combat XXI. Improved C2 processes from SSIM CODE can serve to enhance Combat XXI applications in both U.S. and Australian modeling and simulation domains.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

A. THESIS PURPOSE

This thesis develops a representation of a tactical commander's decision cycle and implements it in a computer simulation. A stochastic decision cycle model is applied within the high-resolution combat simulation: Combined Arms Analysis Tool for the 21st Century (Combat XXI).

An approach to developing a decision-making model for Combat XXI includes:

- *Develop the concept of tactical decision-making for command and control (C2) into an analytical model.*
- *Implement the decision-making model in a simulation loosely coupled with Combat XXI's behaviors package.*
- *Evaluate the performance of the decision-making simulation compared to the analytical model.*
- *Link the simulation to all applicable Combat XXI modules (tightly coupled with Combat XXI).*
- *Enhance the abstract features of the simulation to handle all likely applications of Combat XXI.*

This thesis accomplishes the first three steps of this approach. An analytical, stochastic decision-making model is developed. The model is then implemented in a simulation that is loosely coupled with Combat XXI. Finally, the model is evaluated with a test scenario. The thesis objectives and scope are discussed at the end of Chapter II.

B. DECISION-MAKING IN COMBAT SIMULATIONS

1. The Need for a Stochastic Decision-Making Model

The Panel on Modeling Human Behavior and Command Decision Making was formed by the National Research Council in 1996 to evaluate human behavior representation in military simulations (Stephens, 2000). This panel conducted an eighteen-month study that included an in-depth evaluation of decision-making in combat simulations.

According to the panel's 1998 report, most combat simulations assume no variability in decision-making. These simulations apply scripted or deterministic decision-making processes and fail to provide the necessary realism in decision-making:

> The Under Secretary of Defense for Acquisition and Technology has set an objective to "develop authoritative representations of individual human behavior"...Yet...users of military simulations do not consider the current generation of human behavior representations to be reflective of the scope or realism required for the range of applications of interest to the military. (Pew and Mavor, 1998)

The intrinsic randomness in human decision-making must be represented with a stochastic decision-making model. This thesis focuses on the tactical commander. The thesis develops, implements, and evaluates a stochastic tactical decision-making model.

2. The Battlespace's Influence on Tactical Decision-Making

The Marine Corps Combat Development Command (MCCDC) is modeling battlespace phenomena that influence decision-making. These areas include non-linearity, intangibles and co-evolving landscapes. Non-linear effects occur when minor actions can have large impacts on combat outcomes. An example is the receipt or non-receipt of a single message that changes the outcome of an entire battle. Intangible factors include morale, training, leadership-style, command philosophy, etc. The co-evolving landscapes concept describes a setting where commanders on both sides apply their decision-making in anticipation of each other's actions. (Brandstein, 1999)

These three phenomena impact tactical decision-making in the battlespace. Representing these features of warfare contributes to realism in a decision-making simulation. An effective decision-making model should contribute toward the depiction of these sources of realism.

The Combat XXI simulation is currently being co-developed by the U.S. Army TRADOC Analysis Center at White Sands Missile Range (TRAC-WSMR) and MCCDC. These agencies seek to incorporate an appropriate degree of realism in C2 decision-making within Combat XXI. A stochastic decision-making model that contains representations of non-linearity, intangibles and co-evolving landscapes would contribute toward an enhanced C2 decision process in Combat XXI.

C. THE COMBAT XXI SIMULATION

Combat XXI models land and amphibious warfare for applications in the Research, Development and Acquisition (RDA), and the Advanced Concepts Requirements (ACR) domains. Combat XXI is a non-interactive, high-resolution, analytical combat simulation focused on force-on-force tactical combat (brigades, battalions and below). Combat XXI is a Joint Army-Marine Corps effort to develop a replacement for the Combined Arms and Support Evaluation Model (CASTFOREM). CASTFOREM is a legacy combat simulation used to represent combined-arms ground combat. CASTFOREM is a high-resolution, two-sided, stochastic, closed-loop simulation. It has been in use for over fifteen years. (TRAC-WSMR, 1999)

Combat XXI is composed of discrete software packages (collections of programs). Component packages are reusable programming elements. Some of these are

Combat XXI proprietary packages, and others are extensions to components developed independently of Combat XXI. (Olson, 2000)

Figure 1 shows the hierarchy of Combat XXI packages. Foundation packages provide key services and base objects used throughout Combat XXI. Examples include a simulation engine, data base connectivity, and random number generation. Core packages provide more precise functions by building upon foundation packages. These functions include scenario input/output, terrain services, and data logging. (Olson, 2000)

A final layer of abstract services is added by functionality packages that build upon the core and foundation packages. Integration packages combine abstract services to accomplish tangible tasks in the context of a study. These tasks include scenario definition, movement, search and acquisition, and engagement. (Olson, 2000)

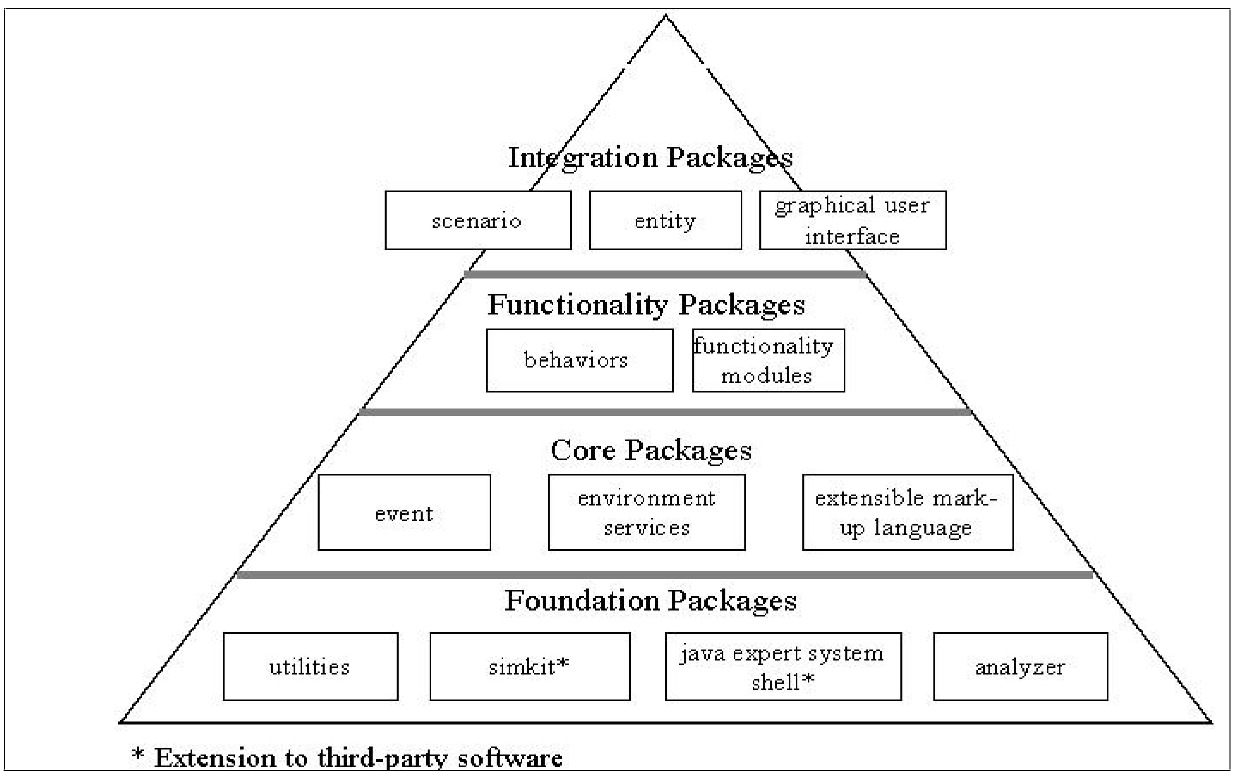


Figure 1. Combat XXI Component Packages (After Olson, 2000)
Each discrete software package builds on the layers below.

1. C2 in CASTFOREM

Figure 2 is an overview of CASTFOREM's structure. CASTFOREM's unit of resolution (UOR) is an individual tank, vehicle or other combat platform. A CASTFOREM UOR can have six physical processes (move, engage, search, communicate, engineering and combat service support) and a C2 process. C2 in CASTFOREM is accomplished using an expert system that refers to a knowledge base. The knowledge base is a set of decision tables that prescribe decision outcomes according to expert judgment. One of the major assumptions in CASTFOREM's C2 module is that tactical "Decision processing takes no [simulation] time." (TRAC-WSMR, 1999)

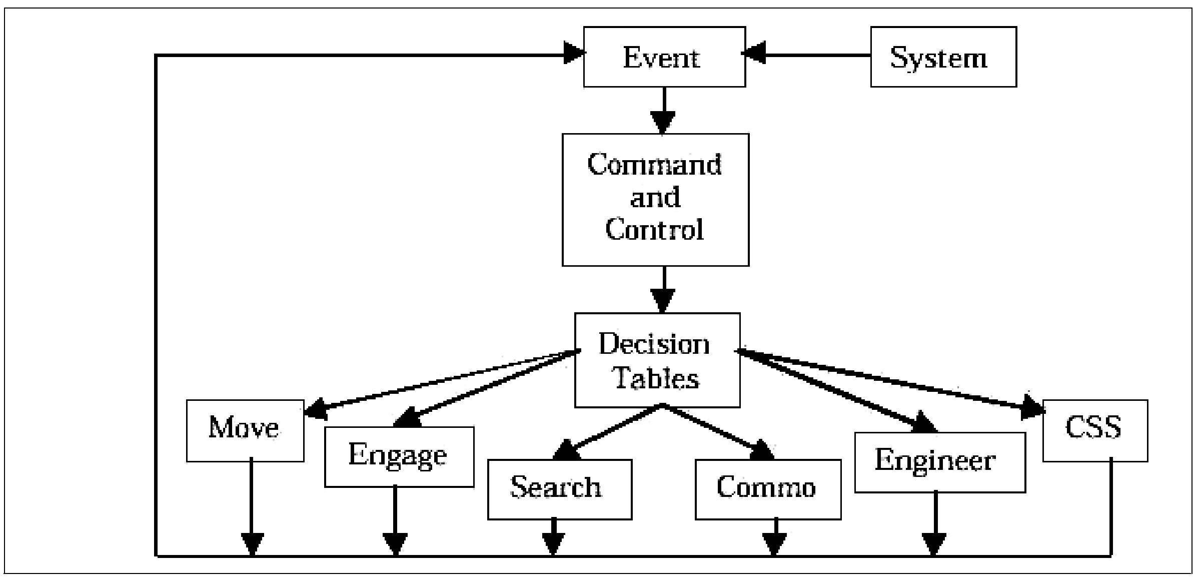
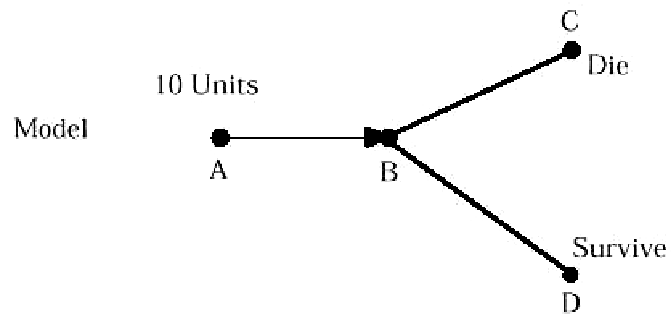


Figure 2. CASTFOREM's Functionality Structure (From TRAC-WSMR, 1999)
Unit functionality consists of six physical process and C2.

Decision tables are invoked as a result of simulation events in CASTFOREM. Each UOR updates it's situational profile (set of 'known' facts) when specific simulation events occur. Based on the knowledge base rules and a UOR's situational profile, the decision tables generate a set of primitive orders (move, engage, search, communicate, etc.) that comprise a UOR's course of action. Random outcomes are included in CASTFOREM. The variability of these stochastic outcomes depends directly on the extensiveness of the decision tables. (TRAC-WSMR, 1999)

Expanding or decreasing available options in the knowledge base changes decision variability in CASTFOREM, as illustrated in Figure 3. The specific variability desired and the adjustments to the decision table knowledge base must be established before simulation run-time. (TRAC-WSMR, 1999)



Knowledge Base	Rules	E (Losses)	Variability
1	If at B, all 10 units go to C with p = 1, and all go to D with p = 0.	10	0
2	If at B, all 10 units go to C with p = 1/2, and all go to D with p = 1/2.	5	25
3	If at B, all 10 units go to C with p = 1/3; five go to C, five go to D with p = 1/3; all go to D with p = 1/3.	5	16-2/3

Figure 3. CASTFOREM Decision-Making Variability (From TRAC-WSMR, 1999)
Variability is controlled by the number of options available in the knowledge base and their associated probabilities.

2. C2 in Combat XXI

Combat XXI's charter includes meeting or exceeding CASTFOREM's capabilities. Combat XXI is being developed in Java; CASTFOREM is programmed in SIMSCRIPT. The object-oriented nature of Java, it's platform independence, the available open-source Java tool kits, and Java's package-based component structure provide Combat XXI significant flexibility and potential for expansion. Combat XXI should exceed most of CASTFOREM’s capabilities. The analysis requirements driving Combat XXI's development call for an enhanced representation of the commander and the command decision process.

The goals for C2 behaviors in Combat XXI include “...modeling the commander’s view of the battlefield and the decision logic that the commander would use to determine a course of action.” (Harless, 2000) The C2 component in Combat XXI can be enhanced by a decision-making model implemented as a functionality module (an interface by which Combat XXI accesses services and specific combat processes such as movement, communications, and engagement). The stochastic simulation of a commander’s decision cycle (SSIM CODE) developed in this thesis seeks to fill that role.

D. MODELING TACTICAL DECISION-MAKING

Forming a tactical decision-making model begins with defining the commander’s decision-making as it relates to C2. Commanders are central to the C2 process and make the vital decisions in the battlespace. They make informational decisions (what is happening?), operational decisions (what actions should be accomplished?) and organizational decisions (how should forces be arranged?) (Orr, 1996). A C2 model should focus on the commander and his decision cycle.

The commander's perception is the pivotal part of his decision cycle (Boyd, 1995). A tactical decision-making model should thus include: a representation of the commander’s decision-making process, an emphasis on his perception, a portrayal of uncertainty and chance, and a decision cycle structure.

1. The Commander's Decision-Making Process

A commander's decision-making begins as an intuitive process. At the initial stage of decision-making, neither the current situation nor the desired end-state may be fully apparent. The commander formulates his objectives based on directives from higher-headquarters. He formulates an understanding of the measures required to accomplish his mission.

By gathering information on the battlespace, the commander clarifies his image of the current situation. He then develops several alternatives or courses of action (COAs) for reaching his desired end-state from the current situation. Finally, the commander reaches a decision and selects a plan to accomplish his objectives. Figure 4 summarizes this process. The commander's decision-making process is continuous. He revisits and updates his decisions, as the dynamic situation requires.

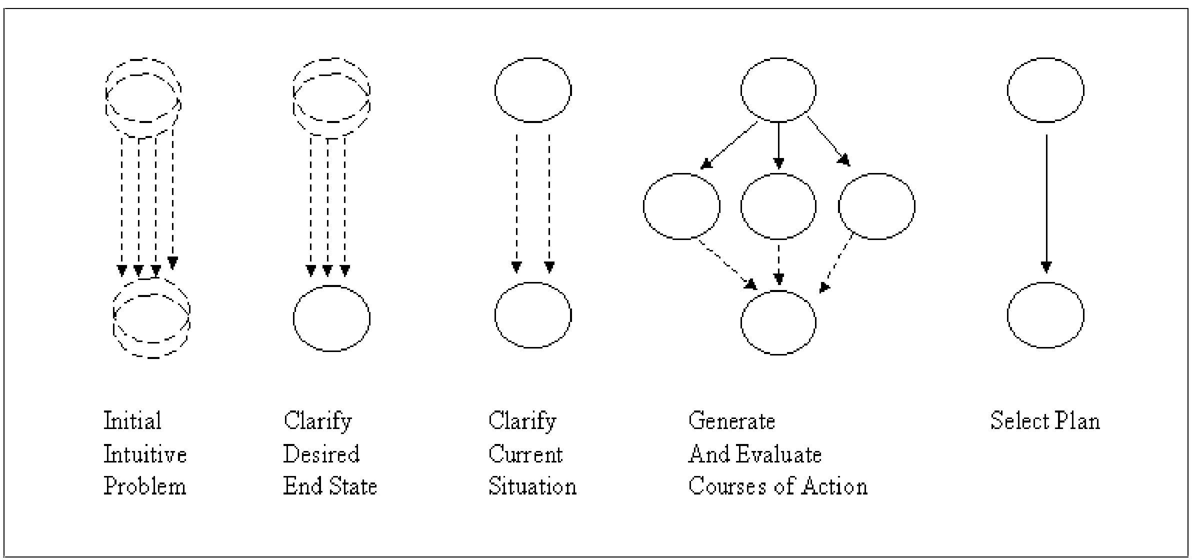


Figure 4. Commander's Decision-Making Process (After Orr, 1996)
The commander clarifies the end-state or goal then chooses a means to attain the goal.

2. Variability in Tactical Decision-Making

The commander applies both an analytical methodology and his intuition to decision-making. Purely analytical decision-making usually produces consistent results in similar situations. However, the commander's intuition introduces variation to the decision-making process. Variability in decision-making is in part due to the commander's human nature. Specifically, the commander's decisions are influenced by personal attributes.

Uncertainty and chance contribute to further variability in the commander's decisions. The specific information available to the commander for a given decision, the degree to which that information represents reality, and the commander's interpretation of the information are all sources of uncertainty in C2. The complexity of the commander's C2 system and the random interaction between the components of that system add more variability to the commander's decisions. It follows that a stochastic model is required to represent the variability in tactical decision-making.

3. The Commander's Perception

An essential element of tactical decision-making is the mental image that represents the commander's "knowing and seeing" (Kahan, Stasz and Worley, 1989). The commander's perception is an estimate of reality influenced by his individual attributes and by the information he collects. A commander builds this perception by evaluating his mission, the enemy, his troops, the terrain, the weather, and the time available (METT-T) (U.S. Marine Corps, 1996). Commanders are taught to conceptualize the battlespace in terms of METT-T through doctrine and training (Kahan, Stasz and Worley, 1989).

Tactical decision-making is the process of transforming the commander's perception into action. Figure 5 summarizes this process. The commander's image is influenced by his current view of the battlespace. His assigned mission, guidance from superiors, training, and individual attributes also shape his image.

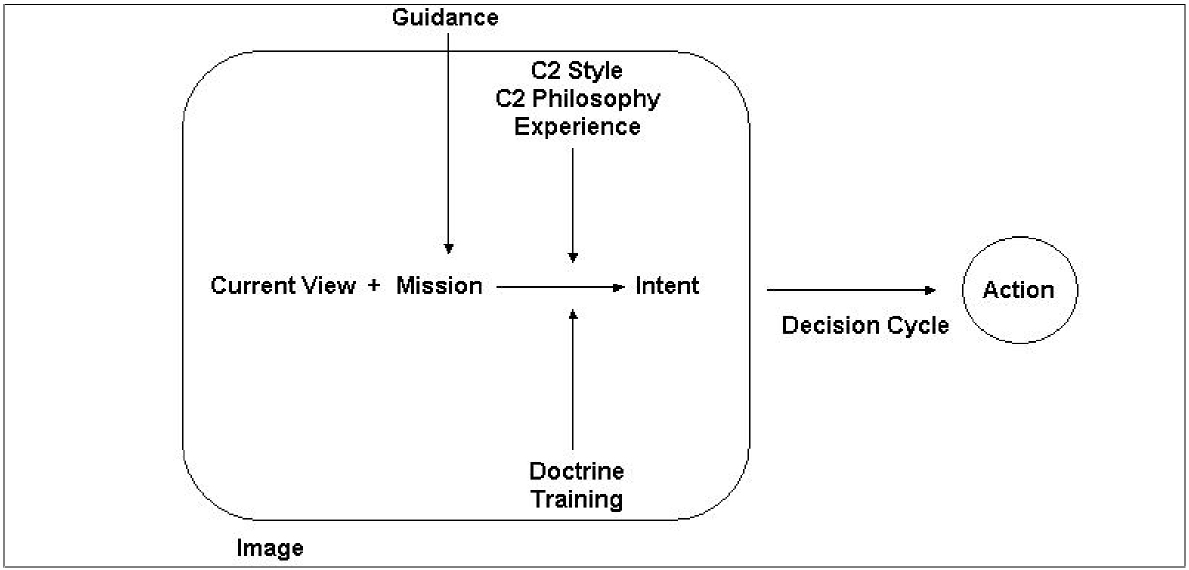


Figure 5. Translating an Image into Action (After Kahan, Stasz and Worley, 1989)
Various elements influence the commander's image. His decision cycle transforms the image into action.

4. Information-Processing Styles

Different information-processing styles determine how and when the commander employs his decision cycle. A study by the RAND Arroyo Center (a U.S. Army research and development center) on commanders' information needs concluded that three information-processing styles are employed by military commanders in decision-making: *directed* (one-way), *triggered,* and *inquiry-based* information-processing (Kahan, Stasz and Worley, 1989). These information-processing styles determine how the commander's knowledge and perception are developed. SSIM CODE's representation of each of these information-processing styles is discussed in Chapter IV.

Directed information-processing involves the presentation of information to the commander in a set order. Decisions are made according to time constraints since a complete set of information may not be attainable (Kahan, Stasz and Worley, 1989). Figure 6 illustrates directed information-processing.

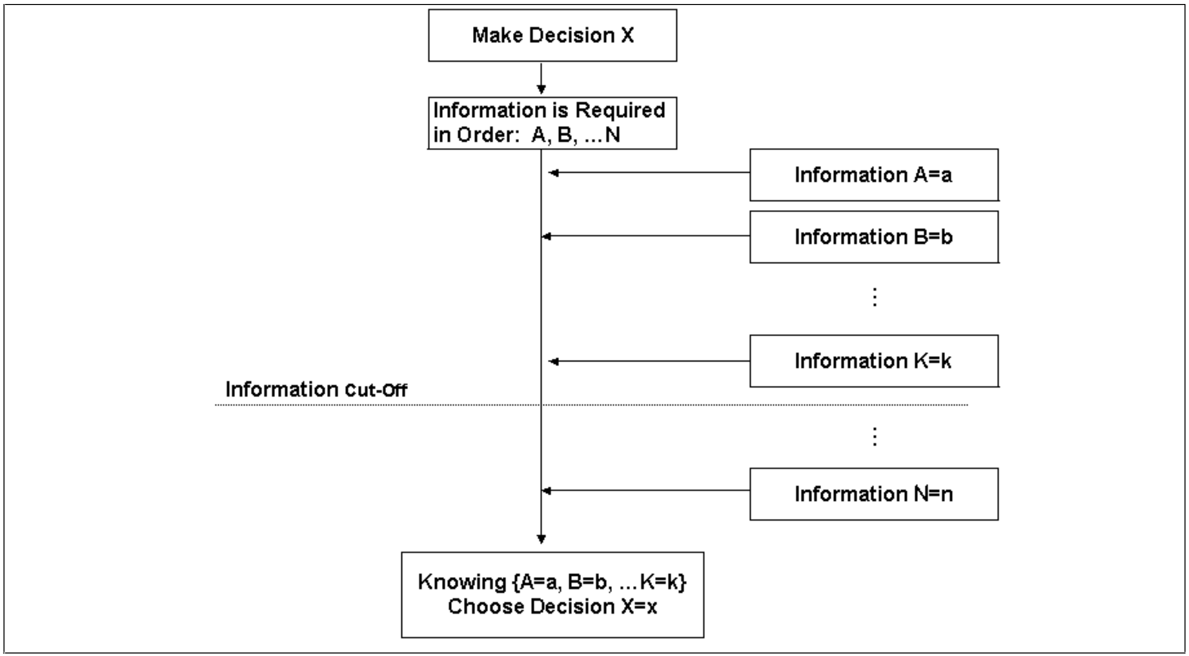


Figure 6. Directed Information-Processing (After Kahan, Stasz and Worley, 1989)
Information is received in a sequential order before the decision outcome is reached.

In triggered information-processing, certain events or thresholds initiate the commander's decision-making. The commander defines what critical information will indicate that a decision is required (Kahan, Stasz and Worley, 1989). Commander's critical information requirements (CCIRs) represent these triggers. CCIRs are information needs identified by the commander regarding enemy forces, friendly forces and the environment. CCIRs are critical to timely decision-making (MSTP Staff, 2001). Figure 7 depicts triggered information-processing.

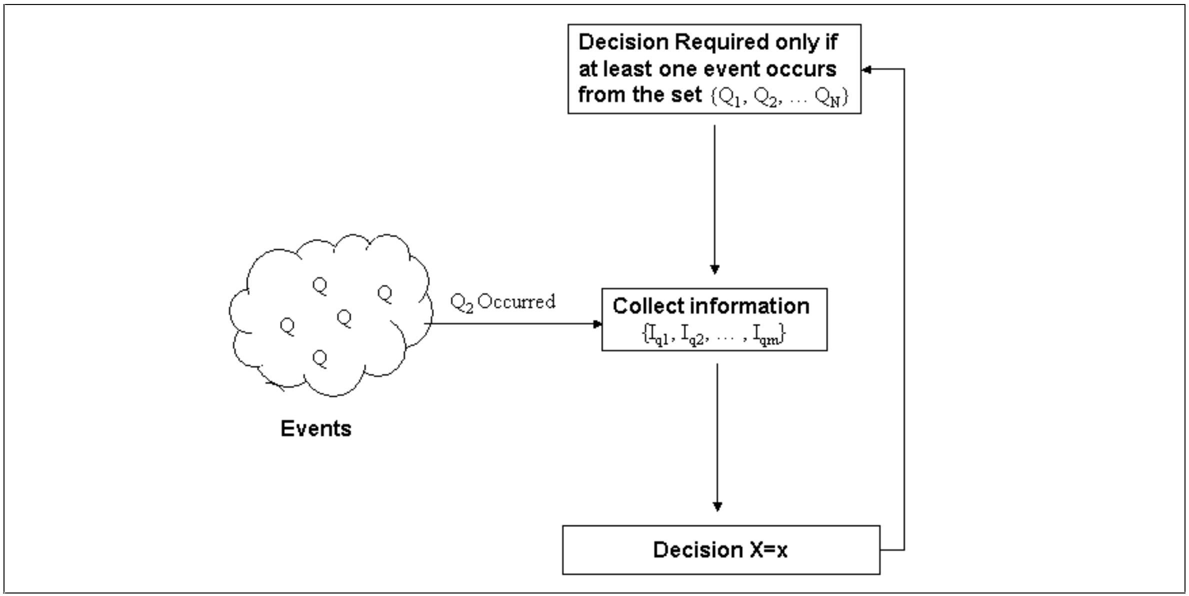


Figure 7. Triggered Information-Processing (After Kahan, Stasz and Worley, 1989)
Key events trigger decision-making as they occur. The commander determines which events will act as triggers or CCIRs.

Inquiry-based information-processing is a demand-pull approach to developing the commander’s knowledge. When the commander determines that a decision is required, he makes inquiries about specific information. Figure 8 is a representation of inquiry-based information-processing.

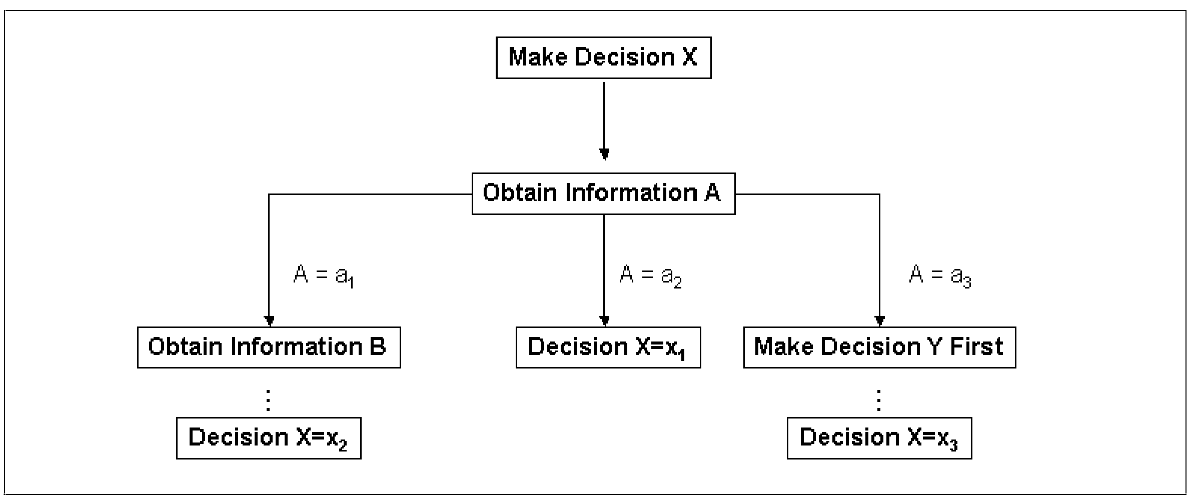


Figure 8. Inquiry-Based Information-Processing (After Kahan, Stasz and Worley, 1989)
Making one decision leads to collection of information and possibly other decisions that must be resolved first.

The information-processing style applied by a commander is influenced by his leadership style; however, the same commander may use each of the three styles or a hybrid method. Information-processing influences a commander's perception—the key element in his decision-making. A tactical decision-making model must be able to represent each of these information-processing styles.

5. The Commander's Decision Cycle

The tactical decision-making process is a cycle repeated continuously by the commander. Colonel John R. Boyd's Observe-Orient-Decide-Act (OODA) loop is a concise model of a commander's decision cycle. A military commander first forms an observation of the battlespace through communications, sensors and intelligence systems. Next, he processes observed information to develop his perception as a frame of reference. Based on his orientation, the commander then makes decisions to attain his mission objective. Finally, those decisions result in actions, which influence the battlespace. Subsequent observations initiate further iterations of the OODA loop. (Boyd, 1995)

The OODA loop encapsulates the decision-making process and includes a representation of the commander's perception in the orientation phase. The OODA loop provides a suitable general structure for a tactical decision-making model.

THIS PAGE INTENTIONALLY LEFT BLANK

II. BACKGROUND

A. ELEMENTS OF A DECISION-MAKING SIMULATION

The key facets of simulating decision-making in C2 include: representing the complete commander's decision cycle, portraying the evolving nature of the commander's awareness, and capturing the stochastic nature of decision-making due to uncertainty and chance. These attributes are desired in a tactical decision-making model.

Techniques for simulating these intangible combat phenomena have been developed by several modeling and simulation organizations. Previous simulation modeling efforts (described below) are used in the development of SSIM CODE. The SSIM CODE model builds on three basic elements: stochastic decision-making, an OODA loop-based decision cycle, and dynamic situational awareness.

1. A Decision Cycle Simulation

The Command, Control, Communications, Computers and Intelligence (C4I) Modeling, Simulation, and Assessment Directorate of the Defense Information Systems Agency (DISA) has developed and implemented a C2 simulation model. This C2 model is an element of the DISA Joint C4I, Surveillance, and Reconnaissance (C4ISR) model (DISA, 2000). The DISA C4ISR model has been used in studies to support Commanders-in-Chief (CINCs) and the Joint Staff.

The DISA C4ISR model is a federation of five interacting simulations: a combat model, a sensor model, a communications assessment model, an information model, and a C2 model. The DISA model is focused on the operational level. DISA's model is a more aggregated representation of the battlespace than the tactically oriented Combat

XXI. However, DISA's C2 module effectively implements a commander's decision cycle that has applications at all levels of warfare.

The functionality in DISA's C2 simulation fully encompasses the commander's OODA loop. This C2 simulation is robust. It is capable of representing a decision cycle while interacting with other elements of a combat simulation. DISA's C2 model has been tested in several analyses, including CINC operations plan (OPLAN) assessments. This C2 simulation is used to structure the functional requirements of SSIM CODE.

2. A Dynamic Situational Awareness Module

A methodology for modeling a commander's Situational Awareness (SA) has been developed by TRAC-WSMR. Combat XXI implements an SA module construct. This structure represents the commander's dynamic SA.

The SA module "listens" to events and property changes (target detections, force movements, modifications to entity attributes, etc.) during a simulation run. The SA module then interacts with an expert system—a collection of facts, rules, and actions. This interaction between the SA module and the expert system results in prescribed actions if pre-defined conditions are met.

The Combat XXI SA module fulfills the role of the decision table based expert system in CASTFOREM. Furthermore, the SA module is capable of dynamically changing the set of potential outcomes and actions during simulation run-time. The dynamic SA structure developed by TRAC-WSMR provides a means for the commander's decision cycle in SSIM CODE to interact with other elements of the Combat XXI simulation.

3. A Stochastic Decision-Making Model

Computing Technologies, Inc., with MCCDC's Studies and Analysis Division, has developed an approach for simulating command and control as a behavioral model. An exploration report on C2 titled "*Project Albert and JWARS,*" (Stephens, 2000) details this approach and the application of a Bayesian joint-probability network to represent the stochastic results in C2.

In MCCDC's Bayesian C2 model, state variables from throughout the simulation (sensor module, combat module, etc.) are measured to determine decision factors. The decision factors are defined as binary random variables that generate variability in the commander's decision-making process. The stochastic nature of the Bayesian C2 model is derived from these decision factors. This decision-making model is used in SSIM CODE.

4. Combining the Decision Cycle Simulation Elements

The functionality of the SSIM CODE is based on the DISA C2 model. The Combat XXI SA module structure is used by SSIM CODE to model dynamic SA while providing a means for interaction with other combat simulation elements. The MCCDC Bayesian C2 model provides a methodology for stochastic decision-making in SSIM CODE.

The DISA C2 model, the Combat XXI SA module structure, and the MCCDC Bayesian C2 model are the primary sources for the design of SSIM CODE. These characteristics are described in detail in Chapter III.

SSIM CODE is designed as a Combat XXI functionality module. This design goal required the use of Java and Simkit (a Java-based simulation engine). The relationship between SSIM CODE, Java and Simkit are described in the following sections.

B. SSIM CODE AND JAVA

SSIM CODE is programmed in Java. Java is an object-oriented, platform independent programming language developed by Sun Microsystems. Java's characteristics support SSIM CODE's objectives. Because SSIM CODE's model structure is object-oriented and event-driven, Java is an appropriate programming language choice. More importantly, Combat XXI is being developed in Java. Therefore, the use of Java allows SSIM CODE to be developed as an object-oriented, event-driven model that meets the Combat XXI functionality module requirements described below.

1. SSIM CODE as an Object-Oriented Model

The object-oriented nature of Java allows for the creation of generic object templates, such as a commander. Commanders are modeled as individual entities or objects. Each object meets the generic description of its class (or type) with a set of basic properties. For example, a SSIM CODE commander entity always includes a command level, a C2 philosophy, a C2 style, an experience level, a set of OODA loops, etc. Specific characteristics individualize these objects. A specific individual commander entity is referred to as an instance of the commander object. (A detailed discussion of the commander attributes is provided in Chapter III.)

Java objects can be nested: an object may have a property that is also an object. The commander entity has properties that are also objects, such as OODA loops. OODA loops consist of a decision type, delay times between phases, and a reference to a specific instance of the commander object. OODA loops contain individual decisions as properties. These decisions are objects that are instantiated (created from a general class) when an OODA loop starts. Decisions consist of a decision type, a request time, a start time, report data, an end time, and a decision result. A decision object includes a reference to the OODA loop that instantiated the decision. Java's object-oriented trait allows for the straightforward implementation of the SSIM CODE model into a computer program.

2. SSIM CODE as a Combat XXI Functionality Module

Java is a significant common feature shared by SSIM CODE and Combat XXI. The common programming language makes it possible to design SSIM CODE as a Combat XXI functionality module. Combat XXI implements several types of entities, such as platforms. Platforms are Java representations of vehicles and personnel. Functionality modules are components of platform instances. Functionality modules serve as process delegates for platforms in Combat XXI. Examples of processes handled by functionality modules on behalf of a platform are movement, search, communications, and engagement.

To meet the Combat XXI functionality module requirements, SSIM CODE must implement the methods (subroutines or processes) specified by the Combat XXI functionality module interface. These prescribed methods primarily ensure that a platform can employ its modules generically and without explicitly modifying the platform's Java code for any particular module. For example, each module defines its type (e.g., "mobility") from a list of predefined values.

Extensions to the functionality module interface prescribe the methods associated with a specific type of module. The commander entity in SSIM CODE is a functionality module extension. Thus, the commander entity contains methods specified by the Combat XXI functionality module interface and specialized methods required to make decisions using a decision cycle.

C. SSIM CODE AND SIMKIT

SSIM CODE uses Simkit as a simulation engine. Simkit is a Java class library (collection of Java programs) for event-driven, component-based simulation. LtCdr Kirk Stork designed Simkit in his thesis: *Sensors in Object Oriented Discrete Event Simulation* (Stork, 1996). Professor Arnie Buss, at the Naval Postgraduate School, further developed Simkit as a Java class library.

1. Simkit Modeling

Simkit is a discrete event simulation tool. A process modeled by Simkit is a set of discrete events that occur according to a schedule or event list. The Simkit event list drives the discrete event simulation (Buss, 2000). For example, the activation of a sensor (initiated by an event) schedules the conduct of a search. When executed, the search may acquire potential targets and may initiate state changes in a targeting system. Simkit events (SimEvents) activate methods within Java objects invoked at a scheduled time to cause state changes in the model.

Implementing a model using Simkit requires representing the system or process with simulation objects. The states and state transitions in each simulation object must be specified. State variables define a simulation object's state at a specific time. SimEvents initiate property changes in state variables. For example, simulation objects may include sensors and targets. The number of acquired targets may be represented in the state of the model.

SimEvents define state transitions. As methods are invoked within a simulation object, the Simkit engine generates SimEvents and schedules them on the event list. At the appropriate (scheduled) time, a SimEvent is passed to the proper method, and the state changes included in the state transition are initiated. A SimEvent can schedule other SimEvents. The time order of events is maintained by the event list.

2. Simkit Links Combat XXI and SSIM CODE

Combat XXI uses Simkit as its simulation engine. Because SSIM CODE must interact with Combat XXI as the simulation runs, SSIM CODE must be capable of placing events on the event list and monitoring state variable changes from the Combat XXI simulation. Thus, SSIM CODE also employs Simkit. SSIM CODE is capable of collecting information from the Combat XXI simulation to develop reports for the commander. SSIM CODE places each individual phase of the commander's OODA loop on the event list. Thus, delays within the commander's decision process are included in the simulation along with all other time-consuming processes modeled by Combat XXI (such as movement, search, etc.).

Java and Simkit are the major features shared by SSIM CODE and Combat XXI. These commonalities contribute to the loose coupling of SSIM CODE (the functionality module) and Combat XXI (the combat simulation). Figure 9 presents a simplified relationship between Combat XXI and SSIM CODE. The platform entity, SA module and functionality module interface are all elements (Java classes) of Combat XXI. The commander entity is part of SSIM CODE and complies with the functionality module interface requirements.

Simkit is the simulation engine for both Combat XXI and SSIM CODE. SimEvents link the SA module and the commander entity. The SA module monitors and schedules SimEvents through the use of facts and actions (described in the *Model Structure* section). The commander entity uses its OODA loops to monitor and schedule SimEvents.

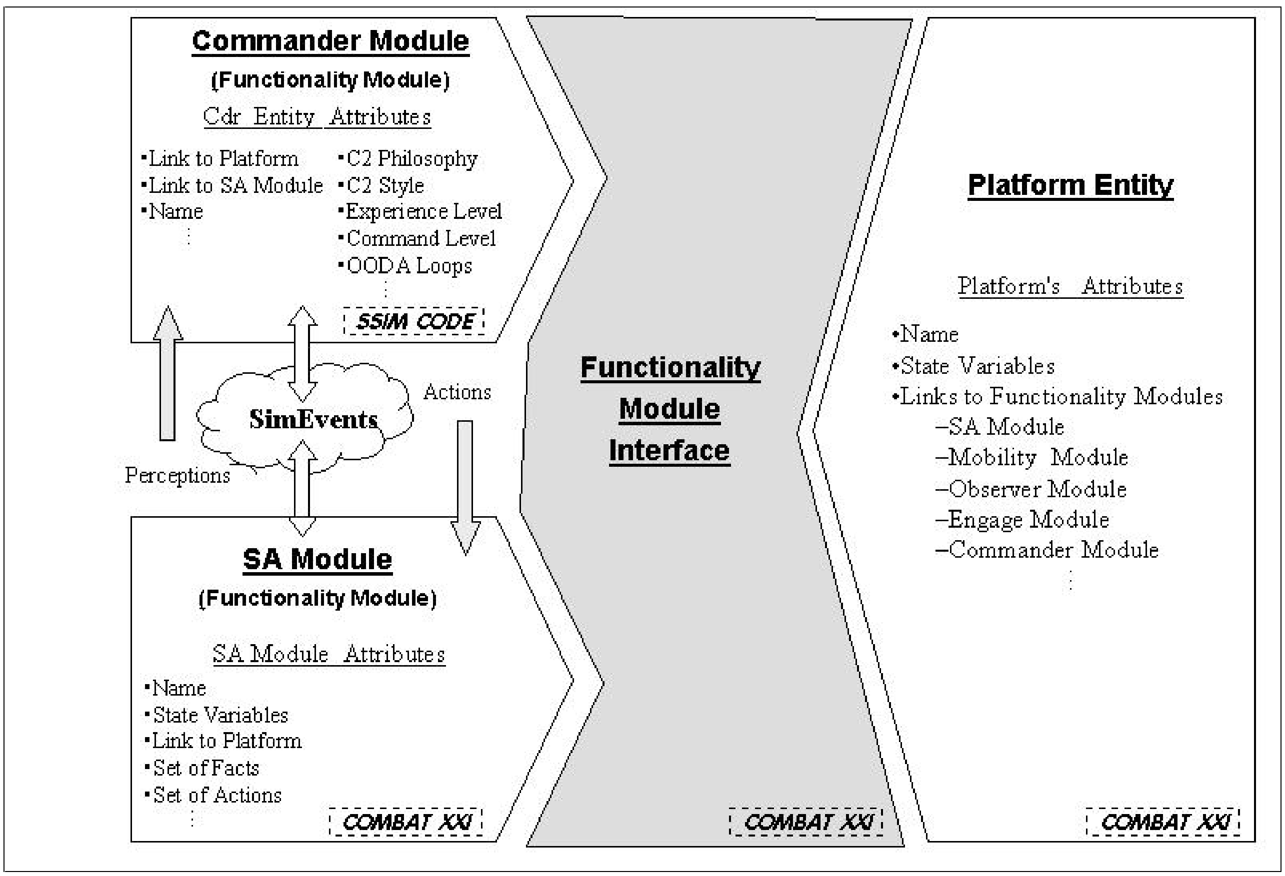


Figure 9. Combat XXI / SSIM CODE Relationship
SSIM CODE's commander entity is a Combat XXI functionality module that interfaces with the rest of the simulation through the SA module.

D. THESIS OBJECTIVES

This thesis contributes toward the Combat XXI enhanced C2 decision process component by forming a representation of the tactical commander's decision. The thesis objectives include:

- *Model tactical commander decision cycles (battalion and below).*
- *Apply C2 doctrine.*
- *Develop a functionality module for Combat XXI.*
- *Exercise the SSIM CODE as a stand-alone simulation.*
- *Evaluate the effectiveness of SSIM CODE's decision-making.*

E. THESIS SCOPE

This thesis develops, implements and evaluates SSIM CODE. SSIM CODE is loosely coupled with a fixed version of Combat XXI. Because Combat XXI is currently under development, its features and structure change daily. Certain essential features of Combat XXI (such as the engagement process) were not complete at the time SSIM CODE was being developed. For these reasons, evaluation of SSIM CODE's performance is conducted with a stand-alone simulation. The evaluation simulation is coupled to Combat XXI through the SA module.

Model assessment includes testing SSIM CODE with a combat scenario. The scenario centers on a company commander's decision. The test scenario involves assumptions about the capabilities and characteristics of the forces involved. The assumptions include force structure, commander characteristics, offensive and defensive tactics, etc. The thesis analysis focuses on comparing SSIM CODE's performance to the analytical models developed in Chapter III. The evaluation also involves the use of quantitative MOEs that represent a commander's intent as discussed in Chapter V.

Analysis of SSIM CODE also involves a face validation (U.S. Army, 1999). A discussion of the requirements in a rigorous validation of a simulation, such as SSIM CODE, is included in Chapter VII. However, a full validation of SSIM CODE is not within the scope of this thesis.

III. MODEL DEVELOPMENT

SSIM CODE's characteristics include functionality based on the DISA C4ISR C2 model, a basis in Marine Corps C2 philosophy, stochastic decision-making modeled by the MCCDC Bayesian network, and the capability to interface with the Combat XXI SA module structure.

A. MODEL FUNCTIONALITY

Based on DISA's C4ISR model, SSIM CODE's functionality is structured according to the OODA loop. The elements in each OODA loop phase include:

- *Observe*
  - *– Get Combat State Data.*
  - *– Receive Reports.*
- *Orient*
  - *– Fuse Report Data to Develop Decision Factors.*
  - *– Develop a Combined State Perception.*
- *Decide*
  - *– Apply Decision Factors to the Decision Process.*
  - *– Choose a COA.*
- *Act*
  - *– Develop a Set of Commands to Represent the COA.*
  - *– Issue Commands.*

B. C2 PHILOSOPHY

Marine Corps C2 doctrine describes two C2 philosophies: detailed C2 and mission C2. Detailed C2 pursues certainty while minimizing uncertainty. Detailed C2 is analytical, centralized and technology intensive. Mission C2 accepts uncertainty and risks. Mission C2 is a decentralized, flexible process that relies on lower-level decision-making. (U.S. Marine Corps, 1996)

The philosophy behind mission C2 views uncertainty as an unavoidable product of war that cannot be eliminated. While mission C2 calls for reducing uncertainty, its focus is on generating a rapid tempo. Reducing uncertainty involves the timely process of collecting and processing information. Speed is a key element of mission C2. Therefore, in mission C2 tempo is not sacrificed to eliminate uncertainty.

Detailed C2 is based on the idea that nearly all information in the battlespace is ultimately available. The focus of detailed C2 is eliminating uncertainty through superior information-processing. Tempo in detailed C2 is derived from knowledge. Detailed C2 chooses the most effective COA by trying to develop a complete picture of the battlespace.

The commander's C2 philosophy affects his choice of actions. A mission C2 commander may decide to take actions to accomplish his objective in the face of an incomplete or uncertain picture of the battlespace. Given the same situation, a detailed C2 commander may choose to request guidance from his superior or continue to gather information. SSIM CODE's C2 philosophy is considered in the *decide* phase of the commander's OODA loop.

C. AN INDIVIDUAL COMMANDER'S DECISION-MAKING

A commander's individual characteristics are considered in SSIM-CODE's decision-making process. The commander is modeled as an entity with properties (Java object attributes) including a command style (conservative vs. aggressive), a C2 philosophy (mission vs. detailed), and an experience level (high or low).

Command style influences the likelihood of certain actions in a given situation. For example, an aggressive commander applying mission C2 is more likely to attack in an environment that makes an attack difficult. A conservative, detailed C2 commander may elect to bypass the enemy in a similar situation.

The commander’s C2 philosophy determines the application of mission or detailed C2. A commander with a mission C2 philosophy is more likely to make a decision without requiring further direction from a higher command or increased certainty. Probabilities associated with specific actions in SSIM CODE are determined by the commander entity's C2 philosophy and C2 style.

An inexperienced commander takes more time to process incoming information, develop his orientation, and reach a decision. In SSIM CODE, the commander’s experience level is used to determine time delays in the phases of the commander’s OODA loop. In the SSIM CODE evaluation, discussed in Chapter V, all combinations of commander attributes are examined. Chapter VII describes potential sources for populating these attributes in practice.

1. Commander’s Intent

Commanders deliver a commander’s intent to their subordinates as a means to communicate the key elements of a mission. Marine Corps Doctrinal Publication (MCDP)-1 *Warfighting* describes commander’s intent as a tool for subordinates to “understand the larger context of their actions.” Tactical commanders rely on their superior’s commander’s intent to focus their decision-making and assess the effectiveness of their decisions.

A commander's intent can include the commander's focus, concerns, CCIRs and desired end-state. The most important element of the commander's intent is typically the desired end-state (Posadas, 2000). The effect of time as a critical element of the mission is typically captured in the commander's intent. In SSIM CODE, a simplified representation of a commander's intent is included by the desired end-state. The end-state in this model is comprised of a quantitative objective description and an end-state event. For example, the desired end-state may consist of achieving a 1:3 friendly to enemy force ratio within two hours of detecting enemy forces in a specific area.

Expanding the SSIM CODE model could develop a more robust commander's intent. However, the purpose for the commander's intent in SSIM CODE is to define a means for evaluating the effectiveness of the tactical commander's decisions. A simplified, quantifiable commander's intent achieves this purpose.

2. Decision Factors

The commander entity in SSIM CODE is linked to an SA module in Combat XXI. The SA module monitors information throughout the combat simulation, maintains a collection of perceived facts, starts the commander's decision cycle when a decision is required, and implements actions that result from the commander's decisions.

Decision factors, influenced by state variables in the combat simulation, are updated in the commander's *observe* decision phase. Decision factors are binary discrete random variables computed as functions of varying states in the combat simulation. Decision factors are aggregated elements that influence tactical decision-making. While decision factors have discrete states, commander entities in SSIM CODE do not have direct access to the discrete states. Commander entities are provided probabilistic estimates of decision factor states (uncertain information). This concept is developed in more detail later in this chapter.

Key decision factors are described by MCDP-*6 Command and Control*. When describing the *observe* phase of the OODA loop, MCDP-6 states: "…we take in information about our own status, our surroundings and our enemy." (U.S. Marine Corps, 1996)

Examples of decision factor states include: whether the condition of the commander's own forces is positive or negative, the favorable or unfavorable state of the environment (relative to a specific action), and the weak or strong state of enemy forces. Based on this guidance, SSIM CODE captures the essential elements of military judgment with three-decision-factors: own forces, environment, and enemy forces.

The model could employ an abstract n-factor design. However, according to MCDP-1-3 *Tactics*, a tactical commander develops his understanding of a situation by specifically considering METT-T (U.S. Marine Corps, 1997). The key elements in METT-T are enemy forces, the environment, and friendly forces, according to MCDP-6 *Command and Control* (U.S. Marine Corps, 1996).

In SSIM CODE, mission and time available are elements of the higher commander's intent. The decision factors represent the commander's consideration of his troops (own forces), terrain and weather (environment), and the enemy (enemy forces). Thus, the five elements of METT-T are represented in SSIM CODE. Table 1 lists the states for the three binary decision factors. (A discussion of multinomial decision factors is included later in this chapter.) These states are similar to those applied by MCCDC in the Bayesian network decision-making model (Stephens, 1998).

Decision Factor	Description	States
B (Blue)	Condition of Own Forces	P = positive
		N = negative
R (Red)	Condition of Enemy Forces	S = strong
		W = weak
E (Environment)	Environment State Relative to Own Mission	F = favorable
		U = unfavorable

Table 1. Decision Factor States

Each decision factor's state can be determined by observations on related state variables from within the combat simulation. State variables from within Combat XXI are indicators for decision factors in SSIM CODE. For example, the condition of the commander's subordinates (*own forces* factor) can be determined by measuring the degree to which the forces are engaged with the enemy (represented by the Combat XXI variable *platformEngagementFactor* (TRAC-WSMR, 2001)) and the amount of damage incurred (denoted by the variable *platformDamageFactor* in Combat XXI (TRAC-WSMR, 2001)). Additional indicators of the state of own forces may be considered; however, a balance is sought between the number of state variables required to determine a decision factor state and an adequate representation of the decision factor's state.

D. CONDITIONAL PROBABILITY MODEL

1. Detailed Model

The decision-making process can be modeled in detail with conditional probabilities. First, the elements that influence the commander's decision are determined. The commander's experience level (X), C2 style (Y), and C2 philosophy (Z) influence his decision-making. His perception of the higher commander's intent (C) also influences his decisions. The actual situation (S) is equivalent to the combined state of the three decision factors in the Bayesian model. The commander's estimate or perception of the situation (I) is based on reports on the actual situation (S). Figure 10 is an influence diagram (Marshall, 1995) that represents the probabilistic dependencies between the elements of decision-making.

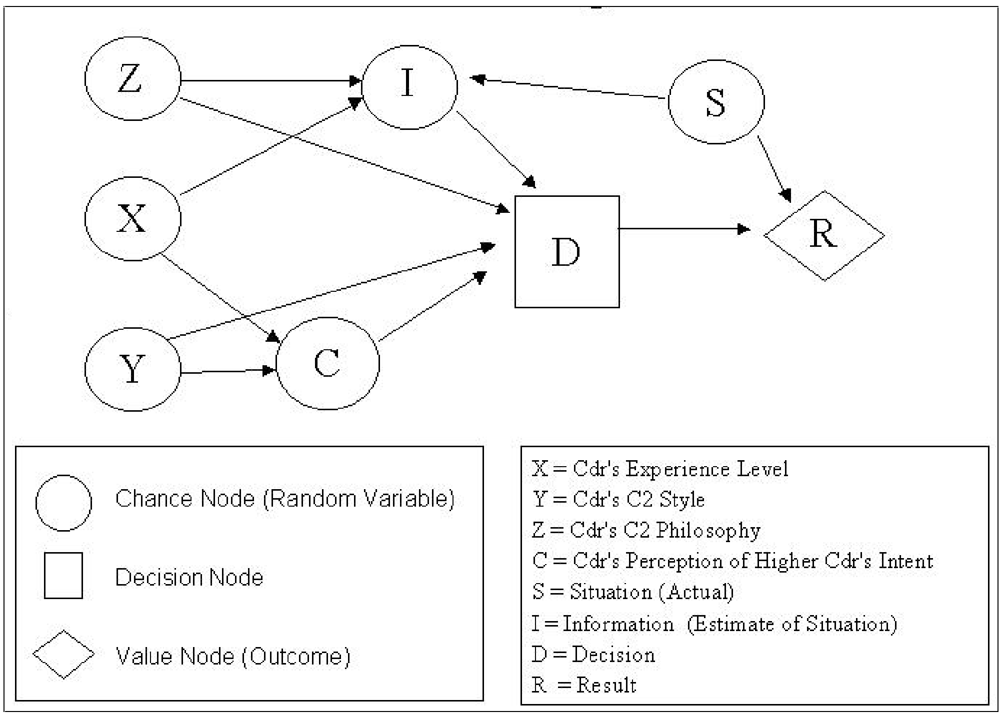


Figure 10. Influence Diagram of a Decision-Making Process

The influence diagram is ordered in time from left to right. The commander's attributes are determined (X, Y and Z), and then the commander develops a perception of the higher commander's intent (C). Next, the commander develops an estimate of the situation (I) and makes his decision (D). The consequence of a decision is a result (R).

The directed arcs denote possible conditional dependence. The absence of an arc between two nodes indicates possible conditional independence (Marshall and Oliver, 1995). The commander's estimate of the situation (I) and perception of his mission (C) depend on his experience level (X). His decision (D) depends on his C2 style, C2 philosophy, situation estimate and his mission perception (Y, Z, I, and C). However, the commander's decision is conditionally *independent* of the actual situation (S), given the estimate of the situation (I). The result of the commander's decision depends on the commander's decision (D) and the actual situation (S), but given these two factors, the result is conditionally independent of the other elements. The following distributions (data) are required to solve the conditional probability model:

Marginal Distributions *P{S=s}* *P{X=x}* *P{Y=y}* *P{Z=z}*
Conditional Distributions *P{C=c | X=x, Y=y}* *P{I=i | X=x, Z=z, S=s}* *P{D=d | I=i, C=c, Y=y, Z=z }* *P{R=r | S=s, D=d}*
Joint Distributions *P{ X=x, Y=y}* *P {X=x, Z=z, S=s}* *P{I=i, C=c, Y=y, Z=z }* *P{S=s, D=d}*

Table 2. Required Data for Conditional Probability Model

For the purposes of this thesis, the commander's decision probabilities in SSIM CODE (P{D=d | I=i, C=c, Y=y, Z=z }) are based on expert judgment for the specific evaluation scenario described in Chapter V. A discussion of potential means for populating such a conditional probability distributions is included in Chapter VII.

According to this model, the commander's attributes (X, Y and Z) are the most influential elements in his decision-making. This is illustrated when solving for the marginal distribution of the commander's decision:

$$P\{D=d\} = P\{D=d \mid I=i, C=c, Y=y, Z=z\} \cdot P\{I=i\} \cdot P\{C=c\} \cdot P\{Y=y\} \cdot P\{Z=z\}$$

$$P\{D=d\} = P\{D=d \mid I=i, C=c, Y=y, Z=z\} \cdot P\{I=i \mid X=x, Z=z, S=s\} \cdot P\{X=x\} \cdot P\{Z=z\} \cdot P\{S=s\} \cdot P\{C=c \mid X=x, Y=y\} \cdot P\{X=x\} \cdot P\{Y=y\} \cdot P\{Y=y\} \cdot P\{Z=z\}$$

$$P\{D=d\} = P\{D=d \mid I=i, C=c, Y=y, Z=z\} \cdot P\{I=i \mid X=x, Z=z, S=s\} \cdot P\{S=s\} \cdot P\{C=c \mid X=x, Y=y\} \cdot P\{X=x\}^2 \cdot P\{Y=y\}^2 \cdot P\{Z=z\}^2$$

This value of $P\{D=d\}$ is expressed in terms of required data. The marginal probabilities of the commander's attributes ($P\{X=x\}$, $P\{Y=y\}$, $P\{Z=z\}$) appear as squared terms in the solution for a decision outcome (R). These terms have the most influence on $P\{D=d\}$. Thus, the commander's attributes are expected to be the most influential elements of his decision-making.

Solving for the probabilistic result yields:

$$P\{R=r\} = P\{R=r \mid S=s, D=d\} \cdot P\{S=s\} \cdot P\{D=d\}$$

$$P\{R=r\} = P\{R=r \mid S=s, D=d\} \cdot P\{D=d \mid I=i, C=c, Y=y, Z=z\} \cdot P\{I=i \mid X=x, Z=z, S=s\} \cdot P\{C=c \mid X=x, Y=y\} \cdot P\{X=x\}^2 \cdot P\{Y=y\}^2 \cdot P\{Z=z\}^2 \cdot P\{S=s\}^2$$

The resulting outcome is influenced most by the actual situation (S) and the commander's attributes (X, Y, and Z). This analytical model is informative in evaluating the probabilistic relationships between decision-making elements.

The quality of the commander's decision-making process could be analyzed with the conditional probability model by comparing the decision result with a desired outcome. However, the conditional probability model requires a substantial amount of data (listed in Table 2) in the form of probability distributions. For example, the marginal distribution that a commander is aggressive, the conditional probability of a commander's decision (given information, commander's intent, C2 style, and C2 philosophy), and the joint probability of commander experience and command style are among the required data to attain an outcome. Extensive prior probabilities would be necessary for a single calculation.

2. Simplified Model

The SSIM CODE model is a simplified version of the conditional probability model. The simplification is required to reduce the quantity of data used to determine decision outcomes and to decrease computational complexity. To simplify the model for simulation, a given set of attributes are assumed for each commander. SSIM CODE assumes the experience level, C2 philosophy and C2 style of a commander are known or can be estimated. Commander attributes are deterministic parameters provided to SSIM CODE.

The commander's perception of his mission, or higher commander's intent, is defined as a set of rules (based on expert tactical judgment) in SSIM CODE. This perception varies with the commander's individual attributes. Thus, the decision outcome is influenced by the commander's attributes.

The probability of a commander's decision outcome, given his attributes and his estimate of the situation (decision factors), remain required data for SSIM CODE. State variables in the Combat XXI simulation define the actual situation at any specific time. The *estimated* situation is a probabilistic input to the commander entity in SSIM CODE. Reports on decision factors estimate the situation and represent the degree of uncertainty.

E. ABSORBING MARKOV CHAIN MODEL

An absorbing Markov chain (Ross, 1997) model can determine decision outcomes based on the simplified model. Modeling the commander's decision-making process with an absorbing Markov chain results in a probabilistic decision outcome that reflects the variability associated with human decision-making and represents the uncertainty inherent to the commander's estimate of the situation.

1. State Space

A discrete time Markov chain can describe the OODA loop process. Each phase in the OODA loop is a discrete time step. The decision factors are represented by the variables *E* (environment), *R* (enemy forces), and *B* (own forces), in accordance with METT-T.

The states in the Markov chain model correspond to decision factor states. For example, *F* is the state where the environment decision factor is favorable. *U* represents an unfavorable environment decision factor. The state *F,S* describes a favorable environment and a strong enemy. Three factor states describe a complete perception of the battlespace, such as *F,S,P*: favorable environment factor, strong enemy forces factor, and positive own forces factor. There are eight such states (the number of states increases exponentially with the number of factor levels). The decision outcomes (e.g., attack or bypass) are absorbing states.

2. Markov Chain Calculations

To determine the stochastic outcome of the decision-making process, decision factor estimates and commander's attributes are combined in an absorbing Markov chain model. A transition matrix is populated based on probabilities associated with each decision factor. The probabilities in the transition matrix are drawn from decision factor reports (probabilistic states) provided to the commander and from the commander's decision outcome conditional probabilities. For example the commander would receive reports that detail $P\{R=r\}$, $P\{B=b\}$, and $P\{E=e\}$. An individual commander's attributes include conditional probabilities for each possible combined state such as:

$P\{D=d \mid R=r, B=b, E=e\}$.

The long-run probability matrix (Ross, 1997) is then calculated. Finally, the probability associated with each decision outcome is retrieved from the long-run probability matrix.

Figure 11 is an example of a transition diagram for a decision to attack or bypass an enemy force. Reports to the commander describe observations on the environment, enemy forces and his own forces. The reports detail the probability that a decision factor takes on a specific state value (e.g., $P\{E=favorable\}=.75$). The transition probability from a combined state (e.g., to *E=favorable and R=strong and B=positive)* to a decision outcome is determined from the commander's C2 style.

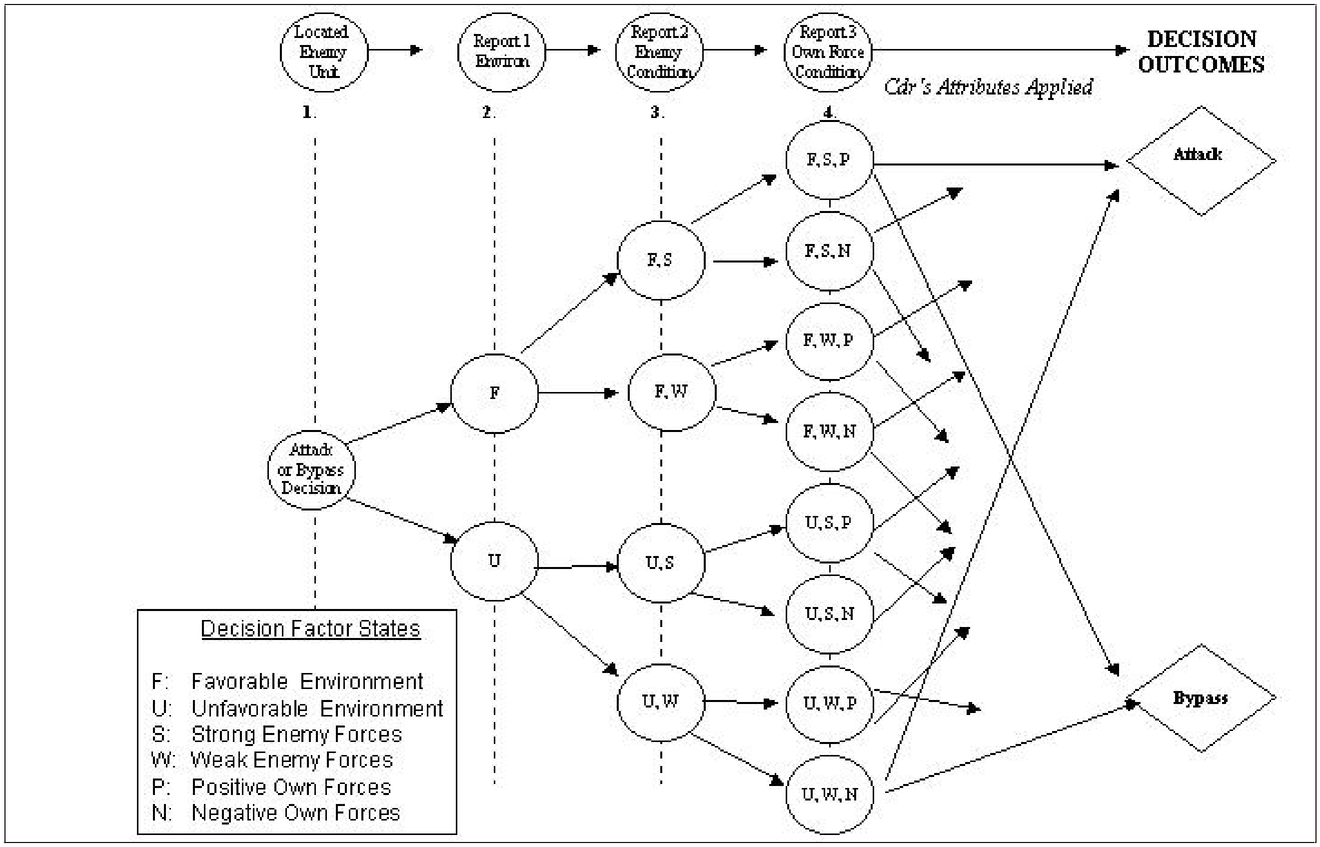


Figure 11. Decision-Making Transition Diagram

From this transition diagram, a transition matrix, *P*, is constructed:

P =

	0. Attack	1.Bypass	2.Decide	3. F, S,P	4. F, S,N	5. F,W,P	6. F, W,N	7. U, S, P	8. U, S,N	9. U, W,P	10.U, W,N
0. Attack	1	0	0	0	0	0	0	0	0	0	0
1. Bypass	0	1	0	0	0	0	0	0	0	0	0
2. Decide	0	0	0	P_{23}	P_{24}	P_{25}	P_{26}	P_{27}	P_{28}	P_{29}	P_{210}
3. F,S,P	P_{30}	P_{31}	0	0	0	0	0	0	0	0	0
4. F,S,N	P_{40}	P_{41}	0	0	0	0	0	0	0	0	0
5. F,W,P	P_{50}	P_{51}	0	0	0	0	0	0	0	0	0
6. F,W,N	P_{60}	P_{61}	0	0	0	0	0	0	0	0	0
7. U,S,P	P_{70}	P_{71}	0	0	0	0	0	0	0	0	0
8. U,S,N	P_{80}	P_{81}	0	0	0	0	0	0	0	0	0
9. U,W,P	P_{90}	P_{91}	0	0	0	0	0	0	0	0	0
10. U,W,N	P_{100}	P_{101}	0	0	0	0	0	0	0	0	0

Probabilities $P_{2,3}$ through $P_{2,10}$ are derived from the decision factor reports, Probabilities $P_{3,0}$, $P_{3,1}$,..., $P_{10,0}$, $P_{10,1}$ are the commander's decision-making conditional probabilities for each combined state. States 0 and 1 are absorbing states; states 2 through 10 are transition states. Every transition state has access to an absorbing state.

Future states are conditionally independent of previous states, given the current state. Therefore, the conditions for a Markov chain are met. (Ross, 1997)

For an absorbing Markov chain, the probability of ever reaching state *j* given that the decision process starts in state *i* (f_{ij}) is given by: $f_{ij} = [I - Q]^{-1} R_{ij}$ (Ross, 1997). This result is the decision outcome probability: $f_{ij} = P\{D=d\}$. The matrix Q holds transient-to-transient transition probabilities, R holds transient-to-absorbing transition probabilities and *I* is the identity matrix.

$$Q = \begin{array}{lc} & \begin{array}{ccccccccc} \text{2.Decide} & \text{3. F, S,P} & \text{4. F, S,N} & \text{5. F,W,P} & \text{6. F, W,N} & \text{7. U, S, P} & \text{8. U, S,N} & \text{9. U, W,P} & \text{10.U, W,N} \end{array} \\ \begin{array}{l} \text{2. Decide} \\ \text{3. F,S,P} \\ \text{4. F,S,N} \\ \text{5. F,W,P} \\ \text{6. F,W,N} \\ \text{7. U,S,P} \\ \text{8. U,S,N} \\ \text{9. U,W,P} \\ \text{10. U,W,N} \end{array} & \begin{bmatrix} 0 & P_{23} & P_{24} & P_{25} & P_{26} & P_{27} & P_{28} & P_{29} & P_{210} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

$$R = \begin{array}{lc} & \begin{array}{cc} \text{0. Attack} & \text{1.Bypass} \end{array} \\ \begin{array}{l} \text{2. Decide} \\ \text{3. F,S,P} \\ \text{4. F,S,N} \\ \text{5. F,W,P} \\ \text{6. F,W,N} \\ \text{7. U,S,P} \\ \text{8. U,S,N} \\ \text{9. U,W,P} \\ \text{10. U,W,N} \end{array} & \begin{bmatrix} 0 & 0 \\ P_{30} & P_{31} \\ P_{40} & P_{41} \\ P_{50} & P_{51} \\ P_{60} & P_{61} \\ P_{70} & P_{71} \\ P_{80} & P_{81} \\ P_{90} & P_{91} \\ P_{100} & P_{101} \end{bmatrix} \end{array}$$

3. Outcome Probabilities

The absorbing Markov chain long-run probability matrix yields a probability that a decision outcome (absorbing state) is reached. A decision with two possible outcomes (e.g., attack or bypass) can be described as a Bernoulli trial (a special case of a Binomial trial, e.g., success=attack, failure=bypass). The probability of success is used as the Bernoulli distribution parameter. A uniform (0,1) random number is then generated and compared with the probability of success (e.g., probability of attack). If the uniform random draw is less than the probability of success, the decision outcome is set to success (e.g., attack). Otherwise, the decision outcome is set to failure (e.g., bypass). (Law and Kelton, 2000)

For decisions with more than one outcome (multi-nominal trials), the Markov chain model would yield a probability associated with each outcome. For example, for three outcomes, *A*, *B*, and *C*, the probabilities can be denoted as: $P\{A\} = p_1$, $P\{B\} = p_2$, and $P\{C\} = p_3$, where $p_1+p_2+p_3 = 1$.

To determine the outcome chosen by the commander, a uniform (0,1) random number, U, is then generated and compared with the probabilities. For $p_1 < p_2 < p_3$, the outcome would be *A* if $0 < U \leq p_1$, *B* if $p_1 < U \leq (p_1+p_2)$, and *C* if, $(p_1+p_2) < U \leq 1$. This procedure can be generalized to a decision with n outcomes:

$$\textit{Apply outcome } \mathrm{k_i} \textit{ if } \sum_{i=1}^{k-1} p_i < U \leq \sum_{i=1}^{k} p_i .$$

4. Computational Complexity of the Markov Chain Model

The absorbing Markov chain model effectively uses decision factor states and commander attributes to produce probabilistic decision outcomes. However, the matrix operations required for each decision outcome result in a large computational complexity. When the transition matrix, *P*, has dimensions *nxn*, calculating an outcome probability with the Markov chain decision-making model involves on the order of n^3 operations (multiplications and additions). Using the notation in Ahuja, Magnanti and Orlin (1993), this model has a complexity of $O(n^3)$.

Each decision's outcome probability is determined by $f_{ij} = [I - Q]^{-1} R_{ij}$ as described in the *Outcome Probabilities* section. With an *nxn* transition matrix, the complexity of $(I - Q)$ is $O(n)$. Inverting the resulting matrix has complexity between $O(n^{2.4})$ and $O(n^3)$, depending on the algorithm used (Ehrling, 1999). Thus, a single outcome probability calculation involves $O(n^3)$ computational complexity.

The number of binary decision factors and the number of decision outcomes determine the transition matrix dimensions *(nxn)* and the computational complexity. For an *m*-outcome decision with *k* binary decision factors, $n = 2^k + m + 1$. In terms of decision factors, the complexity of the Markov chain decision-making model is $O(2^{3k})$.

Because Combat XXI is a high-resolution combat simulation, it is required to continuously generate a large number of computational results. Adding unnecessary computational complexity to the simulation is an undesirable effect of the Markov chain model. A model with similar functionality, but reduced complexity would be more appropriate for a high-resolution combat simulation. A Bayesian network model provides such features.

F. BAYESIAN NETWORK MODEL

A Bayesian network model yields identical probabilistic outcomes as the absorbing Markov chain model with less computational intensity. The three decision factors in SSIM CODE (environment, enemy forces, and own forces) are applied to the Bayesian network model to determine an outcome: the commander's decision.

The decision outcome is probabilistically dependent on the decision factors. The decision factors (random variables) make up a joint probability distribution for the commander's decision outcome (Stephens, 1998). Figure 12 shows a sketch of a Bayesian network with three decision factors.

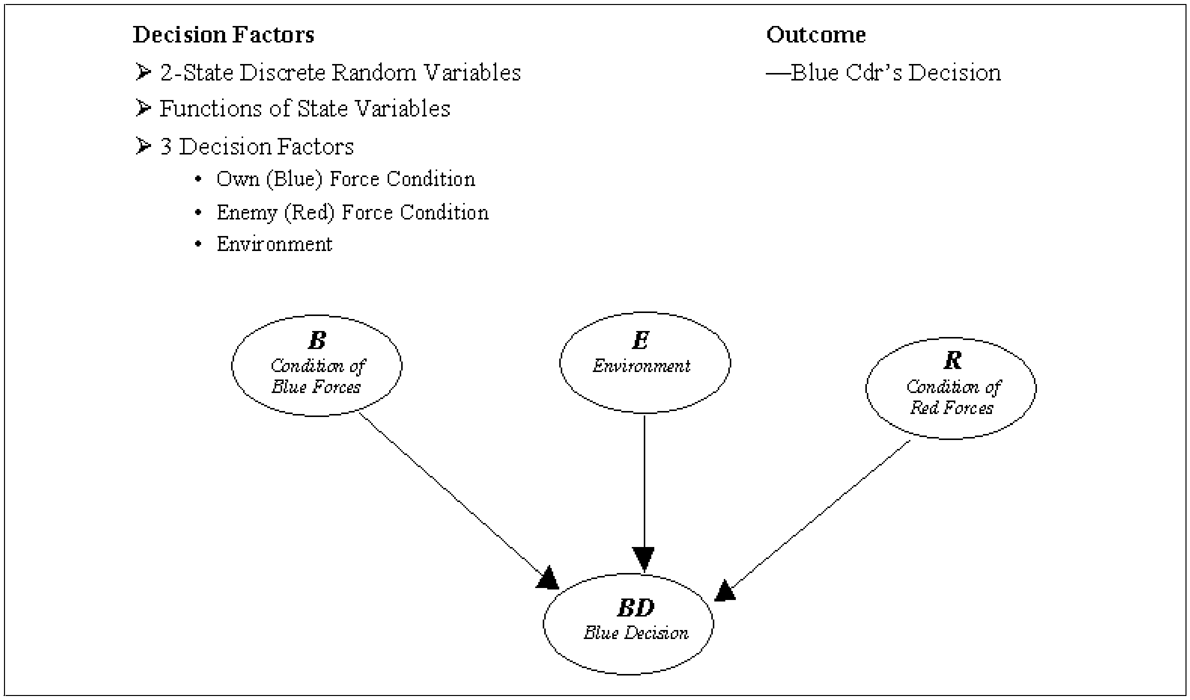


Figure 12. Bayesian Decision-Making Network (After Stephens, 1998)

1. Bayesian Network Model Decision Outcomes

A decision outcome probability from this Bayesian network is determined by:

$$
\begin{aligned}
P\{BD = d\} = \; & P\{BD = d \mid B = b, E = e, R = r\} \cdot P\{B = b\} \cdot P\{E = e\} \cdot P\{R = r\} \\
& + P\{BD = d \mid B = b, E = e, R = \bar{r}\} \cdot P\{B = b\} \cdot P\{E = e\} \cdot P\{R = \bar{r}\} \\
& + P\{BD = d \mid B = b, E = \bar{e}, R = r\} \cdot P\{B = b\} \cdot P\{E = \bar{e}\} \cdot P\{R = r\} \\
& + P\{BD = d \mid B = b, E = \bar{e}, R = \bar{r}\} \cdot P\{B = b\} \cdot P\{E = \bar{e}\} \cdot P\{R = \bar{r}\} \\
& + P\{BD = d \mid B = \bar{b}, E = e, R = r\} \cdot P\{B = \bar{b}\} \cdot P\{E = e\} \cdot P\{R = r\} \\
& + P\{BD = d \mid B = \bar{b}, E = e, R = \bar{r}\} \cdot P\{B = \bar{b}\} \cdot P\{E = e\} \cdot P\{R = \bar{r}\} \\
& + P\{BD = d \mid B = \bar{b}, E = \bar{e}, R = r\} \cdot P\{B = \bar{b}\} \cdot P\{E = \bar{e}\} \cdot P\{R = r\} \\
& + P\{BD = d \mid B = \bar{b}, E = \bar{e}, R = \bar{r}\} \cdot P\{B = \bar{b}\} \cdot P\{E = \bar{e}\} \cdot P\{R = \bar{r}\}
\end{aligned}
$$

The terms on the right side of the expression are data required by SSIM CODE. This is the same set of required data used in the Markov chain calculation. The commander's decision-making conditional probability is P{BD=d | B=b, E=e, R=r }. Reports to the commander define P{B=b}, P{E=e}, and P{R=r}. The probabilistic decision outcome is identical in value to the result from the Markov chain model.

The computational complexity for the Bayesian Network calculation is $O(2^k)$, for k decision factors. This is a significant (exponential) reduction in computational complexity compared to $O(2^{3k})$ for the Markov chain model. So, for the same data requirement, the Bayesian Network model saves on computational effort.

2. Stochastic Decision-Making

The decision factor states and the commander's attributes determine the Bayesian network's underlying joint probabilities. For example, the outcome of a specific commander's decision to attack has several probabilistic outcomes depending on decision factor states:

P{Attack | B=positive, E=favorable, R=weak} = .95
P{Attack | B=positive, E=favorable, R=strong} = .50
P{Attack | B=negative, E= unfavorable, R=weak} = .30
P{Attack | B=negative, E=unfavorable, R=strong} = .15

The commander's attributes determine the probability of a specific decision outcome. The probability that a commander makes a certain decision, given decision factor observations, varies with the individual qualities of the commander. For example:

If C2 Style=aggressive,
Then P{Attack | B=negative, E=unfavorable, R=weak} = .40

However, if C2 Style=conservative,
Then P{Attack | B=negative, E=unfavorable, R=weak} = .20

The probabilities assigned to decision outcomes (for each set of commander attributes) would be provided to SSIM CODE as data in the same manner as the commander attributes. Scripted probabilities were used to test SSIM CODE.

Figure 12 shows a Bayesian network in which a commander's decision depended on direct observations of *E*, *R*, and *B*. In reality, commanders may not have direct access to this information. For example, a company commander does not know the *actual* state of enemy forces (i.e., he cannot readily observe the enemy directly and determine the true state of enemy forces). He bases his decisions on intelligence estimates.

In practice, commanders make decisions based on reported estimates—not on perfect information. To model this concept, additional nodes are introduced to the Bayesian network. These nodes represent reports on decision factor states.

Three sets of nodes are now depicted in the Bayesian network: the commander's decision, reports and decision factors. The lack of perfect information in tactical decision-making is captured in the relationship between the three sets of nodes. The decision outcome is probabilistically dependent on report states and independent of decision factor states. Figure 13 depicts the probabilistic dependencies of a model with imperfect information.

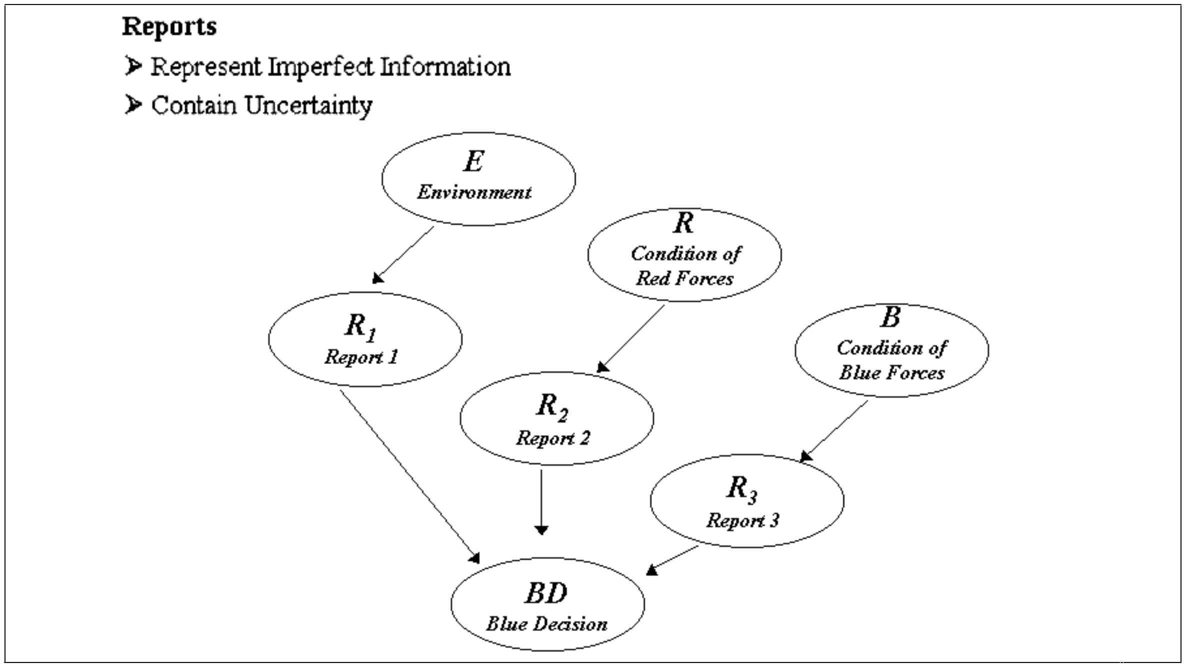


Figure 13. Bayesian Network with Reports (After Stephens, 1998)

The report nodes in the expanded network represent the uncertainty inherent to the commander's information. Based on the Bayesian network in Figure 13, the commander's decision is conditionally independent of E, R and B, given R_1, R_2 and R_3.

In SSIM CODE, the commander entity does not make direct observations of the decision factors. For example, while the environment has a deterministic state (favorable or unfavorable), the commander only has access to an estimate of that state $P\{E=f\}$ or $P\{E=u\}$. He may receive a report estimating the probability of a favorable environment at 85%. The commander may be misinformed and has to weigh the uncertainty in a decision factor report.

For example, given perfect information, a specific commander may attack with 95% probability if the combined state is: *B=positive, E=favorable, R=weak.* But since his information is imperfect, the commander must decide based on uncertain reports: $P\{B=positive\}=0.90$, $P\{E=favorable\}=0.60$, $P\{R=weak\}=0.55$.

After weighing the uncertainty, the commander will attack with a 68% probability. The difference between the 95% likelihood to attack and the 68% likelihood to attack is a result of the disparity between reality and the commander's perception or orientation. (Stephens, 1998)

The use of this Bayesian network model to determine decision outcomes introduces decision variability. Given the same information, the commander will not always reach the same decision. This decision model also accounts for uncertainty. The commander bases his decisions on inexact estimates of decision factors.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. MODEL DESCRIPTION

A. MODEL STRUCTURE

SSIM CODE is applied in Combat XXI as a platform functionality module. This module includes a platform object containing attributes such as a location (grid coordinate) and type (e.g., M1A1). A platform has the potential to move, search, communicate, etc. (enabled by adding appropriate functionality). The primary element of SSIM CODE is the commander entity. The commander entity has an SA module.

In Combat XXI, an SA module maintains facts and executes actions. SSIM CODE is capable of information exchange with Combat XXI by interfacing with the SA module. As a functionality module for Combat XXI, SSIM CODE requires input from various elements of the simulation to execute the commander's decision cycle and to implement decisions. Through the SA module, SSIM CODE monitors changes in state variables, monitors SimEvents, and has access to the current battlespace.

The facts/actions expert system in the SA module updates facts applicable to the commander's decision cycle. This expert system applies rules (e.g., representations of doctrinal tactics) to translate a commander's decision to a set of primitive commands (engage, move, search, etc.). Figure 14 depicts the structure of the interactions between SSIM CODE and Combat XXI. This figure delineates which components are parts of SSIM CODE and which exist in Combat XXI.

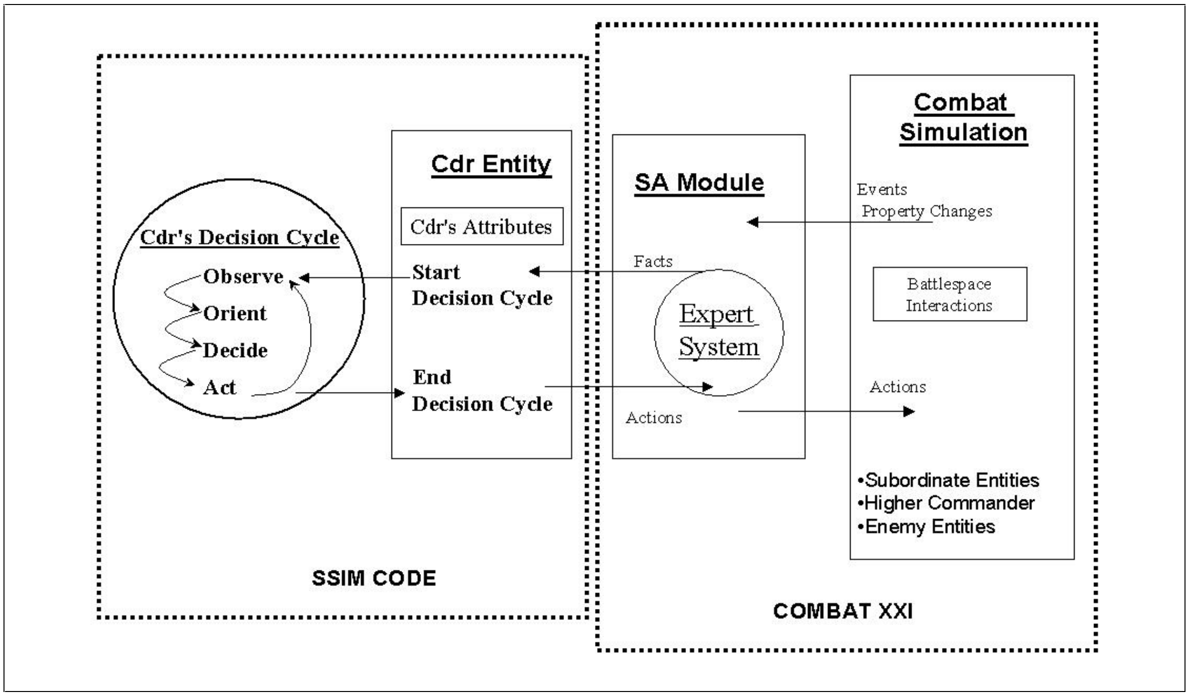


Figure 14. Model Structure

The decision cycle is an attribute of the commander entity. Decision outcomes are communicated to the Combat XXI simulation through the commander's SA module. Observations on simulation events and properties are communicated to the commander through the SA module.

B. MODEL OVERVIEW

The SSIM CODE model is centered on the commander entity. The SSIM CODE commander entity possesses an SA module, a C2 style, a C2 philosophy, an experience level, and a set of decision cycles (OODA loops). Three types of decision cycles are used to test SSIM CODE—one for each decision type (engage, search, move). While several decision cycles may be active in one commander entity, only one of each specific OODA loop type is active at a given time. For example, only one *move* decision can be in progress, but one *engage* and one *search* decision could be active at the same time.

1. The SSIM CODE OODA Loop

A SimEvent in SSIM CODE initiates each phase of the commander's OODA loop. The commander's SA module determines when a decision is required. OODA loops are activated periodically by the commander or by external simulation events and property changes. The time required to complete each phase of the OODA loop is determined by the commander's experience level.

Each OODA loop phase has a time delay. These delays are modeled with exponential distributions. The exponential distribution is memory-less and it "...is frequently used as a model for the distribution of times between the occurrence of successive events." (Devore, 1995).

CCIRs are key questions that the commander wants resolved to focus his decision process (U.S. Marine Corps, 1996). These CCIRs determine which events and property changes trigger OODA loops by requiring decisions. Decisions required while the OODA loop of the same type is active are placed in a decision queue. The commander addresses pending decisions upon completion of his current OODA loop.

In the *observation* phase, reports, and commands from higher headquarters are received. If the commander entity employs a detailed C2 philosophy, additional information is requested to improve the accuracy of the observation. This request for more information increases the duration of the observation phase. Commander entities with mission C2 philosophy accept the accuracy of the reports and continue with the decision cycle. In the *orientation* phase, a combined state is determined based on updated decision factors. The *decide* phase applies the decision factor observations and commander's attributes to the stochastic decision process to obtain an outcome for each decision. The Bayesian network model is implemented in this phase. The resulting set of decisions constitutes the commander's COA.

The *action* phase of the commander's decision cycle requires interaction with other entities in the simulation. The facts/actions expert system accomplishes this interaction by issuing orders, from the commander, to be executed by subordinate entities. The *action* phase involves translating the commander's decisions into a set of actions that represent the commander's decision (move, engage, search, etc.). This output is then communicated to the appropriate entities through the SA module.

2. The SSIM CODE Decision-Making Process

SSIM CODE includes report objects and decision objects. Reports provide information on decision factors with a degree of uncertainty. Decisions are developed as the OODA loop progresses. Figure 15 is an event graph (Buss, 2000) overview of the SSIM CODE model. This figure illustrates the event sequence in a commander's decision cycle.

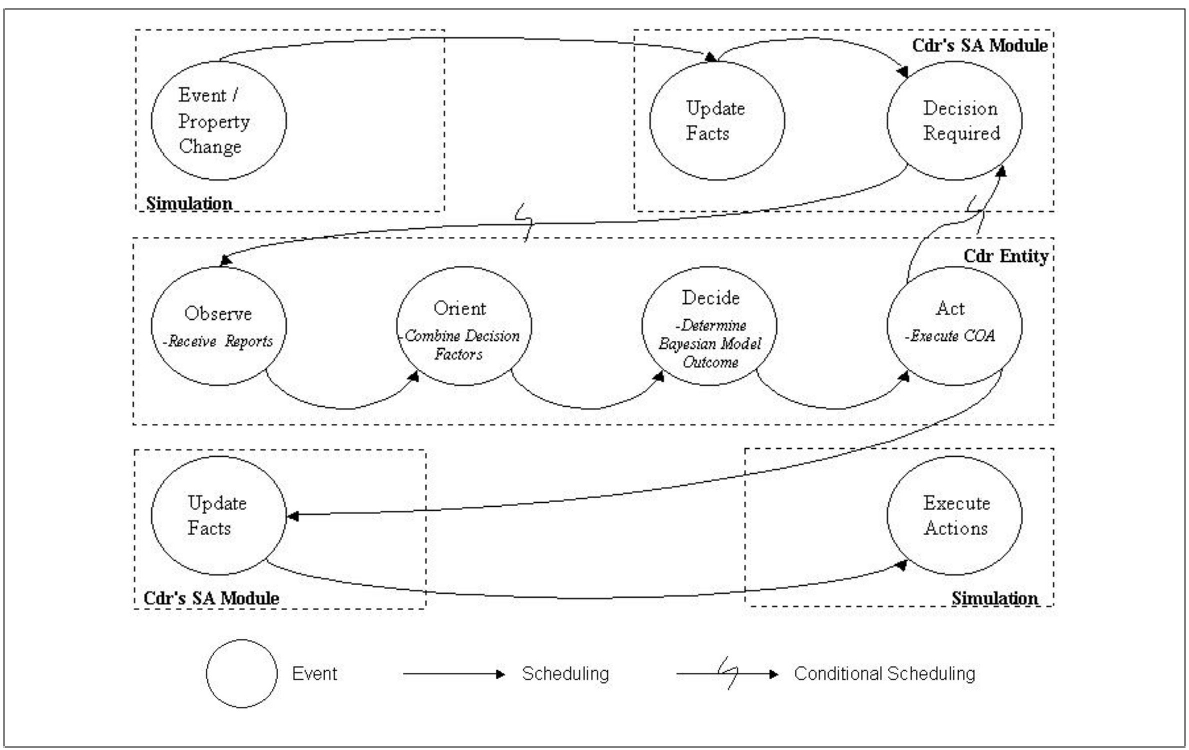


Figure 15. SSIM CODE Event Graph Overview

First, a SimEvent from within Combat XXI triggers a CCIR by the change of a significant property (state variable) or the occurrence of a key event that answers a CCIR. The commander entity in SSIM CODE monitors these changes through its SA module. When a decision is required, the appropriate type of OODA loop is started. Reports on decision factors are received and a perception of the current situation is developed through a combined decision factor. The Bayesian model is implemented to determine a decision outcome. Next, actions are taken to implement the decision. Facts are then updated in the SA module and any subsequent decisions are scheduled.

In Chapter I, desirable attributes of a tactical decision-making model were listed as: a representation of the commander's decision-making process, an emphasis on his perception, a portrayal of uncertainty and chance, and a decision cycle structure. SSIM CODE uses the OODA loop decision cycle structure to represent the tactical commander's decision cycle. The commander's perception is emphasized in the orient phase of the OODA loop. In this phase, SSIM CODE employs decision factors based on C2 doctrine and develops the commander's perception based on reports that include uncertainty. A Bayesian network determines the decisions generated by the commander entity. These probabilistic decision outcomes characterize chance.

SSIM CODE addresses each of the three information-processing styles. Reports on decision factors are received by the commander entity in a set order as in directed processing. CCIRs are used to initiate decisions, as in triggered information-processing. Allowing decisions to induce subsequent decisions and further inquiries about facts as the commander entity develops a COA represents inquiry-based information-processing.

Chapter II added the commander's C2-related characteristics and the commander's evolving awareness as key components in simulating C2 decision-making. SSIM CODE depicts the commander's experience level, C2 style and C2 philosophy and employs these attributes as influences on decision-making. The commander's dynamic SA is portrayed through the link between SSIM CODE and the Combat XXI SA module.

C. MODEL ASSUMPTIONS

General assumptions were made in the development of the SSIM CODE model. The model can be expanded for additional robustness. However, based on these general assumptions, the SSIM CODE model with three decision factors, three commander attributes, and three decision types provides suitable insight to evaluate its performance as a tactical decision-cycle model. The general assumptions include:

- *The three decision factors (environment, own forces, enemy forces) provide the commander with an adequate perception of the battlespace.*
- *The scripted commander attributes provide a reasonable depiction of a tactical commander.*
- *Three decision types (engage, search, move) with two outcomes each provide sufficiently robust COAs.*

Assumption 1 states that the commander's observation of the battlespace can be derived by the elements of METT-T. The mission and time requirements are given in the higher commander's intent. To make a decision, the commander must consider the terrain (*environment factor*) the enemy (*enemy forces factor*) and his own troops (*own forces factor*). These three decision factors represent a thorough observation to the battlespace.

Assumption 2 maintains that the attributes chosen to describe a commander (C2 philosophy, C2 style, and experience level) adequately capture the characteristics that affect a commander's decision-making.

The third assumption states that a tactical commander's COA may be described as a series of decisions on whether or not to search, engage or move. The essence of a tactical course of action is assumed to be portrayed by these three actions.

THIS PAGE INTENTIONALLY LEFT BLANK

V. MODEL EVALUATION

A. TEST SCENARIO

SSIM CODE was tested as a stand-alone entity. The evaluation was loosely coupled with Combat XXI. The test scenario was executed from within Combat XXI. SSIM CODE interacted with Combat XXI through the SA module and Simkit event scheduling. The decision factors, commander attributes, and enemy COAs were scripted to support analysis using a factorial design. A general scenario description is developed in this section. Specific scenario parameters are listed in Appendix A.

The scenario involves an infantry company in the defense (Blue defending against Red). The SSIM CODE test scenario models a company commander’s decision cycle. In the test scenario, only the Blue forces apply the SSIM CODE decision cycle model. Red forces employ scripted actions. The company commander considers three decision factors in his decision-making: the state of the environment, the state of enemy forces, and the state of his own forces. His COAs consist of decisions to move, search and engage.

The company commander entity makes tactical decisions to accomplish an assigned mission. The company commander’s objective is drawn from a battalion commander’s intent. The company commander’s decisions are communicated to three subordinate platoons.

The Blue company is situated in an assembly area while preparing to establish a defense. The Blue company commander's mission is to block any of three avenues of approach (AAs) used by the enemy. His forces have three battle positions (BPs) available to establish a defense. Each of the BPs is associated with a targeted area of interest (TAI) and an AA. TAIs are engagement areas. The company commander is tasked to allocate forces to the appropriate BPs to best defend against an advancing enemy. The battalion commander's intent specifies the requirement to attain a 1:3 (Blue to Red) force ratio at each BP/TAI pairing by a certain time after the enemy reaches the TAI(s). The battalion commander has also directed the company commander to engage enemy forces once they entered a TAI. Figure 16 illustrates the test scenario.

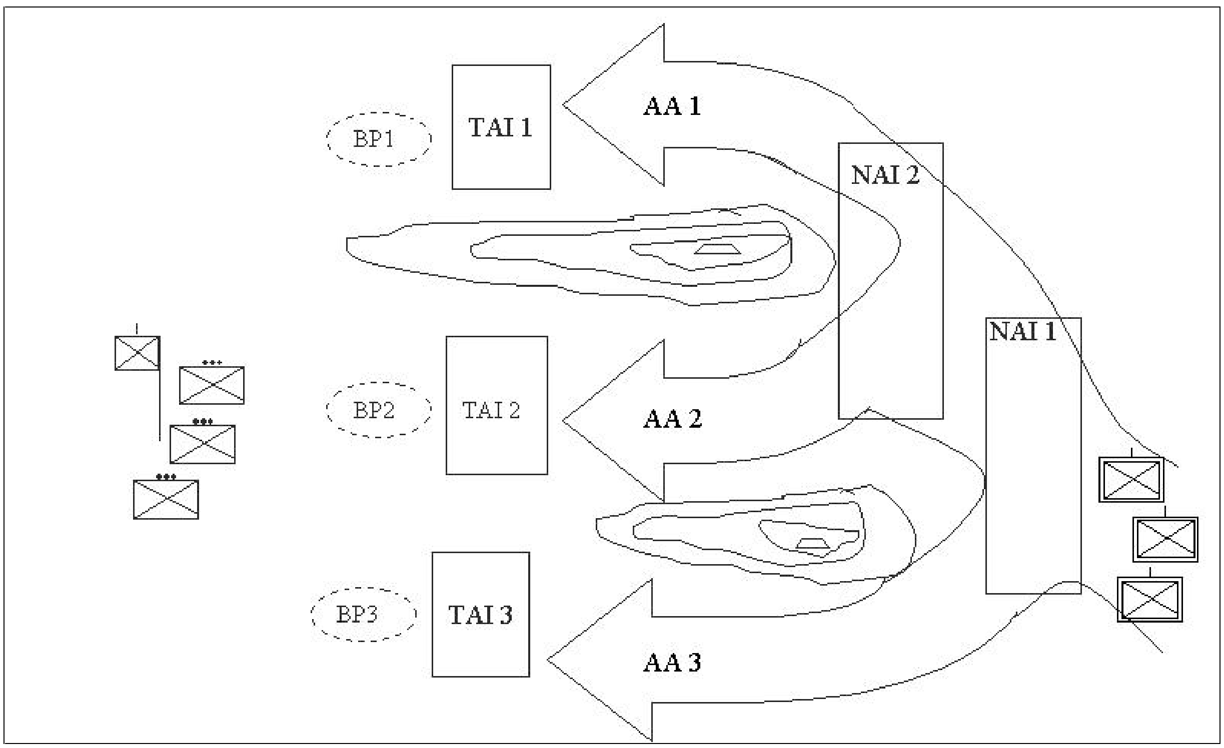


Figure 16. SSIM CODE Test Scenario

The company commander receives reports on the enemy from two named areas of interest (NAIs). Observations of enemy actions at each NAI indicate whether the enemy intends to use AA 1, 2, 3 or a combination. Terrain restricts enemy movement to the three AAs. Only one NAI may be monitored at any time. The sensors used to monitor the NAIs have a fixed detection error. (This detection error is assumed to be the combination of several random effects and is thus modeled with a Normal distribution (Devore, 1995)). Reconnaissance teams constantly monitor TAIs. TAI observations are also subject to detection error.

Enemy forces at each TAI can only be engaged from the corresponding BP. Once the company commander directs forces at a specific BP to engage, those forces must remain in place. The company commander moves and engages with platoon size elements (3 units). The enemy moves in companies (3 units).

To meet the battalion commander's intent, the company commander must decide whether to search in NAI 1 or 2, whether to move to BP 1, 2 or 3 and whether to engage the enemy at TAI 1, 2 or 3. The company commander must attain the specified force ratio by the specified time.

The evaluation includes analyzing the effect of time on tactical decision-making in SSIM CODE. The battalion commander has allocated close air support (CAS) assets to hold the Red forces in the TAIs for a specific period of time. The CAS period starts when the last Red company reaches a TAI and ends a specified time after the last Red Company arrives at a TAI. The Blue company commander must attain the specified force ratio by the end of this CAS period. Several parameterized CAS period times were used as described in Chapter VI

The test scenario is an initial evaluation of SSIM CODE and includes several simplifications. Weapon systems and attrition are not represented in this scenario. The scenario simply serves to evaluate the Blue commander's decisions to allocate forces.

Once the command to engage is issued to a Blue platoon, that remains in place. Force ratios are determined at the meeting point of the two forces without adjusting for attrition. The CAS period serves to hold Red forces in place at the TAIs, but does not diminish their force strength.

Marine Corps doctrinal C2 is applied in the scenario. Doctrinal planning and decision-making tools such as NAIs and TAIs are used. The company commander entity is issued a battalion commander’s intent and a mission. A set of rules is developed to represent doctrine, the battalion commander’s intent and the company commander’s CCIRs. Responses to enemy actions (decisions) are determined by the commander's decision-making. The simulation is stopped after all Red forces reach a TAI and the Blue CAS period expires. The end-state BFR is used as a measure of Blue's success.

B. DECISION RULES

The commander entity applies a set of decision rules to attain the mission goal (the assigned force ratio). These rules are invoked according to the decision outcomes. One set of rules details the company commander’s CCIRs. Three other sets of rules describe the commander’s actions according to the outcomes for search decisions, movement decision and engagement decision. Appendix B details the decision rules used in the test scenario.

1. CCIR Rules

The Blue company commander considers enemy detections as critical information. Each time Red forces are detected at an NAI or TAI, the Blue commander would like to be informed. SSIM CODE accomplishes this by establishing an event key for each type of enemy detection. When an enemy detection SimEvent takes place, the commander entity's SA module updates the commander's set of facts and triggers a CCIR action. This is triggered information-processing in SSIM CODE.

The CCIR action is invoked to determine what further action is required and results in the scheduling of a decision. This is an example of SSIM CODE's inquiry-based information-processing. Based on the detection event that triggered a CCIR action, either a search decision, a movement decision, or an engagement decision is scheduled.

2. Search Rules

In the *act* phase of a search decision, the commander entity applies the decision outcome through a set of search rules. The commander entity's OODA loop sets a decision outcome, the SA module updates the commander's facts, and the search rules are invoked to carry out the decision action. Then, a choice is made: search in NAI 1 or in NAI 2.

3. Movement Rules

A movement decision invokes the movement rules through the commander entity's SA module. The decision outcome determines whether Blue forces will be moved or not. The updated enemy detections are considered and Blue platoons are ordered to a BP according to the interpretation of the Red force movement.

4. Engagement Rules

The *decide* phase of a commander's engagement decision sets the decision outcome. The *act* phase invokes the engagement rules through the commander's SA module. Detections of enemy forces at the TAIs are considered by the engagement rules. Aggressive commanders may engage with up to all three platoons. Conservative commanders engage with only one platoon at a time. Once a platoon engages the enemy, it is unavailable for further movement.

C. SCRIPTED COMMANDER ATTRIBUTES

Commander attributes (experience level, C2 philosophy, and C2 style) were set at a specific level for each experimental run in the SSIM CODE evaluation. These attributes remain constant throughout the entire run. The arrangement of attribute levels per run is described in the factorial design section.

Commander decision probabilities used in the Bayesian network calculations depend on the decision type, the combined state (decision factors) and the commander's C2 style. Probabilities, for each of the eight possible combined states, were set according to the commander's C2 style. Appendix A lists the probabilities used in the test scenario and shows decision probabilities for each decision type and C2 style across the eight possible combined states. These probabilities were chosen by expert judgment and are intended to reflect the differing nature between aggressive and conservative C2 styles.

D. MEASURES OF EFFECTIVENESS

The measures used to evaluate SSIM CODE's decision-making capabilities are described in this section. The face validation is framed with the questions:

- *Does SSIM CODE arrive at realistic decisions?*
- *Do the decisions support a commander's intent?*
- *Is tactical decision-making depicted realistically?*

1. Does SSIM CODE Arrive At Realistic Decisions?

Measuring the degree of realism in SSIM CODE is subjective. A face validation evaluates whether the tactical decisions generated by SSIM CODE are similar to those typically made by tactical commanders. Comparing SSIM CODE's results to the analytical models supports the face validation. The analytical models presented in Chapter III highlighted the commander's attributes and his estimate of the situation as the key elements in tactical decision-making. The face validation also examines how elements of the model influence quantitative measures of effectiveness (MOEs).

2. Do the Decisions Support a Commander's Intent?

The battalion commander's intent is represented as a goal (1:3 Blue-to-Red force ratio) with an associated time constraint (by the end of the CAS period). To determine whether the result of a SSIM CODE run meets the battalion commander's intent, the force ratio and the time to complete the mission are used as MOEs.

The Blue-to-Red force ratio at each TAI is measured at the end of each simulation run. A force ratio of 1:3 is specified by the battalion commander's intent. This MOE allows for a quantitative analysis of the commander entity's decision-making.

An *adjusted* force ratio is used to capture a more robust range of success or failure. The adjusted force ratio penalizes the commander for leaving TAIs undefended. This measure may take on negative values. When Blue forces are engaging Red forces at a TAI, the adjusted force ratio is simply: $\textit{adjusted force ratio} = \dfrac{\textit{number of blue forces}}{\textit{number of red forces}}$ (as before). However, when Red forces are present in a TAI that is undefended by Blue force: $adjusted\ force\ ratio\ =\ \frac{-1}{number\ of\ red\ forces}$. If Blue forces defend at a TAI that is unoccupied by Red, the force ratio is set to zero. Finally, to measure the overall adjusted force ratio (across all TAIs) a *battle force ratio* (the response variable) is computed:

$$battle\ force\ ratio\ =\ \frac{\sum_{i}^{3} adjusted\ force\ ratio\ at\ TAI_i}{number\ of\ TAIs\ occupied\ by\ red\ forces}$$

The battle force ratio (BFR) is normalized by the number of TAIs occupied by the Red forces and accounts for the use of only one or two TAIs by Red forces. This response variable also penalizes the commander for defending TAIs that are not occupied by Red forces. The difference between measuring the commander's success with a traditional force ratio and using a BFR is best illustrated by an example.

If Red forces send one company (or three platoons) to each TAI and Blue sends all three platoons to BP 1, the forces are arranged as shown by Table 3:

Blue Platoons		**Red Platoons (1Company = 3 Platoons)**	
BP 1	**1 1 1**	**3**	TAI 1
BP2	**-**	**3**	TAI 2
BP3	**-**	**3**	TAI 3

Table 3. Sample Force Disposition

Using traditional force ratio computation, the force ratios for TAIs 1, 2, and 3 are $\frac{3}{3}$, $\frac{0}{3}$, and $\frac{0}{3}$. The average force ratio is then $\frac{\frac{3}{3}+\frac{0}{3}+\frac{0}{3}}{3} = 0.333$. Numerically, this average force ratio meets the battalion commander's requirement; yet, Red is able to occupy two TAIs unopposed. The traditional calculation does not penalize the Blue commander for this tactical error.

The *adjusted* force ratios for TAIs 1, 2, and 3 are $\frac{3}{3}$, $\frac{-1}{3}$, and $\frac{-1}{3}$. The BFR is $\frac{\frac{3}{3}+\frac{-1}{3}+\frac{-1}{3}}{3} = 0.111$. This force ratio is more representative of the situation as a measure of success (vice measuring force levels).

Appendix C lists BFRs for the one hundred possible combinations of Blue and Red force dispositions. These combinations span the set of situations in which all three Blue platoons reach a BP and three Red companies are arranged in the TAIs. The dispositions possible when one or more Blue platoons do not arrive at a BP by the end of the simulation are not listed. However, the BFR measures these possibilities as well.

When each of the three Blue platoons reaches a BP by the end of the CAS period, the range of the BFR is (-0.250, 0.333), as shown in Appendix C. However, when the possibility of a Blue platoon not reaching an assigned BP by the end of the CAS period is considered, the range of BFR is (–1.000, 0.333). The worst case is when one Red company is deployed to each of the three TAIs and no Blue platoons reach a BP. The adjusted force ratio in this case is –0.333 at each TAI. The BFR is $\frac{-0.333 * 3}{1} = -1.000$.

BFR is used to measure the quality of decision-making in SSIM CODE simulation runs. BFR is the response variable in a factorial design experiment that examines the main effects and interactions of various SSIM CODE elements.

3. Is Tactical Decision-Making Depicted Realistically?

To quantify the effect of time on tactical decision-making in SSIM CODE, time is first parameterized then evaluated as part of an MOE. Various time constraints (CAS periods) are examined. CAS periods of different time lengths are examined in various simulation experiments. For different time constraints, changes in the quality of decision-making are measured by evaluating the BFR attained at the end of each simulation run. The quality of the tactical decision-making is measured with BFR in each of these simulations. In these cases, time is a simulation parameter.

Then, in a separate simulation, the MOE $\dfrac{BFR}{\textit{Time Required to Complete Mission}}$ is analyzed. The time constraint is removed and commander entities are allowed all the time required to deploy their forces in response to enemy actions. In this simulation, the MOE is used to measure the quality and efficiency of decision-making. A factorial design is used to evaluate the effects of the experiment factors on the MOEs.

E. FACTORIAL DESIGN

In a two-level factorial design experiment, a set of variables or factors is selected and two levels are fixed for each factor. The experiment runs include all possible combinations of the factor levels. Factorial designs are useful for evaluating the effect of each factor on a response variable. (Box, Hunter and Hunter, 1978)

The SSIM CODE test scenario involves three decision factors (enemy, environment, own forces), three commander's characteristics (C2 philosophy, C2 style, and experience) and three enemy AAs (use each of AA 1, 2, 3 or not). The response is the *BFR* at the end of the CAS period (with time constraint) or *BFR / Time to Complete Mission* (no time constraint case). Table 4 lists the levels for each design factor.

Design Factor		Level	
Label	Description	+	-
A	Environment Decision Factor	Favorable	Unfavorable
B	Red (Enemy) Forces Decision Factor	Strong	Weak
C	Blue (Own) Forces Decision Factor	Positive	Negative
D	Cdr's C2 Philosophy	Mission	Detailed
E	Cdr's C2 Style	Aggressive	Conservative
F	Cdr's Experience Level	High	Low
G	Enemy AA 1	Use	Not Use
H	Enemy AA 2	Use	Not Use
J	Enemy AA 3	Use	Not Use

Table 4. Levels of Each Design Factor in Experiment Design

The response in each factorial design experiment corresponds to an MOE (either *BFR* or *BFR/Time to Complete the Mission*). The effect of each factor is the measured change in the response as the factor changes between its low and high levels.

To examine whether SSIM CODE's decision-making supports the commander's intent, a quantitative evaluation of the relationship between design factors and the MOEs is conducted in two phases. First, a main effects screening is completed using all the factors in Table 4. This analysis is focused on the main effect of each factor and does not consider interactions. Then, after determining the factors that have significant effects on BFR, a second factorial design is used to examine both main effects and first-order interactions on both MOEs.

To complete the face validation, significant main effects and interactions are evaluated based on a reasonable approach to tactical decision-making. The relationships between factors and BFR are compared to what would be expected in a typical tactical situation. Model diagnostics are applied in each phase of the evaluation to examine the validity of assumptions made in the model settings. This procedure and its results are detailed in Chapter VI.

1. Main Effects Screening Design

Fractional factorial design experiments include only a fraction of the runs (factor level combinations) in a full factorial design. According to Box, Hunter and Hunter (1978), there are three main applications for fractional factorial designs: when screening a large number of factors for a subset of significant factors, in cases where certain interactions can be assumed negligible, and when groups of experiments are performed in sequence to resolve ambiguities. All three applications pertain to the main effects screening of SSIM CODE.

The nine design factors in Table 4 are screened for significance. Two-factor interactions may provide useful insight. However, the confounding of two-factor interactions is acceptable in preliminary evaluations or screening experiments (Box, Hunter, and Hunter, 1978). Experiments to support the face validation are performed in sequence. First, the significant main effects are identified, then a new factorial design is used to examine two-factor interactions.

Three-factor interactions and above cannot be readily interpreted in terms of tactical decision-making. Furthermore, it is expected that these interactions will be negligible compared to main effects. According to Montgomery (1997), the *sparsity of effects* principle can be invoked to assume that main effects and low-order interactions dominate a system with many factors.

Therefore, a resolution IV design is required for the initial screening of main effects. *"A design of resolution...IV does not confound main effects and two-factor interactions [with each other], but does confound two-factor interactions with two-factor interactions..."* (Box, Hunter and Hunter, 1978)

A 2^{9-4} fractional factorial design has resolution IV and is a $\frac{1}{16}$ fraction of the full 2^9 factorial. A full-factorial design would require 2^9 or 512 runs per replication to capture the effects of each factor and all possible interactions. The fractional factorial design requires thirty-two runs per replication.

Appendix D summarizes the fractional factorial design by indicating each factor's level for each of the required thirty-two runs per replication. Appendix D also lists the design layout, design generators and confounding patterns, as described by Box, Hunter and Hunter (1978). The design for the post-screening experiment is discussed in a later section.

Each replication consists of thirty-two runs. The factors are varied between runs as described by Appendix D. All other elements of the simulation remain constant from run to run. The tactical scenario, decision rules, commander's decision probabilities and report probabilities are each identical from run to run. Uncertainty and randomness are introduced by the commander's decision outcome choices, the detection error at the NAIs and TAIs, and the delays between OODA loop phases.

Decision factors are represented by reports to the commander with an associated probability. The (+) factor level represents a 0.75 probability that the decision factor is in the state associated with the (+) level in Table 3. The (–) factor level represents a 0.25 probability that the decision factor is in the (–) state. For example, the factor levels for the environment decision factor are defined as:

+ $P\{Environ = favorable\} = 0.75 \Leftrightarrow P\{Environ = unfavorable\} = 0.25$
- $P\{Environ = unfavorable\} = 0.75 \Leftrightarrow P\{Environ = favorable\} = 0.25$

2. First-Order Interaction Design

Once significant main effects are determined, an appropriate factorial design is selected to estimate main effects and first-order interactions for the factors that were significant in the screening experiment. In this phase, an appropriate factorial design is selected to prevent confounding two-factor interactions with either main effects or other two-factor interactions. This requires either a resolution V fractional factorial design or a full factorial design. Chapter VI details the selection of this design.

VI. RESULTS AND ANALYSIS

A. PILOT EXPERIMENT RESULTS

An initial estimate of the BFR mean and variance is required to determine the number of replications necessary. These estimates were obtained through a pilot experiment that applies the 2^{9-4} fractional factorial design. The Blue CAS period is set to one hour (simulation time). Thirty replications of the thirty-two runs (960 total runs) are conducted. Appendix E lists sample raw results for the first three replications (96 runs) of this pilot experiment (it is impractical to list all of the pilot results). The raw results include run number, factor levels, and BFR response for each run.

The results for the pilot run are analyzed using S-plus (MathSoft Inc., 1999). Appendix F lists the S-plus code used for analysis. The pilot experiment estimated the mean BFR as -0.058 and the BFR standard error as 0.010.

B. REPLICATIONS AND POWER CALCULATIONS

The model setting for this experiment is:

$$y_{ijk} = \mu + \tau_i + \varepsilon_{ij}$$

where

y_{ijk} = *response observation for i^{th} treatment, j^{th} replication, k^{th} run*

μ = *true mean*

τ_i = *treatment effect,* *$i = 1,\ldots,$ total treatments*

ε_{ij} = *errors,* *assumed to be i.i.d. Normal$(0,\sigma^2)$*

There are nine treatments in the first experiment. The treatments correspond to the factors listed in Table 4. This experiment tests a set of nine (one for each treatment) null hypotheses (H_o). For each treatment, H_o is: the treatment has no effect on the response (H_o: $\tau_i = 0$). The alternate hypothesis (H_a) for each treatment is that the treatment has a significant effect on the response (H_a: $\tau_i \neq 0$). A multi-factor analysis of variance (ANOVA) is conducted to test whether the treatment effects on the response are significant.

The ANOVA considers the deviation from the mean response for each observation. The total sum of squared deviations (*SST*) and the sum of squared deviations associated with each treatment (SST_r) are calculated. The sum of squared deviations due to error (*SSE*) is the difference between *SST* and all the SST_r values. The mean squared for treatment (MST_r) is calculated by dividing SST_r by the appropriate degrees of freedom (*df*). For treatment i, this calculation is: $MST_{r,\,i} = SST_{r,\,i} / df_i$. The mean squared for error (*MSE*) is determined in a similar manner. The ANOVA uses the test statistic MST_r/MSE. (Devore, 1995)

If H_o is true, the test statistic has an *F* distribution. An *F*-test is used in the ANOVA to determine whether the measured test statistic is likely to have come from an *F* distribution. When the test statistic has a value typically found in the *F* distribution, the ANOVA test procedure adjudicates H_o as true. The probability that the test statistic is an observation from the *F* distribution is determined. If this probability is greater than a pre-set significance level, there is no detectible treatment effect. In this case, the variability associated with the treatment can be reasonably attributed to experimental error, and H_o is adjudicated as true. If the *F*-test produces a probability that is less than the experiment's significance level, then the effect of the treatment on the response cannot reasonably be attributed to error and H_o is rejected. In this case, the treatment is deemed to have a significant effect on the response variable. (Devore, 1995)

The p-value (associated with a test statistic observation) is the probability of observing a value of the test statistic as extreme or more extreme than the observed one, assuming H_o is true. The p-value is also the minimum significance level at which H_o is rejected, given realized value of the test statistic. (Devore, 1995)

The objective of hypothesis testing is to determine whether deviations from the true response mean are due to chance variation or if these deviations are associated with a particular factor. Two types of errors may occur. Type I error occurs if H_o is rejected when it is true. Type II error occurs when H_o is accepted but false. The probability of type I error is set by the experiment's significance level (α). (Devore, 1995)

Type II error reflects the sensitivity of the analysis when H_o is true. The probability of Type II error is denoted by β. The power of a hypothesis test is 1-β. When α is fixed, β can be improved by increasing the number of replications or sample observations. If the response variance can be estimated and a level for detectible deviations from the response mean is set, the number of replications required to attain a specific β can be determined by using power calculations. (Devore, 1995)

Figure 17 shows power curves based on response variable mean, response variance, desired detectible deviation from the mean, and the number of treatments. The S-plus code used to generate the curves in Figure 17 is based the power calculation in the thesis *Agent Based Simulation as an Exploratory Tool in the Study of the Human Dimension of Combat* (Brown, 2000). This code is included in Appendix G.

The pilot run provides estimates of the BFR mean and variance: $\hat{\mu} = -0.058, \; \hat{\sigma}^2 = 0.010^2 = 0.0001$. A significance level of 0.01 is used in this experiment. To detect a deviation (τ) of five-percent or more from the estimated mean BFR, the level of detectible deviations from the mean is set at: $\tau = |\hat{\mu}| * 0.05 = 0.058 * 0.05 = 0.0029 \approx 0.0025$. From Figure 17, it takes sixty replications to detect such a deviation with power = 0.99.

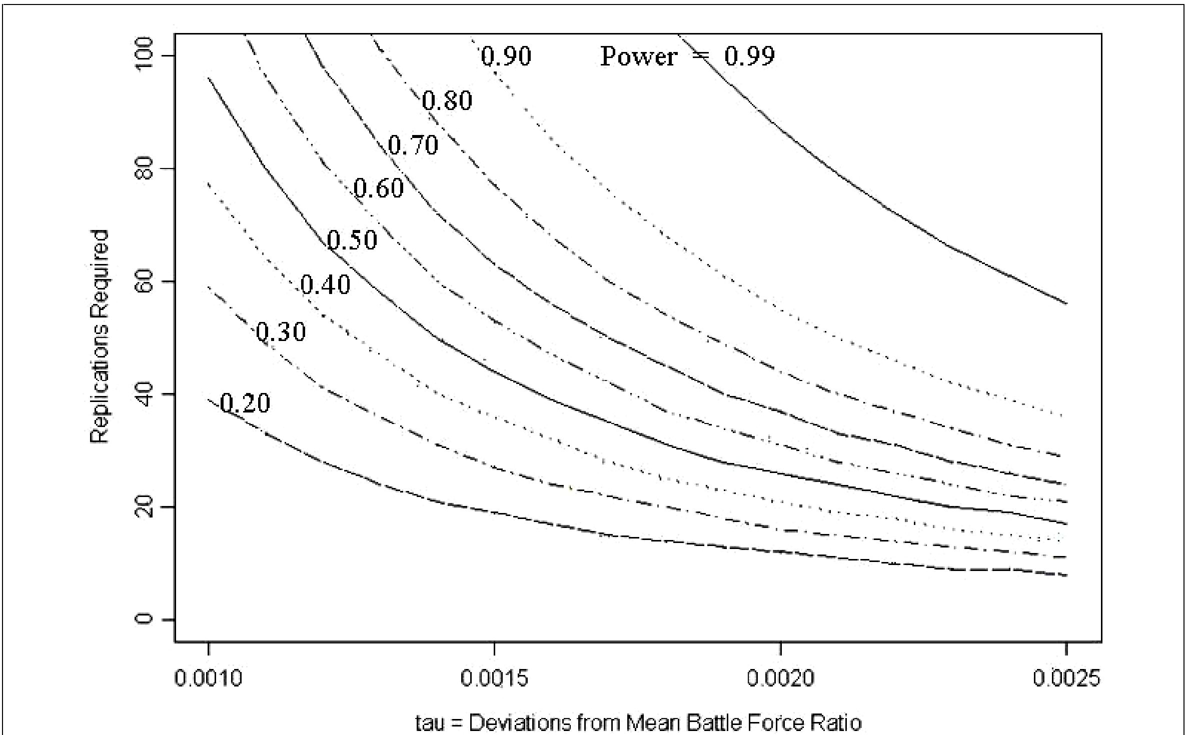


Figure 17. Power Curves for the 2^{9-4} Fractional Factorial Design

C. PHASE 1: MAIN EFFECTS SCREENING

Sixty replications of thirty-two runs (1920 total runs) were conducted to screen the main effects for significance. The raw results were analyzed using the multi-factor ANOVA and the S-Plus code in Appendix F. The ANOVA is summarized in Table 5. P-values are listed in the last column.

ANOVA
(Response Variable: BFR)

Factor	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	1.2905	1.29053	14.1408	0.0001747
R	1	2.0129	2.01286	22.0555	0.0000028
B	1	3.4642	3.46422	37.9585	0.0000000
C2P	1	5.8951	5.89510	64.5944	0.0000000
C2S	1	2.1780	2.17801	23.8651	0.0000011
EXP	1	30.3762	30.37617	332.8406	0.0000000
AA1	1	0.0026	0.00257	0.0282	0.8666986
AA2	1	0.1380	0.13800	1.5121	0.2189642
AA3	1	0.0011	0.00109	0.0119	0.9131193
Residuals	1910	174.3131	0.09126		

Table 5. Results of Main Effects Screening Experiment ANOVA
CAS Period = 60 min.

1. Main Effects Significance

The ANOVA of the main effects screening experiment shows that all the three decision factors and the three commander attributes are highly significant (i.e., p-value $\ll$ 0.01) at $\alpha = 0.01$. The effects of the AAs used by Red are not significant. It is also clear that the F-test statistics for the three AAs differ. This asymmetry in the ANOVA for the AAs is due to the fact that each AA is observed differently within the scenario. Use of AA3 can be determined by observing enemy movement to the south at NAI1 (Figure 16). However, use of AA1 or AA2 can only be determined at NAI 2. Defense against the use of AA2 is the least difficult since its central location allows rapid allocation of forces from either the assembly area, BP1 or BP3. However, movement to defend against use of AA1 or 3 requires more time.

According to Law and Kelton (2000), during factor screening, once a factor is deemed irrelevant, it should be fixed at a reasonable level and omitted from further consideration. In subsequent experiments, the AAs are not included as factors; instead, they are fixed (all Red Companies move to the center TAI using AA2).

The commander experience factor dominates the variance of BFR. The MSE for experience is an order of magnitude larger than for the other five main effects. Further analysis and interpretation of significant main effects are discussed in later sections.

2. Fractional Factorial Model Diagnostics

The adequacy of this model was analyzed to determine if the residuals have a mean of zero, if the normality assumption for model errors is valid, and if there are any points that exert high leverage. The model diagnostics are illustrated in the following figures.

Figure 18 illustrates that the variance in the residuals does not differ greatly from factor to factor. The median residual is slightly greater than zero, which indicates a slight negative skew, assuming that the residual mean is zero in each case. There are many more negative outliers than positive outliers. This confirms the presence of a negative skew in the residuals.

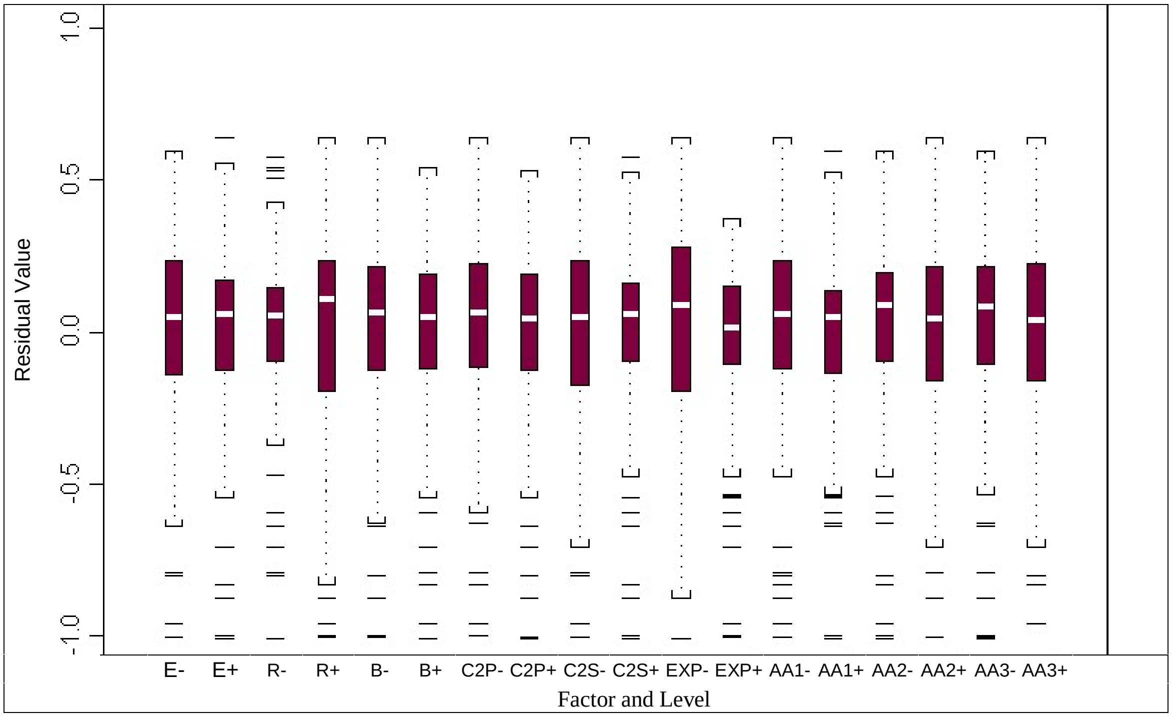


Figure 18. Box Plot of Residuals for each Factor Level
CAS Period = 60 min; Fractional Factorial Design.

The quantile-quantile (Q-Q) plot, Figure 19, indicates that the residuals are close to normal, but the left tail is larger than normal and the right tail is smaller. This characteristic also indicates the presence of a negative skew in the residuals.

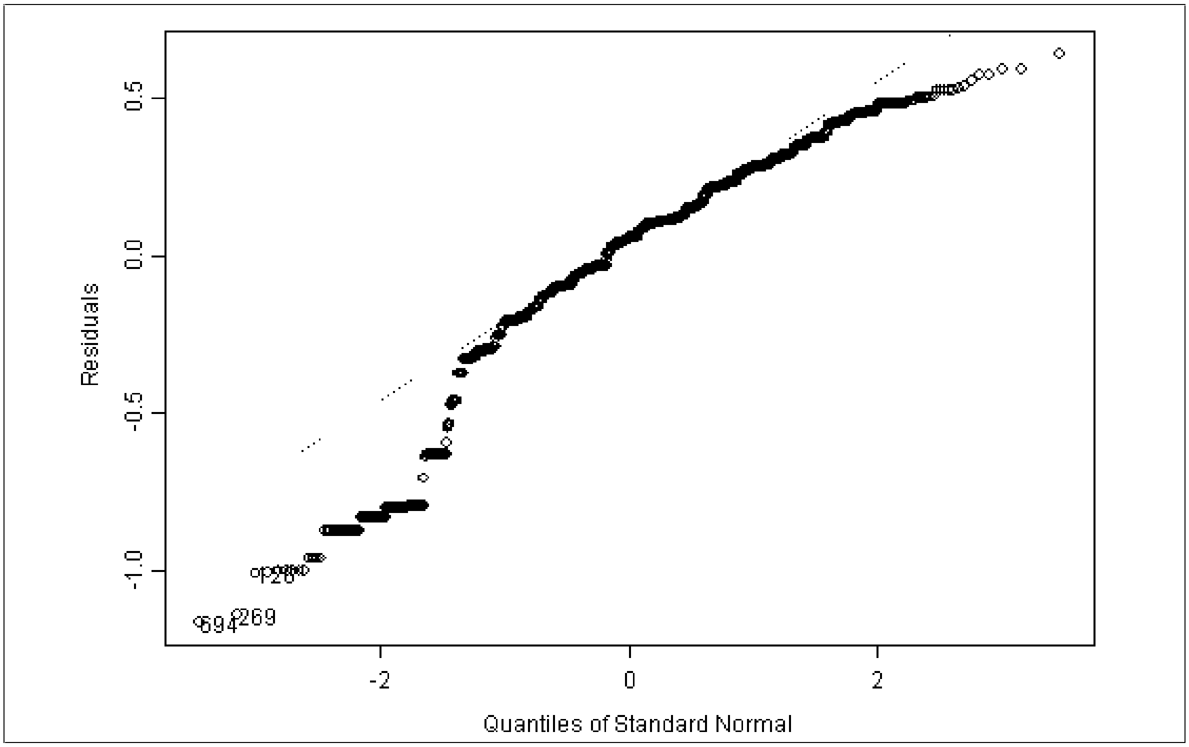


Figure 19. Q-Q-Plot of Residuals
CAS Period = 60 min; Fractional Factorial Design.

Figure 20 shows Cook's distance for each observation. Cook's distance measures the leverage and influence of a single observation on the whole model. A point is considered influential when it's Cook's Distance exceeds 1.0 (Hamilton, 1992). Cook's distance is well below 1.0 for each observation. This indicates that there are no high influence data points and thus no high leverage points.

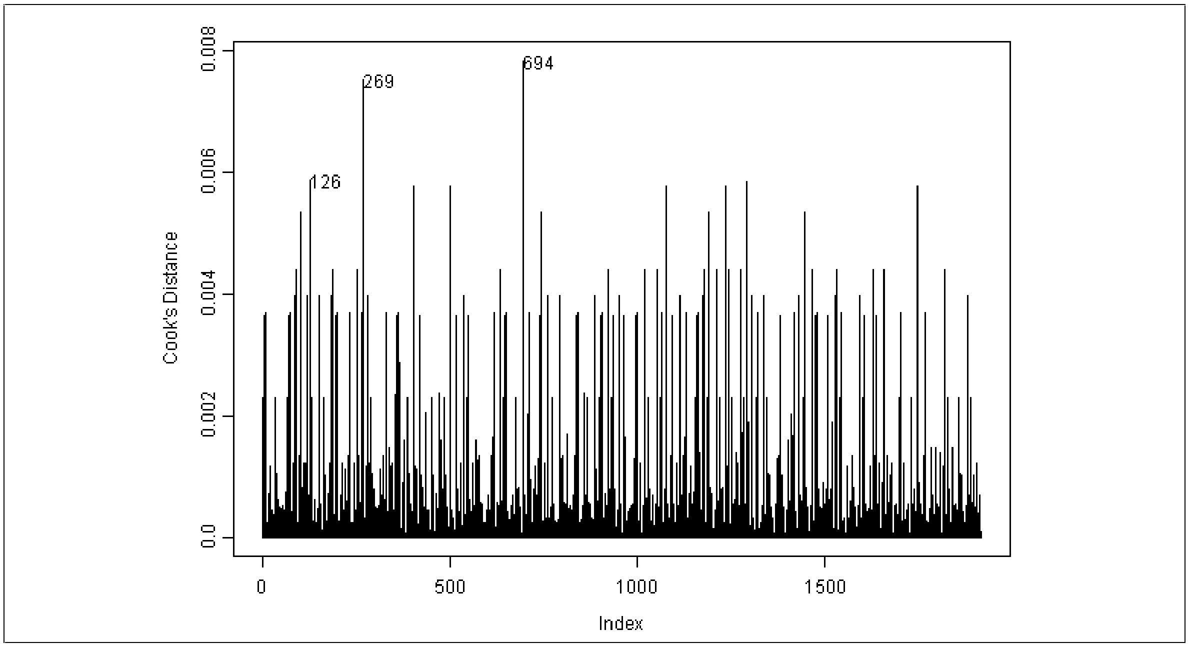


Figure 20. Cook's Distance
CAS Period = 60 min; Fractional Factorial Design.

Figure 21 is a histogram of the residuals with a standard Normal curve superimposed. This graph shows that the residuals are near Normal, but clearly have a negative skew.

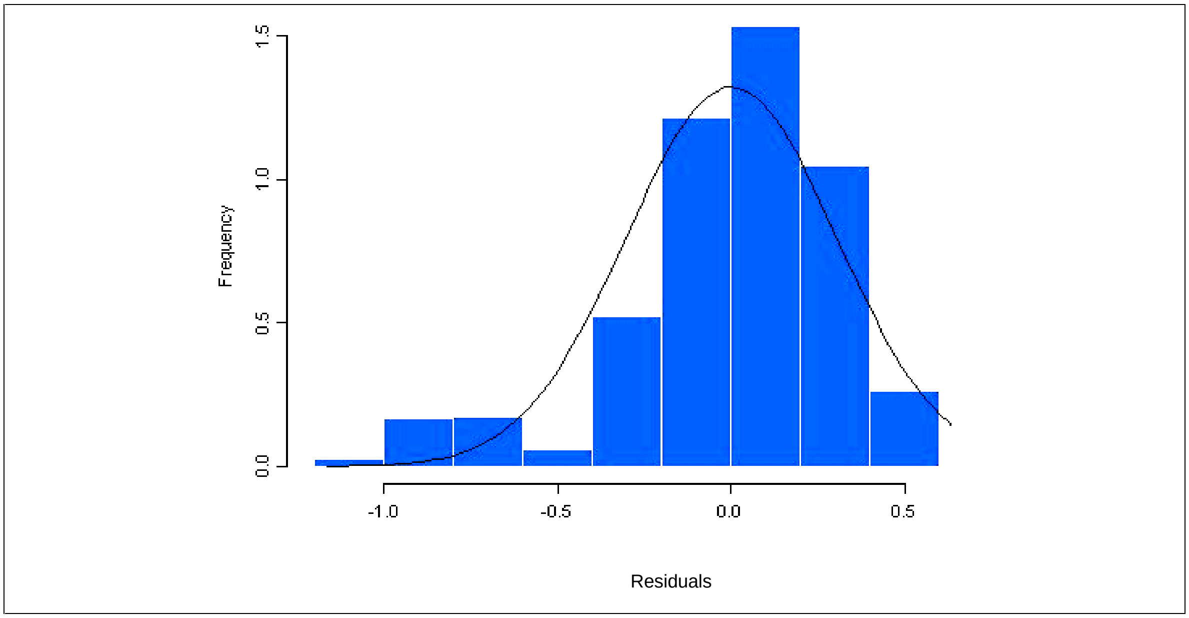


Figure 21. Histogram of Residuals
CAS Period = 60 min; Fractional Factorial Design.

Close examination of the histogram's shape indicates that perhaps the residuals are bi-modal. There appears to be a small group of residuals, located in the left tail of the Normal curve, with a mean of –0.75. This would indicate that the BFR data examined come from two different distributions.

Because the simulation was stopped after the one-hour CAS period, some commander entities had not completed their tactical decision-making and deployment of forces. Thus, this set of observations is censored data. A histogram of the BFR values (Figure 22) confirms this perception. The grouping of BFRs between 0.0 and 0.4 represent commander entities that have completed their mission. The group with negative BFRs is likely to have forces still in motion. Thus, the Blue platoons have not reached their BPs and the adjusted force ratio values at the TAIs have negative values.

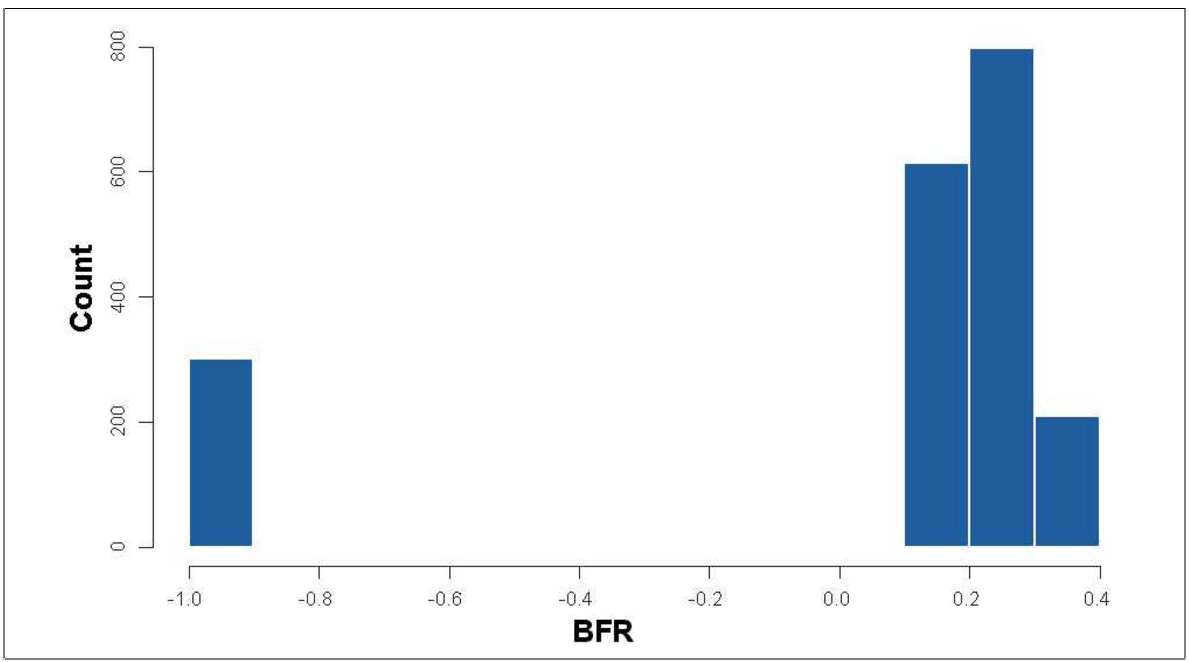


Figure 22. BFR Occurrences for 1,920 Simulation Runs
CAS Period = 60 min; Fractional Factorial Design.

To compensate for the slower decision-making in the censored observations, the CAS period was parameterized over values greater than one hour in subsequent runs. Also, one experiment was conducted after removing the time constraint. This allowed all commander entities to complete their mission.

In general, the model conforms to the ANOVA assumptions. No single point exerts excessive influence or leverage. The residuals have a mean near zero and do not deviate greatly from normality. The residuals are skewed to the left due to censored observations. The assumption of error terms distributed as independent, identically distributed (i.i.d.) Normal (0, σ^2) appears to hold, but the residuals should be examined again with a longer CAS period.

D. PHASE 2: FULL FACTORIAL DESIGN

The next step is choosing a factorial design to examine main effects and first-order interactions among the six significant factors. Since it is not known which two-factor interactions are significant, all possible interactions between pairs of the six remaining factors must be considered. A full factorial design with six factors requires 2^6 or sixty-four runs per replication. The model setting is:

$$y_{ijk} = \mu + \alpha_i + \delta_{ij} + \varepsilon_{ijk}$$

where

y_{ijk} = *response observation for i^{th} treatment, j^{th} replication, k^{th} run*

μ = *true mean*

τ_i = *treatment effect,* $i = 1,\ldots,$ *total treatments*

δ_{ij} = *interaction variable,* $j = 1,\ldots,$ *total replications*

ε_{ijk} = *errors,* *assumed to be i.i.d. Normal$(0,\sigma^2)$*

$k = 1,\ldots,$ *total runs*

This experiment tests a null hypothesis for each effect and for each interaction. Each individual null hypothesis states that the factor (environment decision factor, Red decision factor, Blue decision factor, commander's C2 philosophy, commander's C2 style, or commander's experience level) or first-order interaction has no significant effect on the response (*BFR* or *BFR/Time to Complete Mission*). The alternative hypothesis is that the individual factor or interaction has a significant influence on the response. The design of this experiment allows analysis of two-factor interactions without confounding. Appendix H describes the layout of this design. There are six factors and fifteen (six-choose-two) interactions for a total of twenty-one hypothesis tests.

A similar procedure is followed in the second phase of the SSIM CODE evaluation as in the main effects screening. First, a pilot run for a six-factor design is used to estimate the mean and variance of BFR. These estimates are used in a power calculation to determine the number of replications required. Appendix I includes the estimates from the pilot run and the power curve graphs. With six factors and sixty-four runs per replication, thirty replications (1,920 total runs) allow the detection of a three percent, or greater, deviation from the mean BFR.

First, the time constraint is removed. Then a replicated simulation is conducted for each of five CAS periods (two through six hours). After each simulation, statistical analysis is accomplished using S-plus. An ANOVA is conducted, and the effects of the factors and first-order interactions are calculated.

1. BFR MOE in No Time Constraint Case

Two MOEs were evaluated in this simulation: BFR and $\frac{BFR}{\textit{Time Required to Complete Mission}}$. Table 6 summarizes the results for the BFR MOE.

ANOVA
(Response: BFR)

Factor	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.125130	0.125130	41.345	0.0000000
R	1	0.151506	0.151506	50.060	0.0000000
B	1	0.209492	0.209492	69.219	0.0000000
C2P	1	3.997764	3.997764	1320.915	0.0000000
C2S	1	0.484505	0.484505	160.087	0.0000000
EXP	1	2.034505	2.034505	672.228	0.0000000
E:R	1	0.000040	0.000040	0.013	0.9082729
E:B	1	0.007216	0.007216	2.384	0.1227264
E:C2P	1	0.068880	0.068880	22.759	0.0000020
E:C2S	1	0.009531	0.009531	3.149	0.0761269
E:EXP	1	0.017054	0.017054	5.635	0.0177054
R:B	1	0.010032	0.010032	3.315	0.0688134
R:C2P	1	0.088775	0.088775	29.332	0.0000001
R:C2S	1	0.000040	0.000040	0.013	0.9082729
R:EXP	1	0.017054	0.017054	5.635	0.0177054
B:C2P	1	0.145642	0.145642	48.122	0.0000000
B:C2S	1	0.011074	0.011074	3.659	0.0559160
B:EXP	1	0.039624	0.039624	13.092	0.0003043
C2P:C2S	1	0.550130	0.550130	181.770	0.0000000
C2P:EXP	1	1.782422	1.782422	588.936	0.0000000
C2S:EXP	1	0.141797	0.141797	46.852	0.0000000
Residuals	1898	5.744319	0.003027		

Main Effects

	Effects	se
E	0.01614583	0.002511
R	-0.01776620	0.002511
B	0.02089120	0.002511
C2P	0.09126157	0.002511
C2S	-0.03177083	0.002511
EXP	0.06510417	0.002511

Interactions

	Effects	se
E:R	0.00028935	0.002511
E:B	-0.00387731	0.002511
E:C2P	-0.01197917	0.002511
E:C2S	-0.00445602	0.002511
E:EXP	-0.00596065	0.002511
R:B	0.00457176	0.002511
R:C2P	0.01359954	0.002511
R:C2S	0.00028935	0.002511
R:EXP	0.00596065	0.002511
B:C2P	-0.01741898	0.002511
B:C2S	-0.00480324	0.002511
B:EXP	-0.00908565	0.002511
C2P:C2S	0.03385417	0.002511
C2P:EXP	-0.06093750	0.002511
C2S:EXP	0.01718750	0.002511

BFR

Mean = 0.285 Standard Error = 0.001

Table 6. BFR Results Without Time Constraint

All of the main effects are highly significant (i.e., p-value << 0.01) at the α = 0.01 level. C2 philosophy dominates the MSE in the model. This is a different result than in the screening experiment. With a time constraint (in the screening), experience level is the dominant factor. Now, without a time constraint, C2 philosophy dominates.

The MSE of each of the three commander attributes is at least one order of magnitude larger than the MSE for each decision factor. This indicates that commander attributes have more effect on BFR than decision factors. These observations are depicted in Figure 23, which shows the average effect of each factor on BFR.

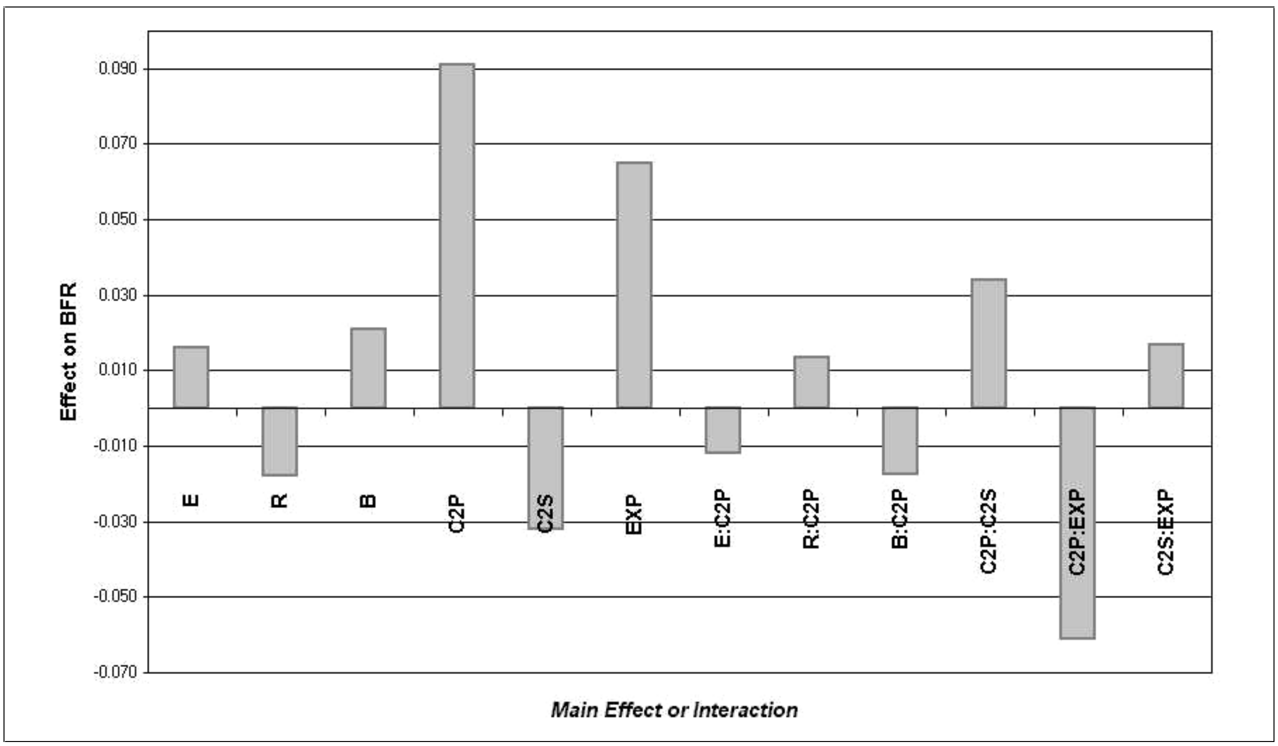


Figure 23. Main Effects and Two-Factor Interaction Effects on BFR
No Time Constraint.
Main effects and interactions significant at α = 0.01 are depicted.

Each significant factor has a positive effect on BFR except for the Red decision factor and C2 style. Because these factors are involved in significant interactions, their effects cannot be determined directly from their magnitude and sign—the interactions must be considered.

C2 philosophy has a significant interaction with each of the other factors. Additionally, the C2 style-commander's experience interaction and the Blue-commander's experience interaction are significant. Significant main effects must be interpreted along with any associated significant interactions. According to Law and Kelton (2000), the combined effect of two interacting factors can be computed as:

$$\textit{Combined Effect} = \frac{e_1}{2}x_1 + \frac{e_2}{2}x_2 + \frac{e_{12}}{2}x_1x_2$$

where
e_1 = *main effect of factor 1*
e_2 = *main effect of factor 2*
e_{12} = *interaction effect of factors 1 and 2*
x_1 = *level of factor 1* (*high = +1 and low = -1*)
x_2 = *level of factor 2*

The C2 philosophy-environment interaction is shown in Table 7. (This is a two-way factor table in the style of Box, Hunter and Hunter (1978).) Regardless of whether the environment is favorable or unfavorable, commanders with mission C2 philosophy have a higher BFR than those with detailed C2 philosophy. When the commander has a mission C2 philosophy, BFR is above the mean. For commanders with mission C2 philosophy, BFR is affected about the same by a favorable or unfavorable environment decision factor. However, when C2 philosophy is detailed, an unfavorable environment reduces BFR by twice the amount than a favorable environment does.

C2 Philosophy	(-) Unfavorable	Environment	(+) Favorable
Mission (+)	0.044	Mean BFR = 0.284	0.048
Detailed (-)	-0.060		-0.032

Table 7. Interaction Between C2 Philosophy and Environment

Table 8 shows the C2 philosophy-Red interaction. Regardless of the Red (enemy forces) decision factor, commanders with mission C2 perform better than those with detailed C2. When the commander has a mission C2 philosophy, BFR is affected about the same by a weak or strong Red decision factor. However, when C2 philosophy is detailed, a strong enemy reduces BFR by twice as much.

C2 Philosophy	(-) Weak	Red	(+) Strong
Mission (+)	0.048	Mean BFR = 0.284	0.044
Detailed (-)	-0.030		-0.062

Table 8. Interaction Between C2 Philosophy and Red

Table 9 shows that a mission C2 philosophy results in a higher BFR, regardless of the Blue (own forces) state. Given a mission C2 philosophy, the effects on BFR of positive and negative Blue decision factors are nearly equal. When C2 philosophy is detailed, positive Blue forces result in a notably higher BFR than negative Blue forces.

C2 Philosophy	(-) Negative	Blue	(+) Positive
Mission (+)	0.044	Mean BFR = 0.284	0.048
Detailed (-)	-0.064		-0.027

Table 9. Interaction Between C2 Philosophy and Blue

Table 10 describes the commander's experience-Blue decision factor interaction. High experience results in a BFR above the mean, regardless of the Blue decision factor.

Experience \ ***Blue***	(-) Negative	(+) Positive
High (+)	0.027	0.039
Low (-)	-0.048	-0.018

Mean BFR = 0.284

Table 10. Interaction Between Experience and Blue

According to Table 11, given mission C2 philosophy, there is almost no difference between a conservative or aggressive C2 style. However, given detailed C2 philosophy, a commander entity with aggressive C2 style performs much worse than one with conservative C2 style.

C2 Philosophy \ ***C2 Style***	(-) Conservative	(+) Aggressive
Mission (+)	0.045	0.047
Detailed (-)	-0.013	-0.079

Mean BFR = 0.284

Table 11. Interaction Between C2 Philosophy and C2 Style

Table 12 shows the C2 style-commander's experience interaction. Given high experience, an aggressive C2 style results in a better BFR. If experience level is low, it is much better to have a conservative C2 style.

		(-) Conservative		(+) Aggressive
High	(+)	0.040		0.025
Experience			Mean BFR = 0.284	
Low	(-)	-0.008		-0.057
			C2 Style	

Table 12. Interaction Between C2 Style and Experience

The interaction between-commander's experience and C2 philosophy is described by Table 13. High experience results in a BFR above the mean, regardless of C2 philosophy. Given a mission C2 philosophy, experience level makes a small difference in BFR. A combination of low experience level and detailed C2 philosophy has a very large negative effect on BFR.

		(-) Detailed		(+) Mission
High	(+)	0.018		0.048
Experience			Mean BFR = 0.284	
Low	(-)	-0.109		0.044
			C2 Philosophy	

Table 13. Interaction Between C2 Philosophy and Experience

The mean BFR for the no time constraint case (0.284 with a standard error of 0.001) is close to the goal of 1:3 or 0.333. This indicates that a majority of commander entities completed their mission successfully. A histogram of BFRs (Figure 24) shows that most commanders attained the 1:3 force ratio specified in the battalion commander's intent. A few commander entities, however, still performed poorly even though there was no time constraint. This could have been caused by a misinterpreted force ratio goal (commander's intent interpretation was a function of experience level) or by other combinations of factors that resulted in poor decision-making and a low BFR.

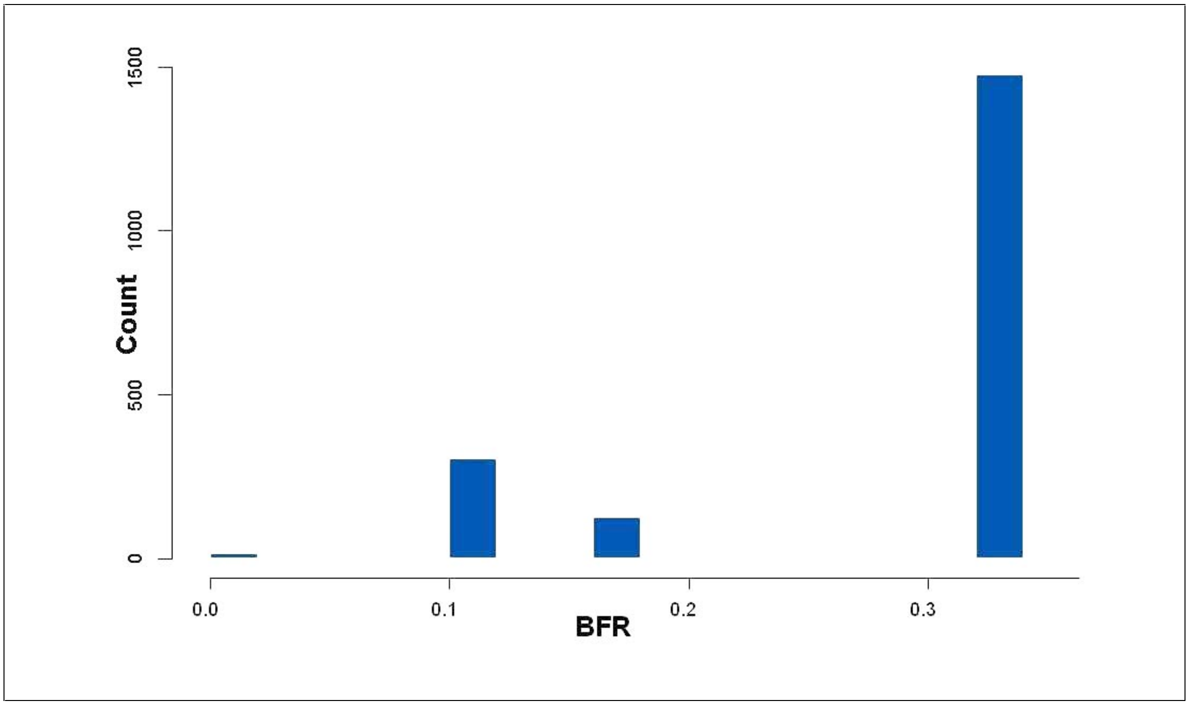


Figure 24. Occurrences of BFR Values for 1,920 Simulation Runs
No Time Constraint.

Even though some BFRs are low, there is no censored data. All the commander entities completed their decision-making and allocation of forces. The BFR values indicate distinct groupings of commander entities that attained the BFR goal and those that fell short. However, because these observations are not censored, the error structure in the model is closer to Normal $(0, \sigma^2)$. Figure 25 shows that the residuals for this case are closer to Normal than for the screening experiment.

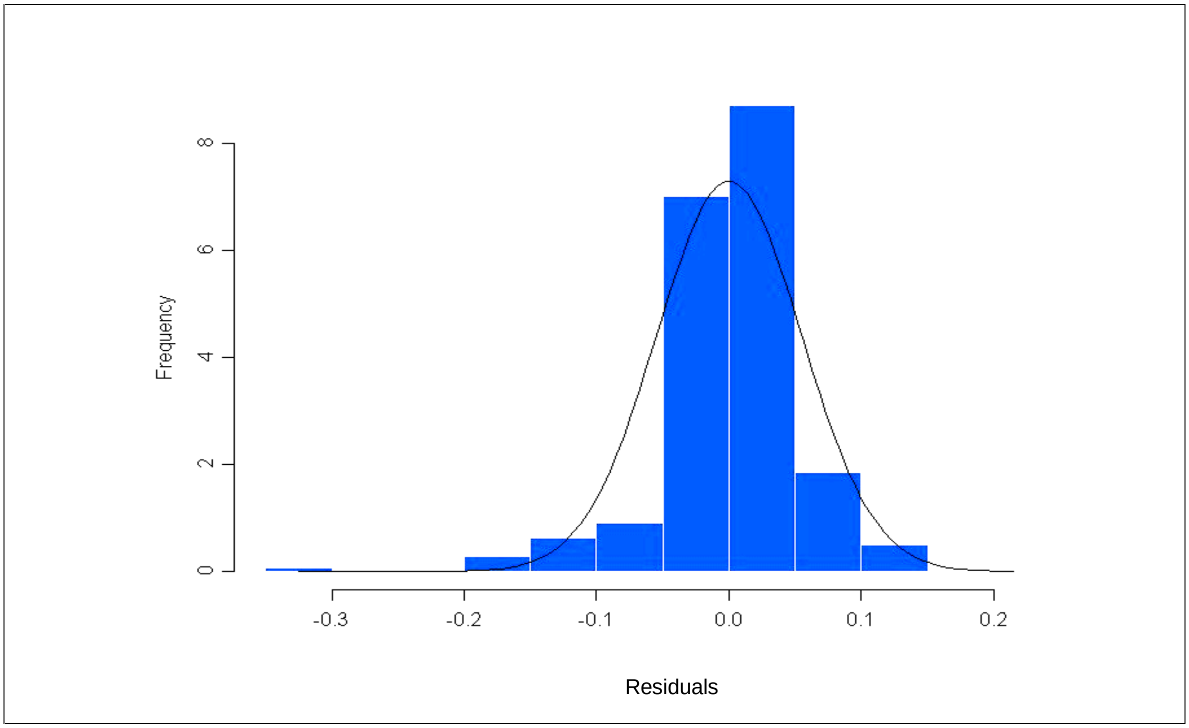


Figure 25. Histogram of Residuals Compared to Standard Normal Curve
No Time Constraint.

2. BFR/Time MOE in No Time Constraint Case

Table 14 summarizes the results of the no time constraint case in terms of the $\frac{BFR}{Time\ Required\ to\ Complete\ Mission}$ MOE. This MOE is described in force ratio per hour units.

ANOVA
(Response: BFR / Time to Complete Mission)

Factor	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.0016604	0.0016604	4.1390	0.0420435
R	1	0.0081968	0.0081968	20.4326	0.0000066
B	1	0.0062089	0.0062089	15.4775	0.0000865
C2P	1	0.2998683	0.2998683	747.5020	0.0000000
C2S	1	0.0047389	0.0047389	11.8129	0.0006009
EXP	1	0.1721357	0.1721357	429.0943	0.0000000
E:R	1	0.0003701	0.0003701	0.9225	0.3369402
E:B	1	0.0000394	0.0000394	0.0982	0.7539758
E:C2P	1	0.0021861	0.0021861	5.4495	0.0196773
E:C2S	1	0.0000000	0.0000000	0.0000	0.9990761
E:EXP	1	0.0012140	0.0012140	3.0262	0.0820926
R:B	1	0.0004247	0.0004247	1.0588	0.3036204
R:C2P	1	0.0059032	0.0059032	14.7153	0.0001291
R:C2S	1	0.0006165	0.0006165	1.5368	0.2152433
R:EXP	1	0.0008980	0.0008980	2.2386	0.1347672
B:C2P	1	0.0066091	0.0066091	16.4749	0.0000513
B:C2S	1	0.0002621	0.0002621	0.6533	0.4190194
B:EXP	1	0.0008499	0.0008499	2.1186	0.1456884
C2P:C2S	1	0.0088133	0.0088133	21.9695	0.0000030
C2P:EXP	1	0.1027208	0.1027208	256.0591	0.0000000
C2S:EXP	1	0.0092836	0.0092836	23.1419	0.0000016
Residuals	1898	0.7614027	0.0004012		

Main Effects

	Effects	se
E	1.8599e-003	0.00091419
R	-4.1324e-003	0.00091419
B	3.5966e-003	0.00091419
C2P	2.4995e-002	0.00091419
C2S	-3.1421e-003	0.00091419
EXP	1.8937e-002	0.00091419

Interactions

	Effects	se
E:R	-8.7806e-004	0.00091419
E:B	-2.8655e-004	0.00091419
E:C2P	-2.1341e-003	0.00091419
E:C2S	-1.0588e-006	0.00091419
E:EXP	-1.5903e-003	0.00091419
R:B	9.4069e-004	0.00091419
R:C2P	3.5069e-003	0.00091419
R:C2S	1.1333e-003	0.00091419
R:EXP	1.3678e-003	0.00091419
B:C2P	-3.7106e-003	0.00091419
B:C2S	-7.3894e-004	0.00091419
B:EXP	-1.3306e-003	0.00091419
C2P:C2S	4.2850e-003	0.00091419
C2P:EXP	-1.4629e-002	0.00091419
C2S:EXP	4.3978e-003	0.00091419

BFR / Time to Complete Mission

Mean = 0.054 Standard Error = 0.0005

Table 14. BFR/Time to Complete Mission Results
No Time Constraint.

Except for the environment decision factor, the main effects are highly significant (p-value $<<$ 0.01) at the $\alpha = 0.01$ level. For this MOE, C2 philosophy and commander's experience dominate the MSE. The other factors have comparable MSE to each other but are an order of magnitude smaller than C2 philosophy and experience.

C2 philosophy has significant interactions with each of the other factors, except with the environment. The C2 style-commander's experience interaction is also significant in this case.

The interpretation of the significant effects and interactions on this MOE is similar to the interpretation for the BFR MOE. Since the environment decision factor and its interaction with C2 philosophy are no longer significant at the $\alpha = 0.01$ level, the implication is that commander entities are unaffected by the environment when attaining *BFR/Time to Complete Mission.* At $\alpha = 0.01$, the environment significantly affects *BFR*, but not *BFR/Time to Complete Mission*. Thus, the effect of the environment is associated with the time to complete the mission.

Figure 26 shows the average effect of each significant factor and interaction on BFR. The environment decision factor and its interaction with C2 philosophy are included for comparison with Figure 23. A similar relationship, between the effects of these factors and interactions, exists for the *BFR* MOE (Figure 23) and the *BFR/Time to Complete Mission* MOE (Figure 26).

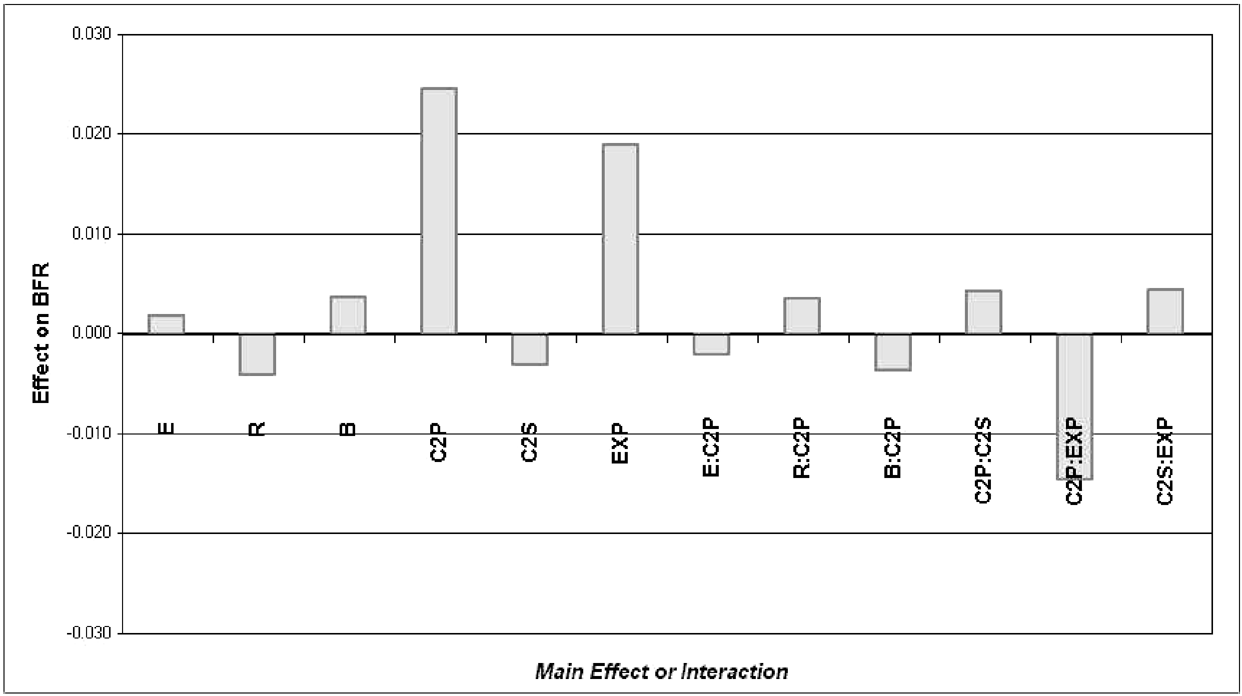


Figure 26. Main Effects and Two-Factor Effects on BFR/Time
No Time Constraint.
The same main effects and interactions as in Figure 23 are shown for comparison. All of these effects, except E and E:C2P, are significant at α = 0.01.

The time to finish the mission for each of the 1,920 runs is depicted in Figure 27. This statistic appears to be distributed exponentially. However, the set of observations do not pass a Chi-Squared goodness-of-fit test for the exponential distribution.

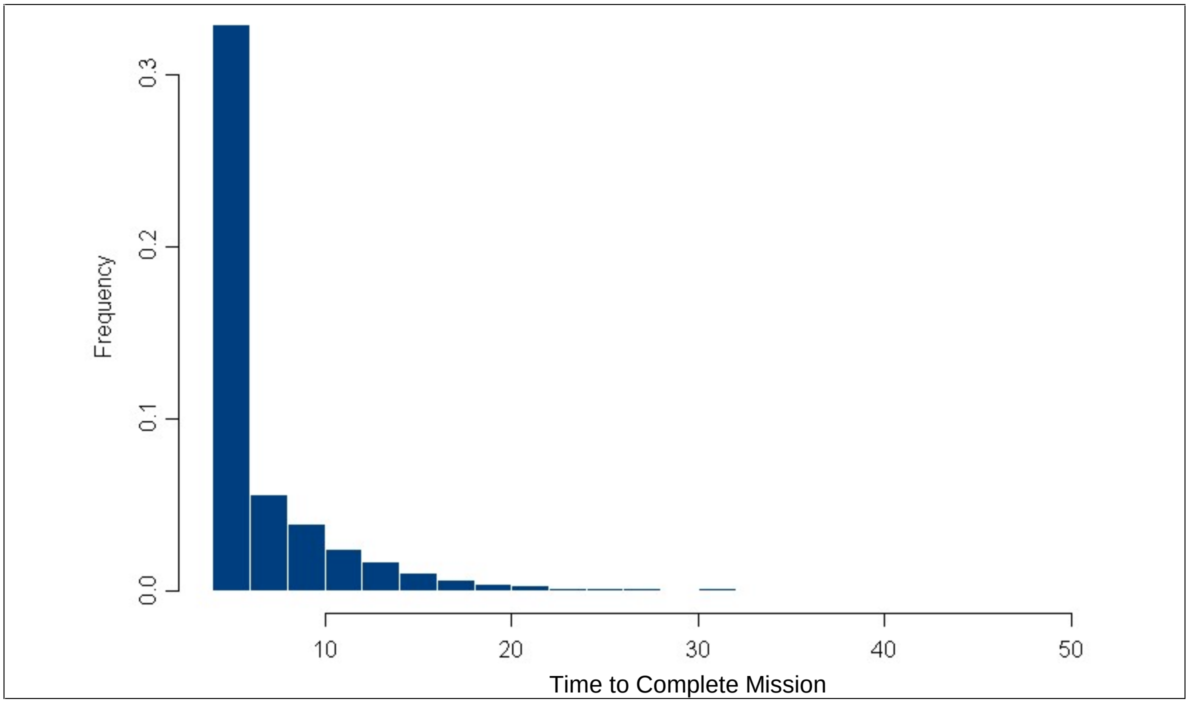


Figure 27. Histogram of Time to Complete Mission
No Time Constraint.
Mean = 6.9 hrs; Standard Deviation = 4.9 hrs.

The MOE $\frac{BFR}{\textit{Time Required to Complete Mission}}$ appears to be bi-modal. A group of observations depicts efficient commander entities with an observed $\frac{BFR}{\textit{Time Required to Complete Mission}}$ of 0.06 to 0.08. A second group has observed values between 0.00 and 0.04. The mean (0.054) is clearly not indicative of this MOE.

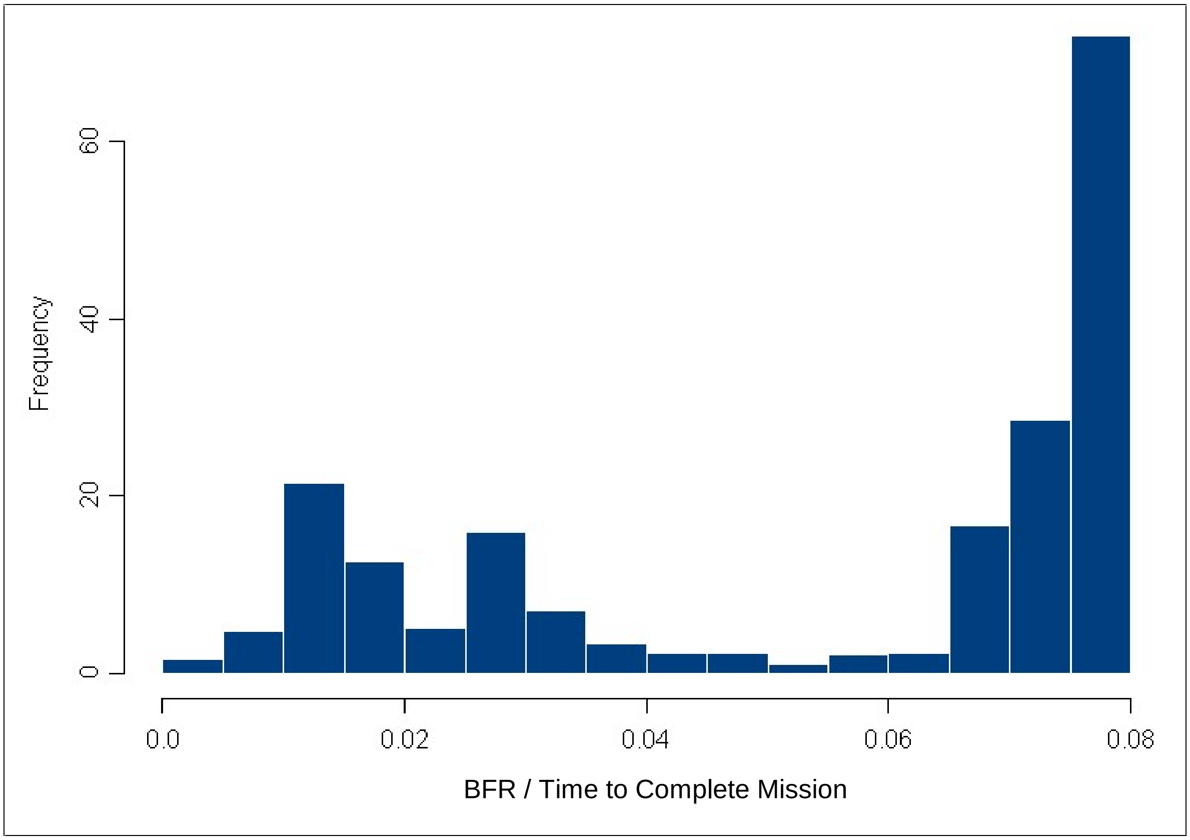


Figure 28. Histogram of BFR / Time to Complete Mission
No Time Constraint.
Mean = 0.054 force ratio/hr; Standard Deviation = 0.0005 force ratio/hrs.

3. Effects of Varying CAS Period

Next, the CAS period is parameterized in one-hour (simulation time) increments. From the previous experiment, 88% of the observed mission completion times are less than 11.0 hours. Red companies arrive at the TAIs between three and five hours after the start of the mission (they are spaced one hour apart). A six-hour CAS period starts when the third Red company arrives at a TAI and continues until 11.0 hours into the mission. With a six-hour CAS period, almost 90% of runs are completed missions.

The CAS period was varied over five experiments from two to six-hours. This parameterization allows the analysis of factor effects over various time constraints. In this setting, the Blue commander must attain the desired BFR by the end of the CAS period. Increasing the CAS period allows more time for the commander entity to observe the battlespace, make decisions, and act on those decisions. The mean BFR, main effects, and first-order interactions were examined for each CAS period setting. Appendix J summarizes the results for the various CAS periods.

a. Mean BFR Over Five CAS Period Durations

Figure 29 shows the relationship between mean BFR and CAS period.

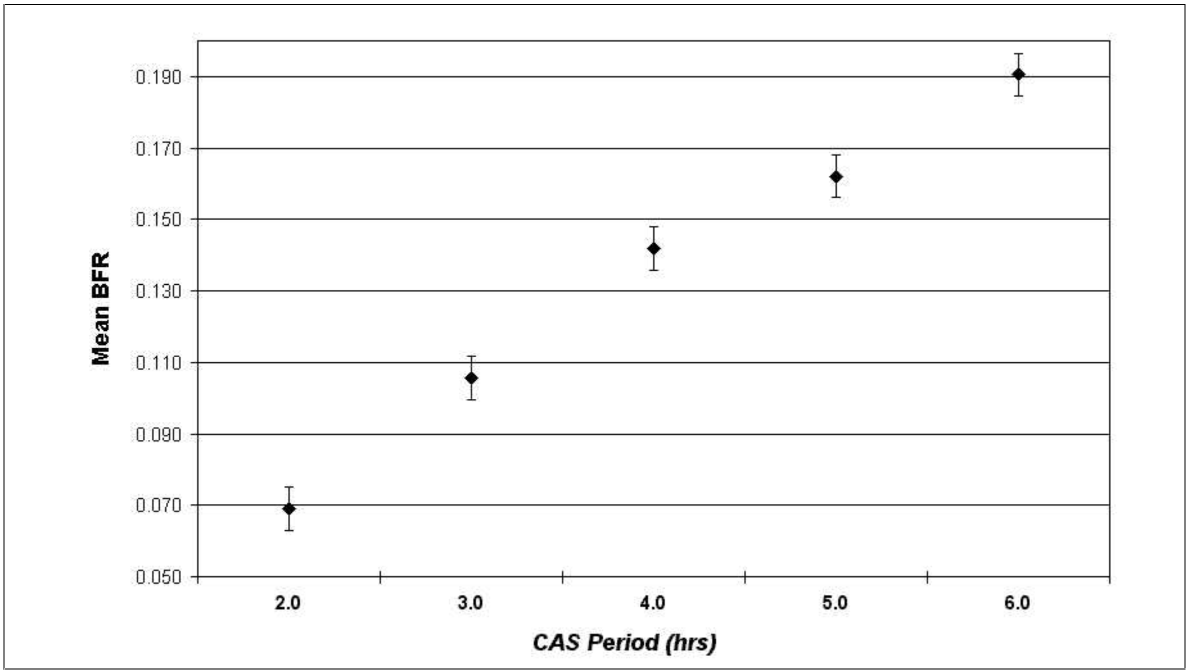


Figure 29. Mean BFR vs. CAS Period
2^6 Fractional Factorial Design.
As commander entities are given more decision-making time, their performance (measured with BFR) improves.

The mean BFR clearly increases as the commander entity is allowed more time for information gathering, decision-making and implementing the decisions. As the CAS periods increase, the commanders with attributes that hinder success overcome their shortfalls and perform closer to the level of the better commanders. This effect makes tactical sense and is routinely demonstrated in practice.

b. Main Effects Over Different CAS Periods

For each experiment, the main effects are significant. Figure 30 shows how the main effects vary with the CAS Period.

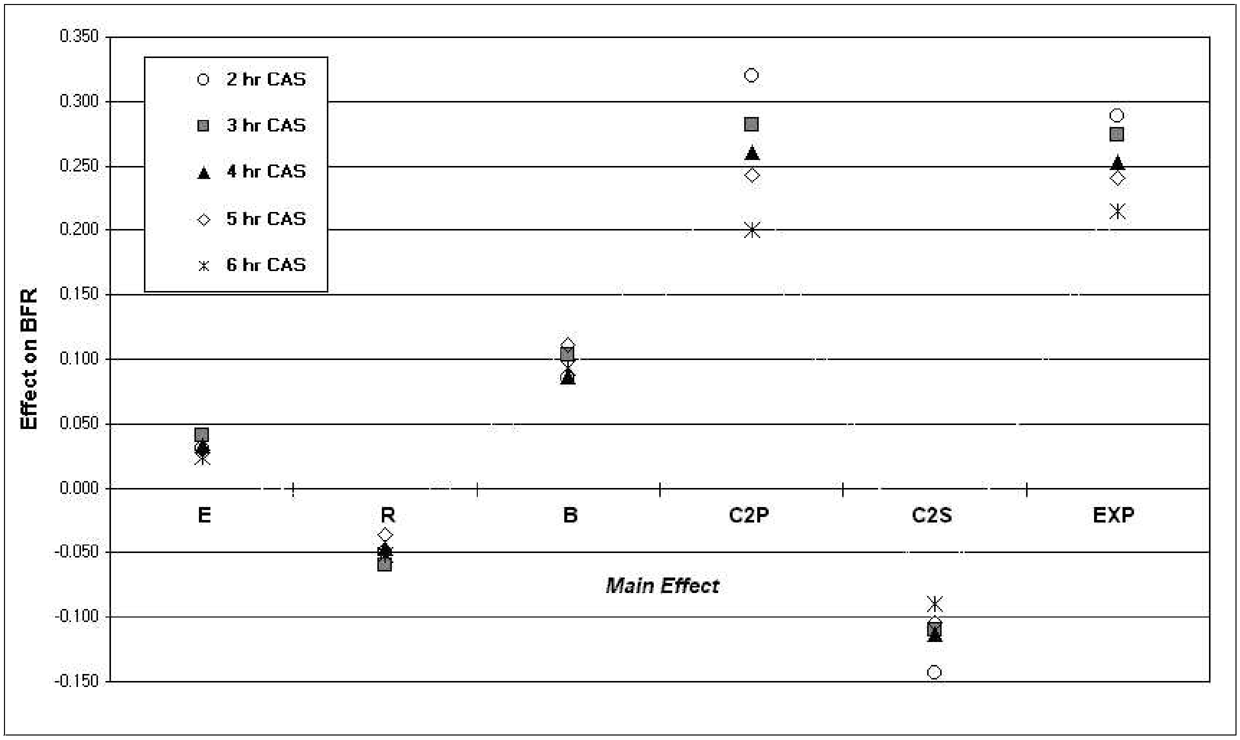


Figure 30. Main Effects on BFR for Various CAS Periods

Compared to the effects of the commander attributes, the effects of the decision factors (E, R, and B) remain fairly constant across the range of CAS periods examined. The environment and Red decision factor effects decrease with longer CAS periods. However, the Blue main effect generally increases with CAS period. These trends represent a lesser impact on BFR of the enemy forces state and the environment when commander entities are given more time to decide and act. The state of own forces has more effect on the BFR as the mission times increase.

As CAS period increases, the effects of the three commander attributes clearly decrease. This indicates that—given enough time—the less experienced commanders (and those with less effective combinations of C2 philosophy and C2 style) perform closer to the level of commanders with a better set of attributes. These results make tactical sense.

c. Significant Interaction Effects Over Different CAS Periods

The interactions that were significant in the unconstrained experiment are also consistently significant throughout this set of five experiments. Figure 31 depicts significant interaction effects over the various CAS periods. All interaction effects, except the Blue-experience interaction, decrease with longer CAS periods. The Blue-experience interaction increases with CAS period because the Blue main effect is increasing with CAS period. The interactions are interpreted in a similar manner as in the unconstrained experiment.

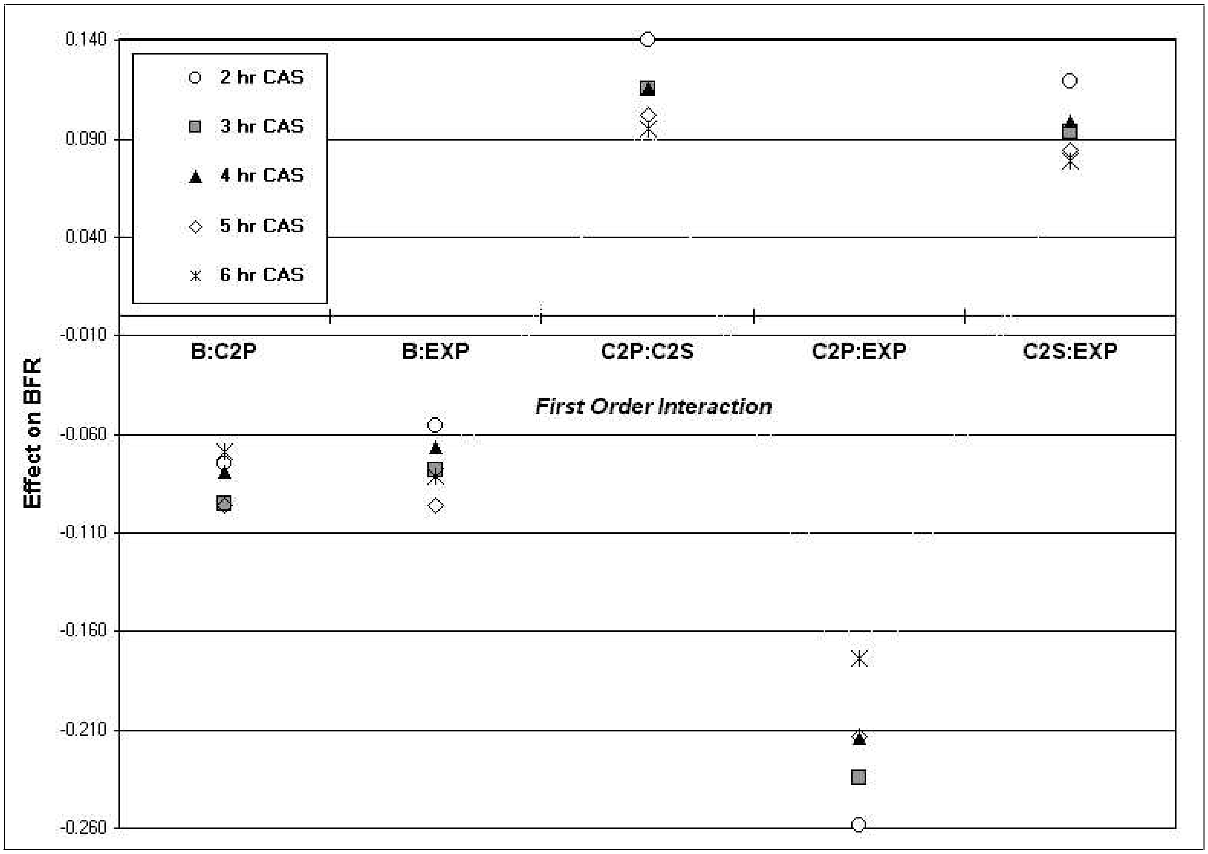


Figure 31. Significant Interaction Effects on BFR for Various CAS Periods

Figure 32 summarizes the effects of the six factors and the five significant interactions on BFR by showing the average magnitudes of factor effects. Figure shows that C2 philosophy, experience, and their interaction dominated the effect on BFR. Once again, the commander attributes were more influential than the decision factors.

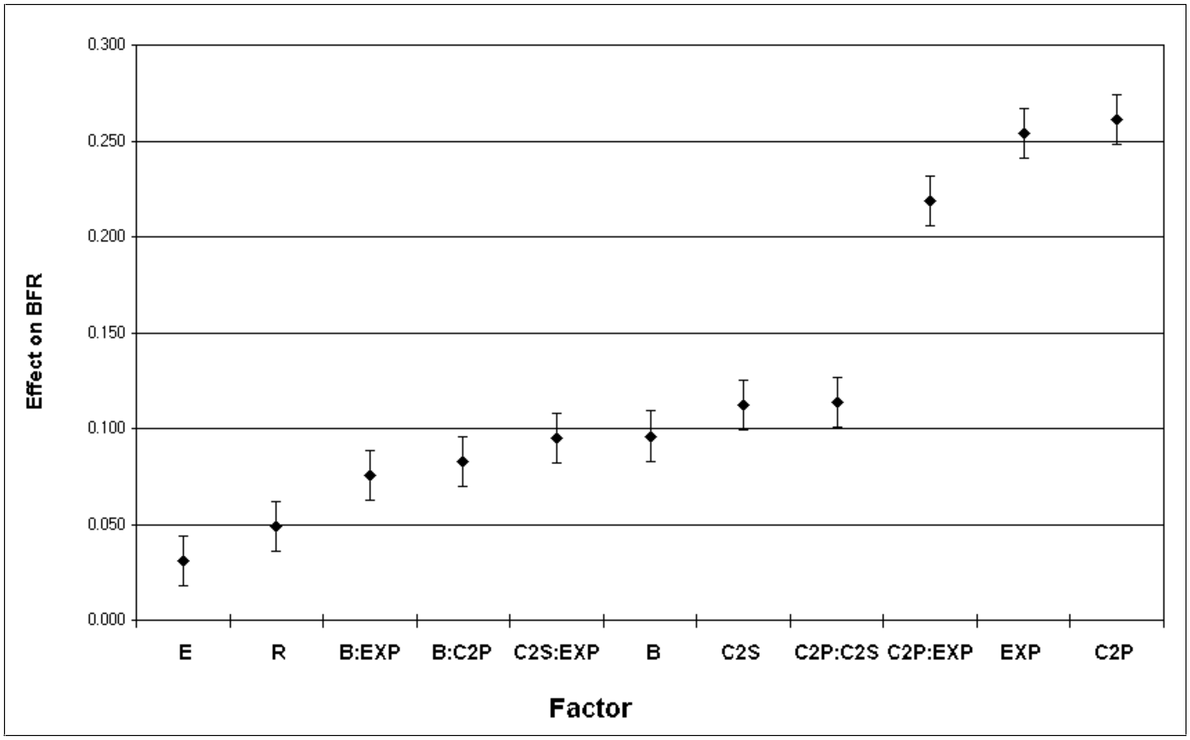


Figure 32. Average Magnitudes of Effects on BFR
Effect magnitudes are averaged over the five cases with different CAS periods.
Standard error ≈ 0.013.

4. Full Factorial Model Diagnostics

A diagnostic check of the model quality is conducted in the same manner as for the main effects screening. Each of the five experiments with differing CAS periods had similar model diagnostics. Figures 33 through 36 depict diagnostics for the full factorial model in the four-hour CAS period experiment (the central case).

The full factorial model has better diagnostic results than the fractional factorial design. The box plots show fairly constant variance among the residuals at each factor level. The median for each box plot is near zero. Because the box plots are quite symmetrical, the mean will also be near zero.

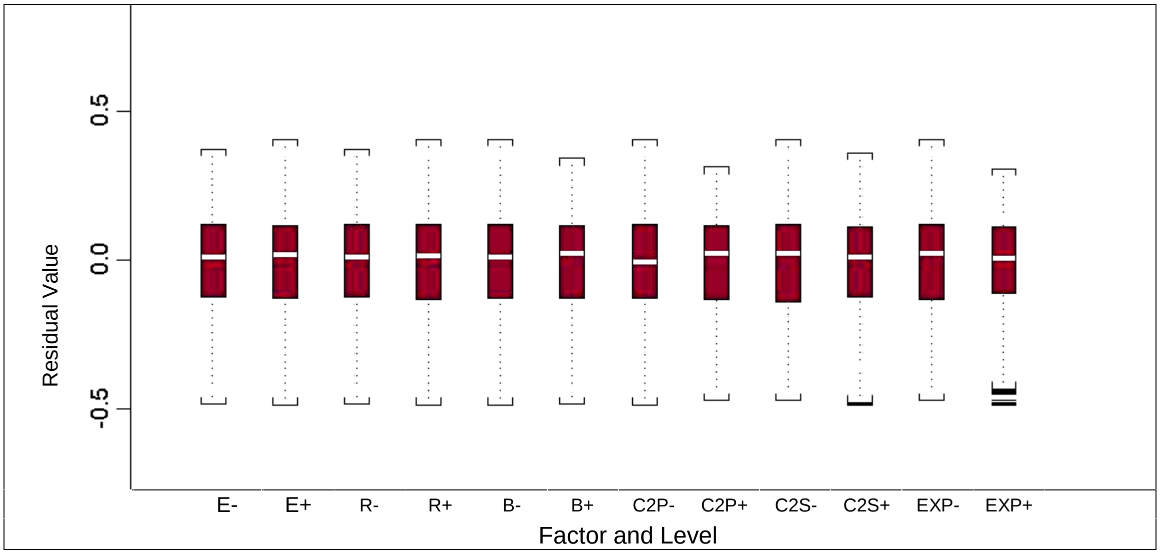


Figure 33. Box Plot of Residuals for each Factor Level
CAS Period = 240 min; Full Factorial Design.

The residuals closely conform to the Normal distribution, according to the Q-Q plot.

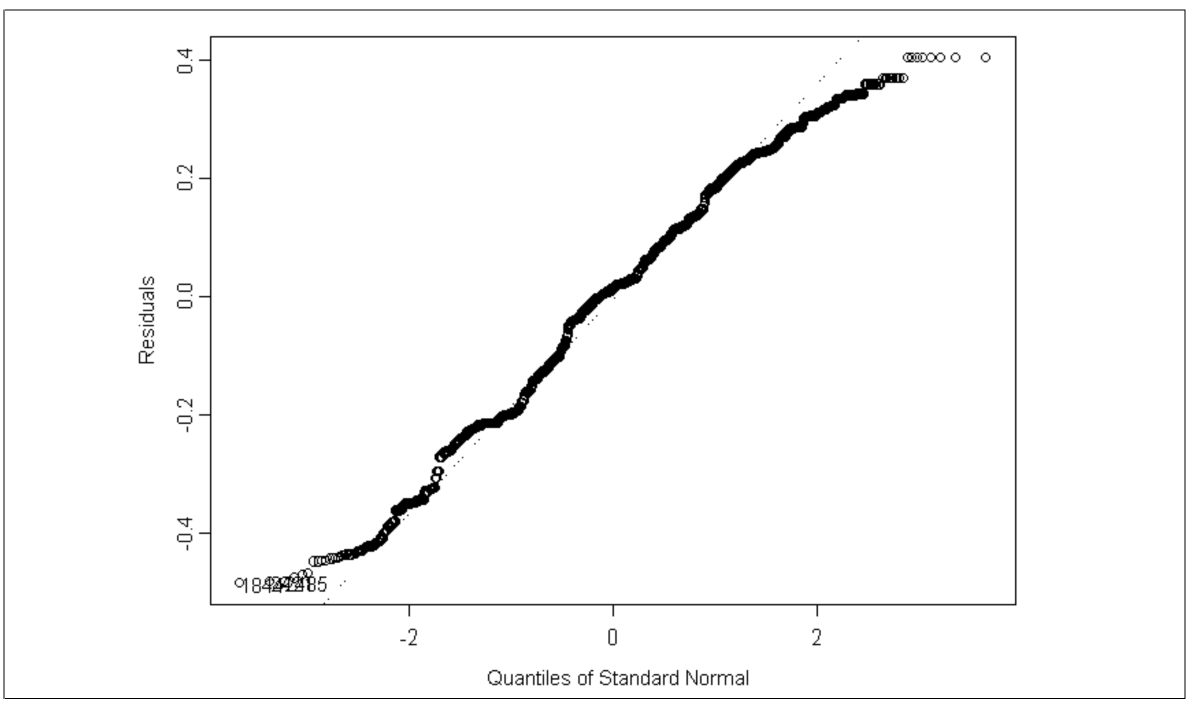


Figure 34. Q-Q-Plot of Residuals
CAS Period = 240 min; Full Factorial Design.

Figure 35 also reflects the near-normal residuals with a mean of zero.

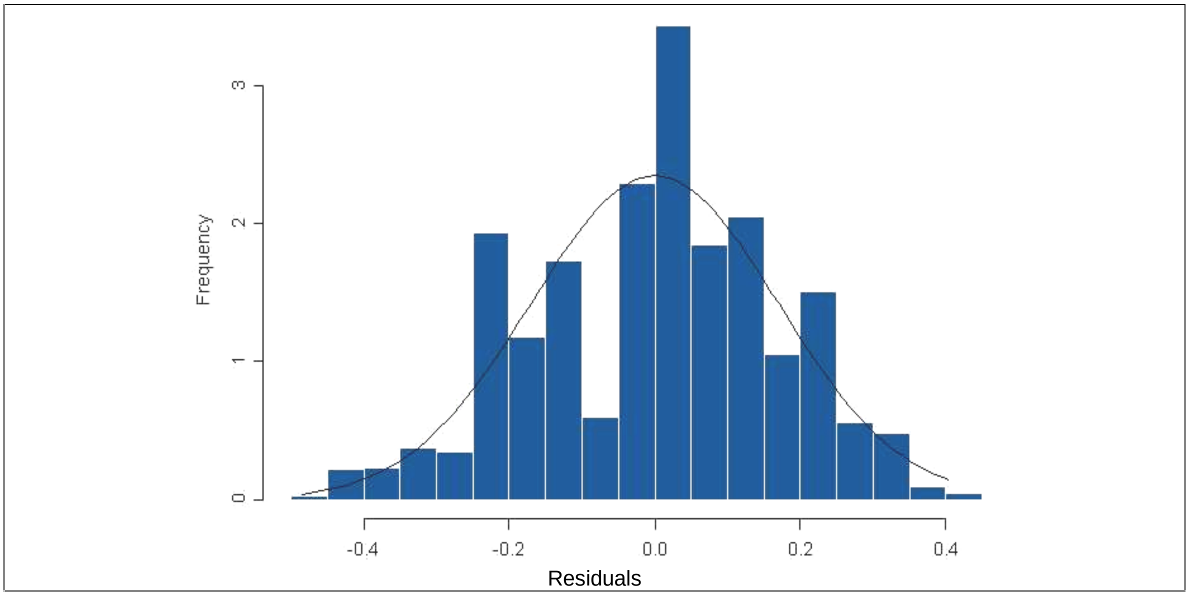


Figure 35. Histogram of Residuals & Standard Normal Curve
CAS Period = 240 min; Full Factorial Design.

Cook's distance is much smaller than 1.0 for each observation. Thus, there are no high influence or high leverage points.

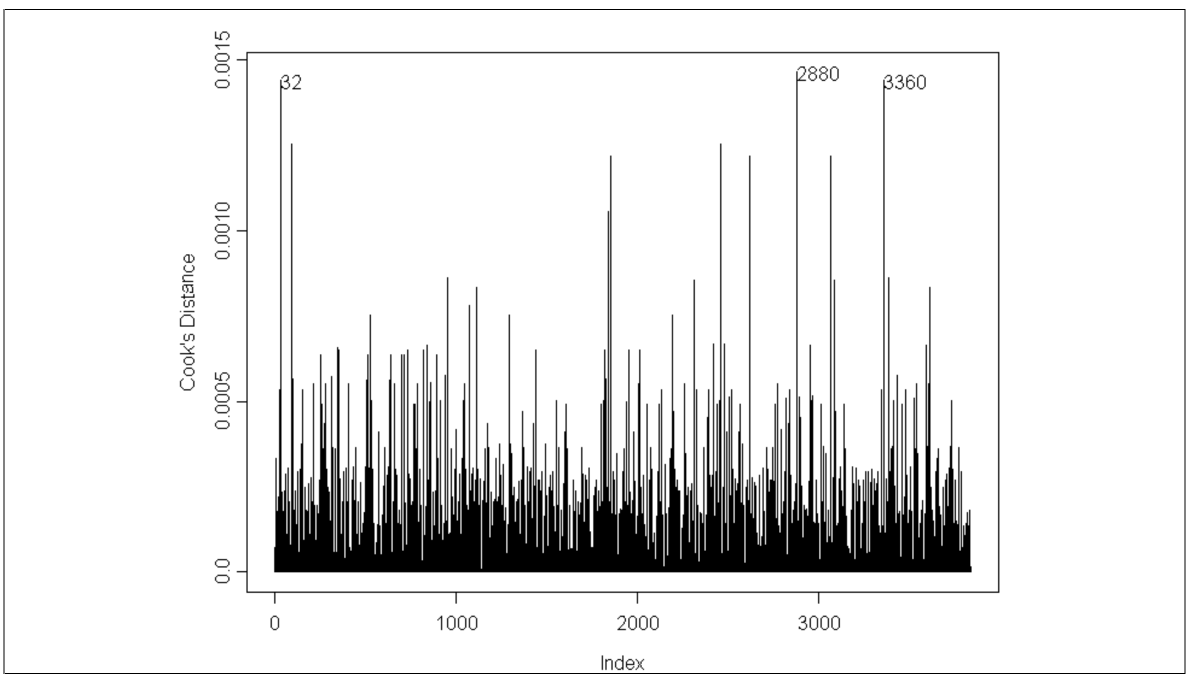


Figure 36. Cook's Distance
CAS Period = 240 min; Full Factorial Design.

E. FACE VALIDATION

1. Realism of Decision-Making

The evaluation of SSIM CODE found tactical realism in the experimental results. Commanders improved their performance with time. Commanders with mission C2 philosophy performed better in a scenario that required rapid allocation of forces in the face of uncertainty. Commanders with a detailed C2 philosophy performed better when given more time. Commanders with a high experience level performed much better than those with low experience levels, but given more time to decide and act, those with low experience performed closer to the level of those with high experience. The performance of the commander entity was not significantly affected by changing the enemy COA.

The effects of the Blue, Red and environment decision factors changed less than those of the commander attributes, as the CAS period time was increased. However, the Blue decision factor increased with the CAS period while the other two decision factors decreased with the CAS period. The significant interactions have interpretations that make tactical sense.

Time played an important role in the SSIM CODE evaluation. As commander entities had more time for decision-making, their performance improved. In the unconstrained experiment, most of the commander entities were able to attain the 1:3 force ratio goal. In the five experiments with varying CAS periods, the BFR MOE clearly increased when commander entities had more decision-making time.

2. Comparison to Analytical Model

In Chapter III, the conditional probability model indicated that the commander attributes and the actual situation (decision factor states) would have the most influence on the results of a tactical commander's decisions. The six significant factors in the evaluation of SSIM CODE are the three commander attributes and the three decision factor states. These results agree with the analytical model.

The detailed conditional probability model identified the commander attributes as the most influential factors in tactical decision-making. The results of the SSIM CODE evaluation also identified commander attributes as having the most effect on BFR.

VII. CONCLUSIONS

A. THESIS OBJECTIVES

As listed in Chapter II, the thesis objectives are:

- *Model tactical commander decision cycles (battalion and below).*
- *Apply C2 doctrine.*
- *Develop a functionality module for Combat XXI.*
- *Exercise the SSIM CODE as a stand-alone simulation.*
- *Evaluate the effectiveness of SSIM CODE's decision-making.*

Each of these objectives was addressed in the development and evaluation of SSIM CODE.

B. TACTICAL DECISION CYCLE MODEL

SSIM CODE implements the OODA loop concept and includes inquiry-based, triggered, and directed information-processing in a representation of a tactical commander's decision cycle. The commander traits applied by SSIM CODE are typical of those used to measure tactical commanders and their individuality: experience level, C2 style, and C2 philosophy. The decisions that SSIM CODE commander entities make (search, move and engage) develop tactical level courses of action. The results of the SSIM CODE evaluation demonstrate tactical sense and reflecte the nature of the analytical models. While the tactical decision cycle model in SSIM CODE can be developed further to improve its resolution and flexibility, this model is an effective first step in representing the decision cycle of a tactical commander.

C. MARINE CORPS C2 PHILOSOPHY APPLICATION

Marine Corps C2 philosophy was applied in SSIM CODE by distinguishing between mission and detailed C2. The results showed that mission C2 was more successful than detailed C2, in the test scenario. In the cases with a shorter CAS period, commander entities with mission C2 had less accurate information, but were able to attain a higher BFR by accepting the limited information and making quicker decisions. Commander entities with detailed C2 used up time in improving their information and attained lower BFR values. However, when the CAS period was increased, commander entities had more time to decide and C2 philosophy had less of an effect. This is in keeping with the Marine Corps philosophy that mission C2 is effective when quick victories are required.

D. SSIM CODE AS A STAND-ALONE SIMULATION

SSIM CODE was employed effectively as a stand-alone simulation. For the evaluations, SSIM CODE was linked to Combat XXI through the SA module. The Combat XXI SA module served in dynamically updating the facts available to the commander entities and in allowing the commander entities a means to invoke the actions that resulted from decision-making. The next step in developing SSIM CODE as a part of Combat XXI C2 behaviors is to tightly couple SSIM CODE with other functionality modules (search, movement, communication, etc.) in Combat XXI. SSIM CODE can then be structured to meet all the abstract level requirements of Combat XXI functionality modules.

E. EFFECTIVENESS OF SSIM CODE DECISION-MAKING

Two stages of fractional factorial design experiments were used successfully in evaluating SSIM CODE. First, only main effects were evaluated to conclude that the enemy COA (combination of AAs) did not have a significant effect on BFR. However, the other six factors had significant effects on BFR across the range of CAS periods considered.

Next, two-factor interactions were examined with a full factorial design. All possible two-factor interactions of the six significant factors (decision factors and commander attributes) were considered. The main effects and interactions had reasonable interpretations.

SSIM CODE was deemed to make tactical sense through a face validation. Its results reflected the analytical models described in Chapter III. The evaluation concluded that the first steps in developing a decision-making model for Combat XXI and the purpose of this thesis have been accomplished. Additional development will complete the task.

F. ADDITIONAL DEVELOPMENT

1. Extended Features and Applications

Chapter I describes the process for developing a decision-making model for Combat XXI as:

- *Develop the concept of tactical decision-making for C2 into an analytical model.*
- *Implement the decision-making model in a simulation coupled to Combat XXI's behaviors package (loosely coupled with Combat XXI).*
- *Evaluate the performance of the decision-making simulation compared to the analytical model.*
- *Link the simulation to all applicable Combat XXI packages (tightly coupled with Combat XXI).*
- *Enhance the abstract features of the simulation to handle all likely applications of Combat XXI.*

The SSIM CODE model developed and evaluated in this thesis is merely an initial step that addresses the first three elements of completing a robust decision-making model that is fully integrated with an operational version of Combat XXI. As Combat XXI is completed, SSIM CODE should expand in its capabilities.

Expansion of SSIM CODE should address the final two steps in developing a decision-making model for Combat XXI. Full interaction with other Combat XXI modules (such as the search, movement, and engagement modules) should be completed. SSIM CODE's abstraction level should equal the abstract capabilities of other Combat XXI components.

Additional features for SSIM CODE should be considered. These features include expanding the number and levels of decision factors, implementing decision-making to support doctrinal targeting procedures, enabling the commander entity to develop and issue a commander's intent.

Another possible enhancement for SSIM CODE could be the dynamic updating of conditional probabilities associated with each commander entity. CCIRs could trigger decision cycles and also update the conditional probability distribution based on key state variables. For example, detecting an enemy force greater than a threshold size would not only initiate an *engage* decision, but would also change the probability that a commander entity would engage, given the decision factor stochastic state.

Potential studies using SSIM CODE include: measuring the effects of degraded communication between the commander entity and other simulation entities, measuring the value of information accuracy by varying uncertainty in reports, and measuring the influence of a commander's individuality by varying the commander entity's attributes. Commander entities on all tactical levels within each participating force can employ a

SSIM CODE–based decision-making model. The interactions of multiple OODA loops can then be evaluated.

SSIM CODE's development can further enable the representation of non-linearity, intangibles, and co-evolving landscapes. The non-linear effects of tactical decisions by individual commanders on the outcomes of battles can be evaluated. Commander attributes can be expanded to include other intangibles such as fatigue and morale. Multiple instances of commander entities employing OODA loops can be used to analyze co-evolving landscapes.

2. Model Validation

In addition to the face validation in this thesis, a procedural validation could test the effectiveness of SSIM CODE. Such a procedural approach could consist of peer validation. A test scenario can be formulated as a tactical decision game and solutions from a sample of officers could be compared to SSIM CODE's results. A complete validation would apply technical methods described in *Validation and Verification of Knowledge-Based Systems* (Gupta, 1991) *and Verification, Validation and Accreditation of Army Models and Simulations* (U.S. Army, 1999).

A rigorous validation would include examining the data used to populate commander attributes and decision outcome probabilities. An assessment of the degree of realism associated with the data would be required. Conditional probabilities associated with commander entities could be developed in a broad sense. For example, all commanders of a certain service branch for a specific combatant would include similar data. These probabilities can be assigned with expert judgment based on doctrine, observed tactics and intelligence reports.

A more detailed estimation of commander decision probabilities and commander entity attributes could be derived from operational data and population surveys. For example, observations of tactical decision-making during exercises could be used to estimate probability distributions.

Surveying tactical decision-makers (such as groups of company and field grade officers at resident professional schools) could lend insight into details that may be difficult to observe directly. Information relating to the hierarchy of decision factor importance for various situations could be obtained through surveying. Relationships between commander attributes and decision-making can also be examined in this manner.

Experiments to directly attain values for decision-making probabilities or commander attributes would be an effective (albeit costly) means to estimate the data required by SSIM CODE. Small-scale experimentation could be applied to improve data sets used in SSIM CODE. Scenarios based on actual data with verified results either from experimentation or from validated simulations could be approximated using Combat XXI and SSIM CODE. The results could be used to determine the quality of the decision-making probabilities and commander attributes. Improvements to the data could be attained from an iterative approach.

Perhaps the best sources for data to use in the SSIM CODE model are the various research efforts already in place in the Department of Defense modeling and simulation community. This work was detailed during a Military Operations Research Society workshop titled: *Evolving the Practice of Military Operations Analysis in the Department of Defense.* The Industrial College of the Armed Forces, the National

Ground Intelligence Center, and the Simulation Interoperability Standards Organization all have ongoing research efforts to provide data on tactical decision-making. The inputs, outputs, and processes involved in decision-making on the individual combatant level are being investigated (Burnett, Tamucci and Timian, 2000). Rule sets and characteristics to define tactical decision-makers are also being produced (Bjorkman, 2000). This data, developed specifically for use in combat simulations, can be used in the many potential applications for SSIM CODE and Combat XXI in the RDA and ACR domains.

G. SSIM CODE APPLICATION

SSIM CODE was developed as a Combat XXI functionality module and has a direct application in Combat XXI. Because Combat XXI is required to meet the Department of Defense high-level architecture (HLA) standards, it will be capable of exchanging inputs, outputs and models with other HLA compliant simulations. HLA enables simulation interoperability and reuse. This implies the potential application of the SSIM CODE model with other HLA-compliant simulations.

Simulation results attainted with SSIM CODE can be applied directly to lower resolution simulations (regardless of HLA compliance). For example, one result from the SSIM CODE evaluation was that the mission completion time MOE could potentially be modeled with an exponential distribution. A more aggregated simulation may model several sequential missions, assigned to one commander, without adjudicating each battle. This type of simulation could apply the SSIM CODE result by using a Poisson process to model the number of completed missions. If the missions are completed independently, a counting process for completed missions with exponential mission completion times (interarrival times) meets the requirements for a Poisson process (Ross, 1997).

Stochastic decision-making in Combat XXI has applications beyond the U.S. Department of Defense. The Australian armed forces currently use CASTFOREM for high-resolution combat simulation (Australian Defence Simulation Office, October 2000). Combat XXI will be replacing CASTFOREM as Australia's high-resolution combat simulation of choice. Improved C2 processes from SSIM CODE can serve to enhance Combat XXI applications in Australian modeling and simulation domains.

The development of SSIM CODE resulted in over nine thousand lines of Java code. It is impractical to include the lengthy source code in this thesis. Also, source code related to Combat XXI is copyrighted. Therefore, the Java source for SSIM CODE is available by contacting Major S. Posadas on the Combat XXI development team, TRADOC Analysis Center - White Sands Missile Range, NM 88002. Appendix K provides an overview of the central classes in SSIM CODE. Methods and attributes for the classes are listed in the appendix.

LIST OF REFERENCES

Ahuja, R.K., Magnanti, T.L., Orlin, J.B., *Network Flows*, Prentice-Hall, 1993.

Australian Defence Simulation Office, "Current and Future Simulation Projects 2000-2005," Industry and Procurement Infrastructure Division of the Defence Materiel Organisation, October 2000.

Bjorkman, E., "A Research Road Map for Incorporating Agent-Based Modeling into Campaign Models," [http://www.mors.org/evolving], March 2000.

Box, G.E., Hunter, W.G., Hunter, J.S., *Statistics for Experimenters*, John Wiley & Sons, 1978.

Boyd, J.R. "The Command and Control Process," Presentation at the Command and Control Systems Course, August 1995.

Brandstein, A.G., "Operational Synthesis: Applying science to Military Science," Phalanx, v.32, no. 4, pp 1, 30-31, December 1999.

Brown, L.P., "Agent Based Simulation as an Exploratory Tool in the Studey of the Human Dimension of Combat," Masters Thesis, Naval Postgraduate School, March 2000.

Burnett, S.K., Tamucci, M.S., Timian, D., "Conceptual Modeling of Foreign Command Decision Processes," [http://www.mors.org/evolving], March 2000.

Buss, A.H., System Simulation Notes, Naval Postgraduate School, July 2000.

Devore, J.L., Probability and Statistics for Engineering and the Sciences, Brooks/Cole Publishing, 1995.

Defense Information Systems Agency "C4ISR Model Capabilities Brief," [http://www.disa.mil/D8], October 1998.

Ehrling, E. Fast Parallel "Matrix Multiplication-Strategies for Practical Hybrid Algorithms," [http://www.f.kth.se/~f95-eeh/exjobb/background.html], May 1999.

Gupta, U.G., Validation and Verification of Knowledge-Based Systems, IEEE Computer Society Press, 1991.

Hamilton, L.C., Regression with Graphics, Duxbury Press, 1992.

Harless, G. "Combat XXI Primitive Behaviors Brief," U.S. Army TRADOC Analysis Center-White Sands Missile Range, April 2000.

Kahan, J.P., Stasz, C., Worley, R.D., *Understanding Commanders' Information Needs*, Rand, 1989.

Law, A.M., Kelton, W.D., *Simulation Modeling and Analysis,* McGraw Hill Higher Education, 2000.

Marine Corps Staff Training Program (MSTP) Staff., "Commander's Critical Information Requirements," Marine Corps Gazette, v.85, no. 4, pp. 35-36, April 2001.

Marshall, K.T., and Oliver, R.M., *Decision Making and Forecasting*, McGraq-Hill, 1995.

MathSoft Inc., S-Plus 2000 Professional Release 1, Lucent Technologies Inc., 1999.

Montgomery, D.C., *Design and Analysis of Experiments*, John Wiley & Sons, 1997.

Olson, A.S., "Combat XXI Brief," U.S. Army TRADOC Analysis Center-White Sands Missile Range, October 2000.

Orr, G.E., "20th Century Decision Models: 21st Century Applications," Presentation at the Command and Control Systems Course 1996 Spring Symposium, April 1996.

Posadas, S., "Commander's Intent in the Cyber Age," *Officer Review, v.39, pp. 12-13,* January 2000.

Pew, R.W., Mavor, A.S. (Eds.), *Modeling Human and Organizational Behavior*, National Academy Press, 1998.

Ross, S.M., *Introduction to Probability Models*, Academic Press, 1997.

Stephens, C.D., "Project Albert and JWARS Agent Based Modeling Tools and Techniques Exploration Report #2: Command and Control," Marine Corps Combat Development Command, February 2000.

Stork, K.A., "Sensors in Object Oriented Discrete Event Simulation," Masters Thesis, Naval Postgraduate School, September 1996.

TRADOC Analysis Center-White Sands Missile Range, "CASTFOREM Technical Documentation," White Sands Missile Range, March 1999.

TRADOC Analysis Center-White Sands Missile Range, Combat XXI Source Code, version 1.02, White Sands Missile Range, February 2001.

United States Army, "Verification, Validation and Accredition of Army Models and Simulations," Headquarters Department of the Army, Washington D.C., September 1999.

United States Marine Corps, "Marine Corps Doctrinal Publication-6: Command and Control," Headquarters Marine Corps, Washington D.C., October 1996.

United States Marine Corps, "Marine Corps Doctrinal Publication-1-3: Tactics," Headquarters Marine Corps, Washington D.C., July 1997.

THIS PAGE INTENTIONALLY LEFT BLANK

BIBLIOGRAPHY

Jensen, F.V., *An Introduction to Bayesian Networks*, University College London Press, 1996.

Siegel, P., *Expert Systems*, Tab Books, 1986.

Smith, J.Q., *Decision Analysis A Bayesian Approach*, Chapman and Hall, 1988.

United States Army Artificial Intelligence Center, Command Decision Modeling Technology Assessment, National Simulation Center, Fort Leavenworth, KS., July 1996.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX A. TEST SCENARIO PARAMETERS

Environment Parameters	
Distance from Red Force Origin To NAI 1	10 km
Distance from NAI 1 to NAI 2	20 km
Distance from NAI 1 to TAI 3	40 km
Distance from NAI 2 to TAI 2	20 km
Distance from NAI 2 to TAI 1	20 km
Distance from Blue Force Assembly Area To BP 1	35 km
Distance from Blue Force Assembly Area To BP 2	25 km
Distance from Blue Force Assembly Area To BP 3	35 km

Red (Enemy) Force Parameters	
Number of Companies	3
Combat Forces per Company	120
Average Speed	12 km / hr
Separation in Time between Companies	1 hr

Blue (Own) Forces Parameters	
Number of Platoons	3
Combat Forces per Platoon	40
Average Speed	15 km / hr
Standard Deviation for Detection Error at NAI 1	0.15 * Number of Actual Forces
Standard Deviation for Detection Error at NAI 2	0.10 * Number of Actual Forces
Standard Deviation for Detection Error at all TAIs	0.05 * Number of Actual Forces
Distance from Blue Force Assembly Area To BP 2	25 km
Distance from Blue Force Assembly Area To BP 3	35 km

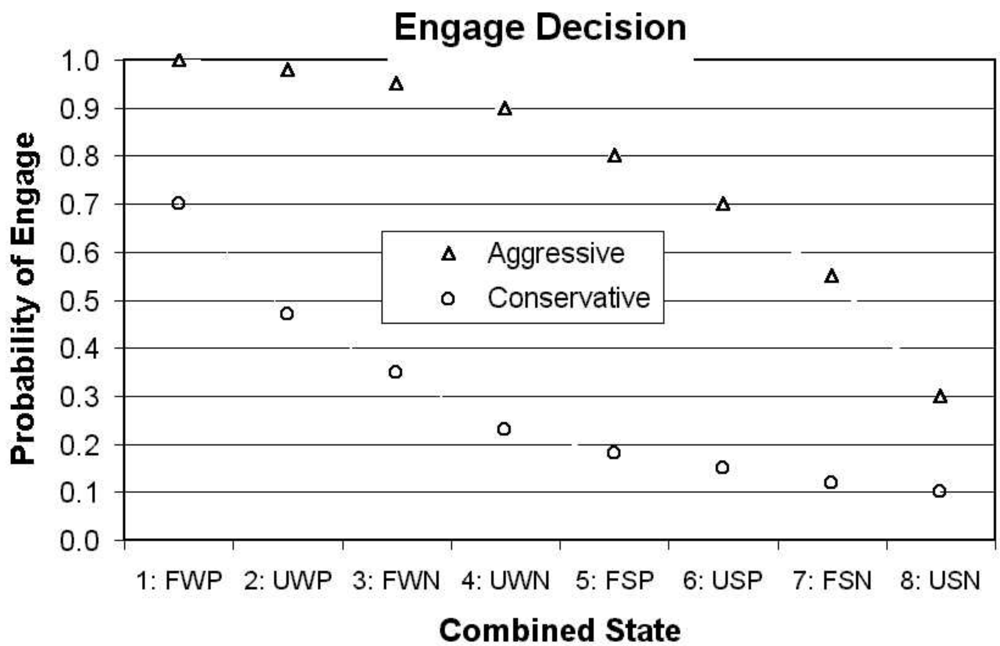
Blue Company Commander Entity OODA Loop Phase Times		
OODA Loop Phase	**Low Experience**	**High Experience**
Observe*	10 min	3min
Orient	10 min	3 min
Decide	10 min	3 min
Act	10 min	3 min
Between OODA Loops	20 min	10 min
*Commander Entities with Detailed C2 Philosophy Take Twice as Long While Requesting More Accurate Information		

Blue Company Commander Entity Deviation from Commanders Intent		
	Low Experience	**High Experience**
Standard Deviation from Specified Force Ratio Goal*	0.050 * Force Ratio Goal	0.025 * Force Ratio Goal

Blue Company Commander Entity Decision Probabilities Conditional Probability of Taking Primitive Action (Search, Move or Engage) Given Combined State		
Combined State	**Aggressive C2 Style**	**Conservative C2 Style**
Search Decision		
1: FWP	0.999	0.750
2: FSP	0.990	0.740
3: FWN	0.980	0.720
4: FSN	0.950	0.700
5: UWP	0.920	0.670
6: USP	0.850	0.600
7: UWN	0.700	0.450
8: USN	0.500	0.250
Movement Decision		
1: FWP	0.999	0.750
2: FSP	0.990	0.730
3: UWN	0.980	0.720
4: USN	0.950	0.700
5: FWN	0.900	0.650
6: FSN	0.800	0.550
7: UWN	0.650	0.400
8: USN	0.450	0.200
Engagement Decision		
1: FWP	0.999	0.700
2: UWP	0.980	0.470
3: FSP	0.950	0.350
4: USP	0.900	0.230
5: FWN	0.800	0.180
6: UWN	0.700	0.150
7: FSN	0.550	0.120
8: USN	0.300	0.100

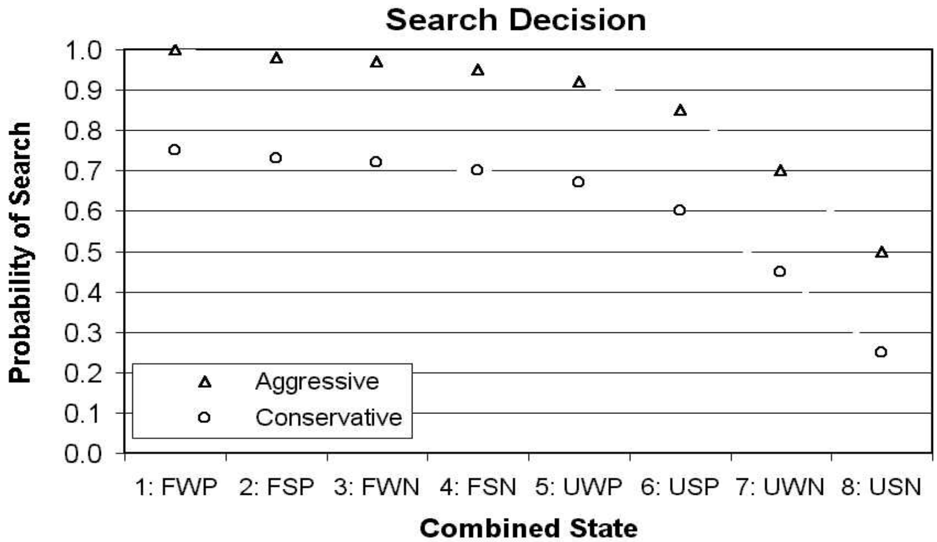
Decision Probabilities

The order of the combined states is from best to worst (left to right) according to the type of decision. This ordering is based on expert judgment. For example, FSP (favorable environment, strong enemy, and positive own forces) is a better state than FWN (favorable, weak, negative) when considering a search decision. This ordering reflects the importance of the environment, own forces and enemy forces, from highest to lowest.

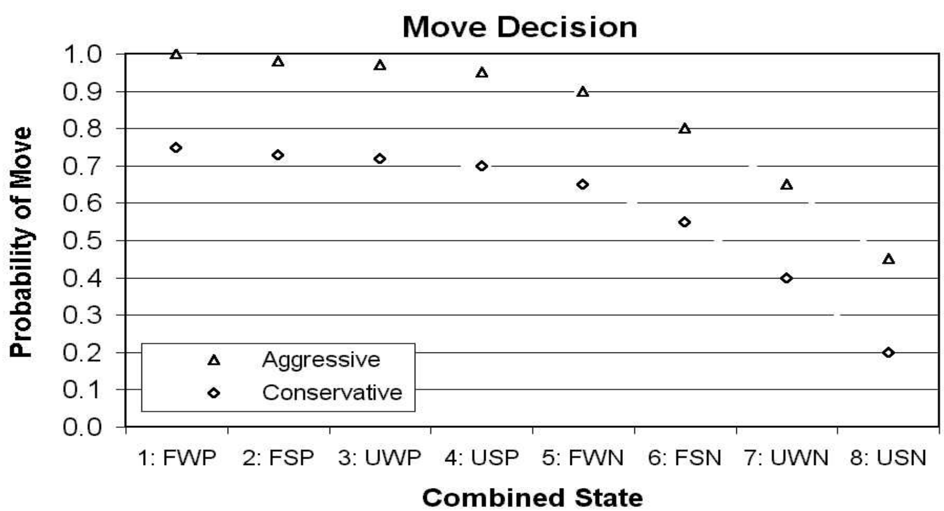


Engage Decision Probabilities

Aggressive and conservative commanders have differing trends. The probability of engaging declines more rapidly for conservative commanders. Conservative commanders are 20 to 65% less likely to engage given the same combined state. Combined states are ordered to rank enemy forces, own forces, then the environment decision factors from most to least critical.



Search Decision Probabilities
Aggressive and conservative commanders have the same trend. Conservative commanders are 20 to 25% less likely to search given the same combined state. Combined states are ordered to rank the environment, own forces, then enemy forces decision factors from most to least critical.



Move Decision Probabilities
Aggressive and conservative commanders have the same trend. Conservative commanders are 25% less likely to move given the same combined state. Combined states are ordered to rank own forces, the environment, then enemy forces decision factors from most to least critical.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX B. TEST SCENARIO DECISION RULES

Search Decision Rules

1. If the search decision outcome was NOT to search, continue collecting information.
2. Otherwise,
   a. Update the number of enemy detected at each NAI.
   b. If at least two-thirds of the total estimated enemy force has passed through NAI 1, search in NAI 2.

Engagement Decision Rules

1. If the engage decision outcome was NOT to search, continue collecting information.
2. Otherwise,
   a. Update the number of enemy detected at each TAI.
   b. Update the number of enemy forces anticipated at each TAI.
      1) Update the TAIs randomly (each equally likely)
      2) If the force ratio goal has not been met at a TAI,
         a) Task any available Blue forces already at the corresponding BP to engage.
         b) Task any available Blue forces in the assembly area to move to the proper BP and engage.
         c) Task any available Blue forces from another BP that has already met it force ratio goal to move to the appropriate BP and engage.
         d) If C2 style is aggressive, task up to three platoons to engage.

Movement Decision Rules

1. If the move decision outcome was NOT to search, continue collecting information.
2. Otherwise,
   a. Update the number of enemy detected at each NAI.
   b. Update the number of enemy forces anticipated at each TAI
      1) Update the TAIs randomly (each equally likely)
      2) If more than two companies have been detected moving north at NAI 2, expect 3 enemy companies at TAI 1.
      3) If more than one company have been detected moving north at NAI 2, expect 2 enemy companies at TAI 1.
      4) If at least one company has been detected moving north at NAI 2, expect 1 enemy company at TAI 1.
      5) If more than two companies have been detected moving south at NAI 2, expect 3 enemy companies at TAI 2.
      6) If more than one company have been detected moving south at NAI 2, expect 2 enemy companies at TAI 2.
      7) If at least one company has been detected moving south at NAI 2, expect 1 enemy company at TAI 2
      8) If more than two companies have been detected moving south at NAI 1, expect 3 enemy companies at TAI 3.
      9) If more than one company have been detected moving south at NAI 1, expect 2 enemy companies at TAI 3.
      10) If at least one company has been detected moving south at NAI 1, expect 1 enemy company at TAI 3
      11) If Blue forces are not in place or enroute to the proper BP to achieve the desired force ratio, move one available platoon from the assembly area to each BP requiring additional forces.

APPENDIX C. BFR FOR 100 FORCE DISPOSITIONS

Force dispositions are shown in terms of platoons. One Red company is represented by three Red platoons. The forces are arranged, from top to bottom, in BP 1,2, and 3 (for Blue) or TAI 1,2,and 3 (for Red). BFR is shown below each corresponding force disposition.

Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red	Blue	Red
1	3	1	33	1	3	1	-	1	-	1	3	1	33	1	333	1	-	1	-
1	3	1	3	1	33	1	3	1	33	1	-	1	-	1	-	1	333	1	-
1	3	1	-	1	-	1	33	1	3	1	33	1	3	1	-	1	-	1	333
0.333		0.250		0.250		0.250		0.250		0.250		0.250		0.111		0.111		0.111	
11	3	11	33	11	3	11	-	11	-	11	3	11	33	11	333	11	-	11	-
1	3	1	3	1	33	1	3	1	33	1	-	1	-	1	-	1	333	1	-
-	3	-	-	-	-	-	33	-	3	-	33	-	3	-	-	-	-	-	333
0.222		0.333		0.278		0.083		-0.083		0.250		0.083		0.222		0.111		-0.111	
1	3	1	33	1	3	1	-	1	-	1	3	1	33	1	333	1	-	1	-
11	3	11	3	11	33	11	3	11	33	11	-	11	-	11	-	11	333	11	-
-	3	-	-	-	-	-	33	-	3	-	33	-	3	-	-	-	-	-	333
0.222		0.278		0.333		0.250		0.000		0.083		-0.083		0.111		0.222		-0.111	
-	3	-	33	-	3	-	-	-	-	-	3	-	33	-	333	-	-	-	-
1	3	1	3	1	33	1	3	1	33	1	-	1	-	1	-	1	333	1	-
11	3	11	-	11	-	11	33	11	3	11	33	11	3	11	-	11	-	11	333
0.222		0.083		-0.083		0.333		0.278		0.000		0.250		-0.111		0.111		0.222	
-	3	-	33	-	3	-	-	-	-	-	3	-	33	-	333	-	-	-	-
11	3	11	3	11	33	11	3	11	33	11	-	11	-	11	-	11	333	11	-
1	3	1	-	1	-	1	33	1	3	1	33	1	3	1	-	1	-	1	333
0.222		0.250		0.000		0.278		0.333		-0.083		0.083		-0.111		0.222		0.111	
1	3	1	33	1	3	1	-	1	-	1	3	1	33	1	333	1	-	1	-
-	3	-	3	-	33	-	3	-	33	-	-	-	-	-	-	-	333	-	-
11	3	11	-	11	-	11	33	11	3	11	33	11	3	11	-	11	-	11	333
0.222		-0.083		0.083		0.000		0.250		0.333		0.278		0.111		-0.111		0.222	
11	3	11	33	11	3	11	-	11	-	11	3	11	33	11	333	11	-	11	-
-	3	-	3	-	33	-	3	-	33	-	-	-	-	-	-	-	333	-	-
1	3	1	-	1	-	1	33	1	3	1	33	1	3	1	-	1	-	1	333
0.111		0.000		0.250		-0.083		0.083		0.278		0.333		0.222		-0.111		0.111	
111	3	111	33	111	3	111	-	111	-	111	3	111	33	111	333	111	-	111	-
-	3	-	3	-	33	-	3	-	33	-	-	-	-	-	-	-	333	-	-
-	3	-	-	-	-	-	33	-	3	-	33	-	3	-	-	-	-	-	333
0.111		0.083		0.278		-0.250		-0.250		0.278		0.083		0.333		-0.111		-0.111	
-	3	-	33	-	3	-	-	-	-	-	3	-	33	-	333	-	-	-	-
111	3	111	3	111	33	111	3	111	33	111	-	111	-	111	-	111	333	111	-
-	3	-	-	-	-	-	33	-	3	-	33	-	3	-	-	-	-	-	333
0.111		0.278		0.083		0.278		0.083		-0.250		-0.250		-0.111		0.333		-0.111	
-	3	-	33	-	3	-	-	-	-	-	3	-	33	-	333	-	-	-	-
-	3	-	3	-	33	-	3	-	33	-	-	-	-	-	-	-	333	-	-
111	3	111	-	111	-	111	33	111	3	111	33	111	3	111	-	111	-	111	333
0.111		-0.250		-0.250		0.083		0.278		0.083		0.278		-0.111		-0.111		0.333	

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX D. 2^{9-4} RESOLUTION IV DESIGN

Run Order	Decision Factors			Commander Attributes			Enemy COAs		
	Environ	Red	Blue	C2 Philos	C2 Style	Exper	AA 1	AA 2	AA 3
1	-	-	-	-	-	+	+	+	+
2	+	-	-	-	-	+	-	-	-
3	-	+	-	-	-	-	+	-	-
4	+	+	-	-	-	-	-	+	+
5	-	-	+	-	-	-	-	+	-
6	+	-	+	-	-	-	+	-	+
7	-	+	+	-	-	+	-	-	+
8	+	+	+	-	-	+	+	+	-
9	-	-	-	+	-	-	-	-	+
10	+	-	-	+	-	-	+	+	-
11	-	+	-	+	-	+	-	+	-
12	+	+	-	+	-	+	+	-	+
13	-	-	+	+	-	+	+	-	-
14	+	-	+	+	-	+	-	+	+
15	-	+	+	+	-	-	+	+	+
16	+	+	+	+	-	-	-	-	-
17	-	-	-	-	+	-	-	-	-
18	+	-	-	-	+	-	+	+	+
19	-	+	-	-	+	+	-	+	+
20	+	+	-	-	+	+	+	-	-
21	-	-	+	-	+	+	+	-	+
22	+	-	+	-	+	+	-	+	-
23	-	+	+	-	+	-	+	+	-
24	+	+	+	-	+	-	-	-	+
25	-	-	-	+	+	+	+	+	-
26	+	-	-	+	+	+	-	-	+
27	-	+	-	+	+	-	+	-	+
28	+	+	-	+	+	-	-	+	-
29	-	-	+	+	+	-	-	+	+
30	+	-	+	+	+	-	+	-	-
31	-	+	+	+	+	+	-	-	-
32	+	+	+	+	+	+	+	+	+
Factor Label	A	B	C	D	E	F	G	H	J

2^{9-4} Fractional Factorial Design Generators: F = BCDE G = ACDE H = ABDE J = ABCE	
Factor or Interaction	**Confounded With**
I	ABFG + ACFH + ADFJ + BCGH + BDGJ + CDHJ
A	BFG + CFH + DFJ + BCEJ + BDEH + CDEG + EGHJ
B	AFG + CGH + DGJ + ACEJ + ADEH + CDEF + EFHJ
C	AFH + BGH + DHJ + ABEJ + ADEG + BDEF + EFGJ
D	AFJ + BGJ + CHJ + ABEH + ACEG + BCEF + EFGH
E	ABCJ + ABDH + ACDG + AGHJ + BCDF + BFHJ + CFGJ + DFGH
F	ABG + ACH + ADJ + BCDE + BEHJ + CEGJ + DEGH
G	ABF + BCH + BDJ + ACDE + AEHJ + CEFJ + DEFH
H	ACF + BCG + CDJ + ABDE + AEGJ + BEFJ + DEFG
J	ADF + BDG + CDH + ABCE + AEGH + BEFH + CEFG
AB	FG + CEJ + DEH + ACGH + ADGJ + BCFH + BDFJ
AC	FH + BEJ + DEG + ABGH + ADHJ + BCFG + CDFJ
AD	FJ + BEH + CEG + ABGJ + ACHJ + BDFG + CDFH
AE	BCJ + BDH + CDG + GHJ + BEFG + CEFH + DEFJ
AF	BG + CH + DJ
AG	BF + CDE + EHJ + ABCH + ABDJ + CFGH + DFGJ
AH	CF + BDE + EGJ + ABCG + ACDJ + BFGH + DFHJ
AJ	DF + BCE + EGH + ABDG + ACDH + BFGJ + CFHJ
BC	GH + AEJ + DEF + ABFH + ACFG + BDHJ + CDGJ
BD	GJ + AEH + CEF + ABFJ + ADFG + BCHJ + CDGH
BE	ACJ + ADH + CDF + FHJ + AEFG + CEGH + DEGJ
BH	CG + ADE + EFJ + ABCF + AFGH + BCDJ + DGHJ
BJ	DG + ACE + EFH + ABDF + AFGJ + BCDH + CGHJ
CD	HJ + AEG + BEF + ACFJ + ADFH + BCGJ + BDGH
CE	ABJ + ADG + BDF + FGJ + AEFH + BEGH + DEHJ
CJ	DH + ABE + EFG + ACDF + AFHJ + BCDG + BGHJ
DE	ABH + ACG + BCF + FGH + AEFJ + BEGJ + CEHJ
EF	BCD + BHJ + CGJ + DGH + ABEG + ACEH + ADEJ
EG	ACD + AHJ + CFJ + DFH + ABEF + BCEH + BDEJ
EH	ABD + AGJ + BFJ + DFG + ACEF + BCEG + CDEJ
EJ	ABC + AGH + BFH + CFG + ADEF + BDEG + CDEH
AEF	BEG + CEH + DEJ + ABCD + ABHJ + ACGJ + ADGH + BCFJ + BDFH + CDFG + FGHJ

APPENDIX E. SAMPLE RAW RESULTS FOR 2^{9-4} PILOT RUNS

run	E	R	B	C2P	C2S	EXP	AA1	AA2	AA3	BFR
1	0	0	0	0	0	1	1	1	1	-0.111
2	1	0	0	0	0	1	0	0	0	0.111
3	0	1	0	0	0	0	1	0	0	-1.000
4	1	1	0	0	0	0	0	1	1	-0.500
5	0	0	1	0	0	0	0	1	0	-1.000
6	1	0	1	0	0	0	1	0	1	0.250
7	0	1	1	0	0	1	0	0	1	0.333
8	1	1	1	0	0	1	1	1	0	-0.083
9	0	0	0	1	0	0	0	0	1	-1.000
10	1	0	0	1	0	0	1	1	0	-0.500
11	0	1	0	1	0	1	0	1	0	0.111
12	1	1	0	1	0	1	1	0	1	0.333
13	0	0	1	1	0	1	1	0	0	0.111
14	1	0	1	1	0	1	0	1	1	0.333
15	0	1	1	1	0	0	1	1	1	-0.111
16	1	1	1	1	0	0	0	0	0	-0.333
17	0	0	0	0	1	0	0	0	0	-0.333
18	1	0	0	0	1	0	1	1	1	-0.333
19	0	1	0	0	1	1	0	1	1	-0.500
20	1	1	0	0	1	1	1	0	0	0.111
21	0	0	1	0	1	1	1	0	1	-0.083
22	1	0	1	0	1	1	0	1	0	0.222
23	0	1	1	0	1	0	1	1	0	0.000
24	1	1	1	0	1	0	0	0	1	0.111
25	0	0	0	1	1	1	1	1	0	0.250
26	1	0	0	1	1	1	0	0	1	0.111
27	0	1	0	1	1	0	1	0	1	-0.083
28	1	1	0	1	1	0	0	1	0	-1.000
29	0	0	1	1	1	0	0	1	1	0.250
30	1	0	1	1	1	0	1	0	0	0.222
31	0	1	1	1	1	1	0	0	0	0.111
32	1	1	1	1	1	1	1	1	1	-0.111
1	0	0	0	0	0	1	1	1	1	-0.111
2	1	0	0	0	0	1	0	0	0	0.111
3	0	1	0	0	0	0	1	0	0	-1.000
4	1	1	0	0	0	0	0	1	1	-0.500
5	0	0	1	0	0	0	0	1	0	0.111
6	1	0	1	0	0	0	1	0	1	-0.500
7	0	1	1	0	0	1	0	0	1	-1.000
8	1	1	1	0	0	1	1	1	0	0.000
9	0	0	0	1	0	0	0	0	1	0.111
10	1	0	0	1	0	0	1	1	0	-0.500
11	0	1	0	1	0	1	0	1	0	0.111
12	1	1	0	1	0	1	1	0	1	0.250
13	0	0	1	1	0	1	1	0	0	0.111
14	1	0	1	1	0	1	0	1	1	0.000
15	0	1	1	1	0	0	1	1	1	-0.333
16	1	1	1	1	0	0	0	0	0	0.111
17	0	0	0	0	1	0	0	0	0	-0.333
18	1	0	0	0	1	0	1	1	1	-0.333
19	0	1	0	0	1	1	0	1	1	-0.083
20	1	1	0	0	1	1	1	0	0	0.111
21	0	0	1	0	1	1	1	0	1	-0.083
22	1	0	1	0	1	1	0	1	0	0.222
23	0	1	1	0	1	0	1	1	0	-0.500
24	1	1	1	0	1	0	0	0	1	0.111
25	0	0	0	1	1	1	1	1	0	0.278
26	1	0	0	1	1	1	0	0	1	-1.000
27	0	1	0	1	1	0	1	0	1	-0.083

run	E	R	B	C2P	C2S	EXP	AA1	AA2	AA3	BFR
28	1	1	0	1	1	0	0	1	0	0.111
29	0	0	1	1	1	0	0	1	1	0.333
30	1	0	1	1	1	0	1	0	0	0.111
31	0	1	1	1	1	1	0	0	0	0.333
32	1	1	1	1	1	1	1	1	1	0.111
1	0	0	0	0	0	1	1	1	1	0.111
2	1	0	0	0	0	1	0	0	0	0.111
3	0	1	0	0	0	0	1	0	0	-1.000
4	1	1	0	0	0	0	0	1	1	-0.500
5	0	0	1	0	0	0	0	1	0	0.222
6	1	0	1	0	0	0	1	0	1	-0.500
7	0	1	1	0	0	1	0	0	1	0.333
8	1	1	1	0	0	1	1	1	0	-0.083
9	0	0	0	1	0	0	0	0	1	0.111
10	1	0	0	1	0	0	1	1	0	-0.500
11	0	1	0	1	0	1	0	1	0	-1.000
12	1	1	0	1	0	1	1	0	1	0.000
13	0	0	1	1	0	1	1	0	0	0.111
14	1	0	1	1	0	1	0	1	1	0.000
15	0	1	1	1	0	0	1	1	1	0.333
16	1	1	1	1	0	0	0	0	0	-0.333
17	0	0	0	0	1	0	0	0	0	-0.333
18	1	0	0	0	1	0	1	1	1	0.111
19	0	1	0	0	1	1	0	1	1	-0.167
20	1	1	0	0	1	1	1	0	0	0.111
21	0	0	1	0	1	1	1	0	1	0.000
22	1	0	1	0	1	1	0	1	0	0.111
23	0	1	1	0	1	0	1	1	0	-0.500
24	1	1	1	0	1	0	0	0	1	-1.000
25	0	0	0	1	1	1	1	1	0	0.333
26	1	0	0	1	1	1	0	0	1	0.111
27	0	1	0	1	1	0	1	0	1	0.333
28	1	1	0	1	1	0	0	1	0	-1.000
29	0	0	1	1	1	0	0	1	1	-0.083
30	1	0	1	1	1	0	1	0	0	0.111
31	0	1	1	1	1	1	0	0	0	0.000
32	1	1	1	1	1	1	1	1	1	0.111

APPENDIX F. S-PLUS CODE FOR ANALYSIS OF 2^{9-4} DESIGN RESULTS

```
function(res, returnDesign = F, runs=32){
#NAME Results
#AUTHOR Posadas
#
#ARGUMENTS
#res is a data.frame of results factors are 0's and 1's
#res includes 9 factor coloumns and one response columns (10th col)
#
#returnDesign is a boolean that indicates whether the factorial design
#is to be returned by the function
#
#DESCRIPTION
#the factors are converted to +,- signs, an anova is performed, then
#the factor effects are determined along with their standard error
#
#RETURNS
#the anova summary, the mean response and its standard error, the
#factor effects & standard errors, and the design matrix, if requested
#
#CREATE AND LABEL FACTORS
      sig <- c("-", "+")
      con <- function(x){2 - x}
      des <- res[, 1:9]
      des[, 1] <- sig[con(des[, 1])]
      des[, 2] <- sig[con(des[, 2])]
      des[, 3] <- sig[con(des[, 3])]
      des[, 4] <- sig[con(des[, 4])]
      des[, 5] <- sig[con(des[, 5])]
      des[, 6] <- sig[con(des[, 6])]
      des[, 7] <- sig[con(des[, 7])]
      des[, 8] <- sig[con(des[, 8])]
      des[, 9] <- sig[con(des[, 9])]
      fnames <- list(E = sig, R = sig, B = sig, C2P = sig, C2S = sig,
         EXP = sig, AA1 = sig, AA2 = sig, AA3 = sig)
      factor.names(des) <- fnames
      BFR <- res$BFR    #
#CONDUCT ANOVA
      dat <- cbind(des, BFR)
      dimnames(dat)[[2]][10] <- "BFR"
      dat.aov <- aov(BFR ~ ., data = dat)
      summ <- summary(dat.aov)      #
#MEAN AND FACTOR EFFECTS WITH STANDARD ERROR
      N <- dim(res)[1]
      BFRmean <- dat.aov$coef[1]
      BFRse <- sqrt(summary(dat.aov)$Mean[10]/N)
      mean <- list(estimate = BFRmean, se = BFRse)
      effects <- model.tables(dat.aov, type = "feffects", se = T) #
#EXTRACT DESIGN
      Design <- des[1:runs, 1:9]    #RETURNS
      if(returnDesign == T) return(Design, summ, mean, effects)
      else return(summ, mean, effects)
}
```

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX G. S-PLUS CODE FOR POWER CALCULATIONS

```
function(var, treat, pow, tau1, alpha = 0.05, runs = 1)
{
#
#AUTHOR LLOYD BROWN, 2000 (MODIFIED BY POSADAS 2001)
#
#ARGUMENTS
#
# var is an estimate of the variance in the data
#
# treat is the number of treatments
#
# pow is the maximum power considered
#
# tau is the minimum detectable departure from the mean
#
# alpha significance level
#
# runs is the number of run sets per replication
#
#RETURNS
#
# x a matrix of tau (detectable departure from the mean) and
# m (number of replications required)
#
#INITIALIZE VALUES
      points <- 16
      x <- matrix(nrow = points, ncol = 2, dimnames = list(NULL,
c("deviation", "replications")))
      m <- 2
      tau <- tau1
      power1 <- 0 #
#
#CALCULATE NUMBER OF REPLICATION REQUIRED
      for(i in 1:points) {
            while(power1 < pow) {
                  lambda <- (m * treat * tau^2)/var   #NON-CENTRALITY
PARAMETER
                  dof1 <- treat - 1
                  dof2 <- treat * runs * (m - 1)
                  cp <- qf(1 - alpha, dof1, dof2)     #CRITICAL POINT
                  power1 <- 1 - pf(cp, dof1, dof2, lambda)
                  m <- m + 1
            }
            x[i, 1] <- tau
            x[i, 2] <- m
            m <- 2
            tau <- tau + tau1/10
            power1 <- 0
      }
      x
}
```

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX H. 2^6 FULL FACTORIAL DESIGN

Run Order	Decision Factors			Commander Attributes		
	Environ	Red	Blue	C2 Philos	C2 Style	Exper Level
1	-	-	-	-	-	-
2	+	-	-	-	-	-
3	-	+	-	-	-	-
4	+	+	-	-	-	-
5	-	-	+	-	-	-
6	+	-	+	-	-	-
7	-	+	+	-	-	-
8	+	+	+	-	-	-
9	-	-	-	+	-	-
10	+	-	-	+	-	-
11	-	+	-	+	-	-
12	+	+	-	+	-	-
13	-	-	+	+	-	-
14	+	-	+	+	-	-
15	-	+	+	+	-	-
16	+	+	+	+	-	-
17	-	-	-	-	+	-
18	+	-	-	-	+	-
19	-	+	-	-	+	-
20	+	+	-	-	+	-
21	-	-	+	-	+	-
22	+	-	+	-	+	-
23	-	+	+	-	+	-
24	+	+	+	-	+	-
25	-	-	-	+	+	-
26	+	-	-	+	+	-
27	-	+	-	+	+	-
28	+	+	-	+	+	-
29	-	-	+	+	+	-
30	+	-	+	+	+	-
31	-	+	+	+	+	-
32	+	+	+	+	+	-

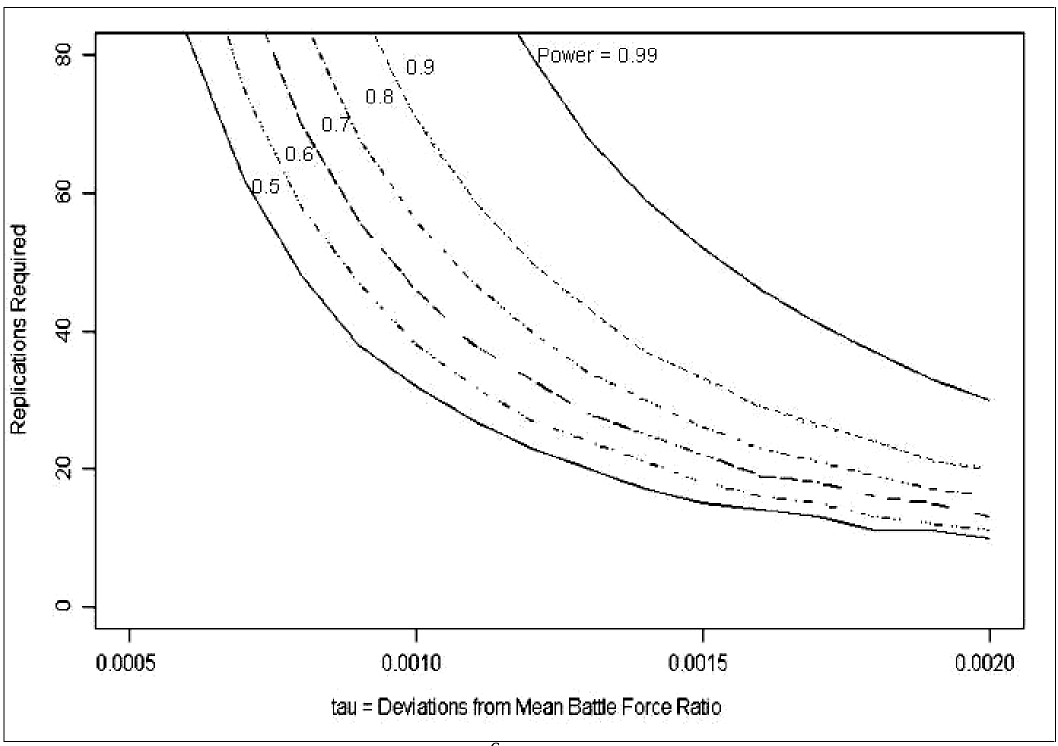
Run Order	Decision Factors			Commander Attributes		
	Environ	Red	Blue	C2 Philos	C2 Style	Exper Level
33	-	-	-	-	-	+
34	+	-	-	-	-	+
35	-	+	-	-	-	+
36	+	+	-	-	-	+
37	-	-	+	-	-	+
38	+	-	+	-	-	+
39	-	+	+	-	-	+
40	+	+	+	-	-	+
41	-	-	-	+	-	+
42	+	-	-	+	-	+
43	-	+	-	+	-	+
44	+	+	-	+	-	+
45	-	-	+	+	-	+
46	+	-	+	+	-	+
47	-	+	+	+	-	+
48	+	+	+	+	-	+
49	-	-	-	-	+	+
50	+	-	-	-	+	+
51	-	+	-	-	+	+
52	+	+	-	-	+	+
53	-	-	+	-	+	+
54	+	-	+	-	+	+
55	-	+	+	-	+	+
56	+	+	+	-	+	+
57	-	-	-	+	+	+
58	+	-	-	+	+	+
59	-	+	-	+	+	+
60	+	+	-	+	+	+
61	-	-	+	+	+	+
62	+	-	+	+	+	+
63	-	+	+	+	+	+
64	+	+	+	+	+	+

APPENDIX I. FULL FACTORIAL ESTIMATES & POWER CURVES

Pilot Run Estimates for 2^6 Fractional Factorial Design:

$\hat{\mu} = 0.059, \quad \hat{\sigma}^2 = 0.004^2 = 0.000016, \ \alpha = 0.01$

For a power of 0.99, using thirty replications detects a three-percent or greater deviation from the mean.



Power Curves for the 2^6 Fractional Factorial Design

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX J. FULL FACTORIAL RESULTS
for CAS Periods of 2 Through 4 Hours

CAS PERIOD = 2 HRS

ANOVA

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.4687	0.46875	5.6461	0.0175930
R	1	1.1779	1.17788	14.1876	0.0001705
B	1	3.5021	3.50208	42.1826	0.0000000
C2P	1	49.0525	49.05249	590.8380	0.0000000
C2S	1	9.8550	9.85496	118.7032	0.0000000
EXP	1	40.1235	40.12348	483.2879	0.0000000
E:R	1	0.0058	0.00579	0.0697	0.7917955
E:B	1	0.1565	0.15648	1.8848	0.1699493
E:C2P	1	0.4618	0.46183	5.5628	0.0184473
E:C2S	1	0.2676	0.26759	3.2232	0.0727625
E:EXP	1	0.7259	0.72593	8.7438	0.0031449
R:B	1	0.7698	0.76978	9.2720	0.0023588
R:C2P	1	0.8241	0.82410	9.9263	0.0016547
R:C2S	1	0.2521	0.25208	3.0363	0.0815809
R:EXP	1	0.1525	0.15249	1.8368	0.1754874
B:C2P	1	2.7000	2.70000	32.5215	0.0000000
B:C2S	1	0.0544	0.05442	0.6555	0.4182417
B:EXP	1	1.4815	1.48148	17.8445	0.0000251
C2P:C2S	1	9.4454	9.44537	113.7696	0.0000000
C2P:EXP	1	32.1483	32.14825	387.2262	0.0000000
C2S:EXP	1	6.8481	6.84815	82.4860	0.0000000
Residuals	1898	157.5756	0.08302		

MAIN EFFECTS

	Effects	se
E	0.0312500	0.013152
R	-0.0495370	0.013152
B	0.0854167	0.013152
C2P	0.3196759	0.013152
C2S	-0.1432870	0.013152
EXP	0.2891204	0.013152

TWO-FACTOR INTERACTIONS

	Effects	se
E:R	-0.0034722	0.013152
E:B	0.0180556	0.013152
E:C2P	-0.0310185	0.013152
E:C2S	-0.0236111	0.013152
E:EXP	-0.0388889	0.013152
R:B	-0.0400463	0.013152
R:C2P	0.0414352	0.013152
R:C2S	-0.0229167	0.013152
R:EXP	0.0178241	0.013152
B:C2P	-0.0750000	0.013152
B:C2S	0.0106481	0.013152
B:EXP	-0.0555556	0.013152
C2P:C2S	0.1402778	0.013152
C2P:EXP	-0.2587963	0.013152
C2S:EXP	0.1194444	0.013152

BFR

Mean = 0.069

Standard Error = 0.007

CAS PERIOD = 3 HRS

ANOVA

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.7787	0.77870	9.8270	0.0017460
R	1	1.7120	1.71204	21.6053	0.0000036
B	1	5.0704	5.07037	63.9862	0.0000000
C2P	1	38.2819	38.28189	483.1033	0.0000000
C2S	1	5.7300	5.73004	72.3110	0.0000000
EXP	1	35.9951	35.99509	454.2447	0.0000000
E:R	1	0.1087	0.10867	1.3713	0.2417278
E:B	1	0.0391	0.03912	0.4937	0.4823745
E:C2P	1	0.3766	0.37657	4.7522	0.0293840
E:C2S	1	0.0093	0.00928	0.1172	0.7321590
E:EXP	1	0.6100	0.60998	7.6977	0.0055832
R:B	1	0.1155	0.11546	1.4570	0.2275529
R:C2P	1	1.2790	1.27904	16.1410	0.0000611
R:C2S	1	0.3169	0.31690	3.9991	0.0456659
R:EXP	1	0.6421	0.64208	8.1028	0.0044672
B:C2P	1	4.3447	4.34468	54.8282	0.0000000
B:C2S	1	0.0058	0.00579	0.0730	0.7870041
B:EXP	1	2.9384	2.93837	37.0812	0.0000000
C2P:C2S	1	6.3531	6.35311	80.1739	0.0000000
C2P:EXP	1	26.3412	26.34115	332.4156	0.0000000
C2S:EXP	1	4.1979	4.19794	52.9765	0.0000000
Residuals	1898	150.4006	0.07924		

MAIN EFFECTS

	Effects	se
E	0.0402778	0.012849
R	-0.0597222	0.012849
B	0.1027778	0.012849
C2P	0.2824074	0.012849
C2S	-0.1092593	0.012849
EXP	0.2738426	0.012849

TWO-FACTOR INTERACTIONS

	Effects	se
E:R	-0.0150463	0.012849
E:B	-0.0090278	0.012849
E:C2P	-0.0280093	0.012849
E:C2S	-0.0043981	0.012849
E:EXP	-0.0356481	0.012849
R:B	-0.0155093	0.012849
R:C2P	0.0516204	0.012849
R:C2S	-0.0256944	0.012849
R:EXP	0.0365741	0.012849
B:C2P	-0.0951389	0.012849
B:C2S	0.0034722	0.012849
B:EXP	-0.0782407	0.012849
C2P:C2S	0.1150463	0.012849
C2P:EXP	-0.2342593	0.012849
C2S:EXP	0.0935185	0.012849

BFR

Mean = 0.106

Standard Error = 0.006

CAS PERIOD = 4 HRS

ANOVA

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.5150	0.51498	7.1546	0.0075414
R	1	1.0340	1.03396	14.3649	0.0001553
B	1	3.6265	3.62655	50.3840	0.0000000
C2P	1	32.6969	32.69692	454.2614	0.0000000
C2S	1	6.1880	6.18802	85.9708	0.0000000
EXP	1	30.6985	30.69846	426.4967	0.0000000
E:R	1	0.3612	0.36117	5.0178	0.0252040
E:B	1	0.0911	0.09106	1.2650	0.2608401
E:C2P	1	0.3735	0.37346	5.1886	0.0228468
E:C2S	1	0.0008	0.00078	0.0108	0.9172058
E:EXP	1	0.5150	0.51498	7.1546	0.0075414
R:B	1	0.2809	0.28087	3.9022	0.0483687
R:C2P	1	1.0032	1.00325	13.9382	0.0001945
R:C2S	1	0.3140	0.31405	4.3631	0.0368579
R:EXP	1	0.4515	0.45155	6.2734	0.0123395
B:C2P	1	3.0171	3.01714	41.9174	0.0000000
B:C2S	1	0.1315	0.13149	1.8268	0.1766701
B:EXP	1	2.1259	2.12593	29.5358	0.0000001
C2P:C2S	1	6.4687	6.46868	89.8700	0.0000000
C2P:EXP	1	22.0306	22.03061	306.0734	0.0000000
C2S:EXP	1	4.7225	4.72254	65.6107	0.0000000
Residuals	1898	136.6146	0.07198		

MAIN EFFECTS

	Effects	se
E	0.0327546	0.012246
R	-0.0464120	0.012246
B	0.0869213	0.012246
C2P	0.2609954	0.012246
C2S	-0.1135417	0.012246
EXP	0.2528935	0.012246

TWO-FACTOR INTERACTIONS

	Effects	se
E:R	-0.0274306	0.012246
E:B	0.0137731	0.012246
E:C2P	-0.0278935	0.012246
E:C2S	0.0012731	0.012246
E:EXP	-0.0327546	0.012246
R:B	-0.0241898	0.012246
R:C2P	0.0457176	0.012246
R:C2S	-0.0255787	0.012246
R:EXP	0.0306713	0.012246
B:C2P	-0.0792824	0.012246
B:C2S	0.0165509	0.012246
B:EXP	-0.0665509	0.012246
C2P:C2S	0.1160880	0.012246
C2P:EXP	-0.2142361	0.012246
C2S:EXP	0.0991898	0.012246

BFR

Mean = 0.142

Standard Error = 0.006

CAS PERIOD = 5 HRS

ANOVA

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.3461	0.34609	5.0823	0.0242855
R	1	0.6340	0.63398	9.3098	0.0023109
B	1	5.9259	5.92593	87.0207	0.0000000
C2P	1	28.3025	28.30249	415.6150	0.0000000
C2S	1	5.2547	5.25473	77.1644	0.0000000
EXP	1	27.7120	27.71204	406.9443	0.0000000
E:R	1	0.5942	0.59424	8.7262	0.0031752
E:B	1	0.0568	0.05682	0.8343	0.3611405
E:C2P	1	0.2676	0.26759	3.9295	0.0475892
E:C2S	1	0.1225	0.12245	1.7982	0.1800905
E:EXP	1	0.2729	0.27287	4.0070	0.0454549
R:B	1	0.1053	0.10535	1.5470	0.2137272
R:C2P	1	0.3642	0.36422	5.3485	0.0208463
R:C2S	1	0.0004	0.00041	0.0060	0.9380451
R:EXP	1	0.3704	0.37037	5.4388	0.0197984
B:C2P	1	4.4083	4.40833	64.7353	0.0000000
B:C2S	1	0.0021	0.00208	0.0306	0.8611696
B:EXP	1	4.4297	4.42966	65.0484	0.0000000
C2P:C2S	1	4.9794	4.97942	73.1216	0.0000000
C2P:EXP	1	21.8643	21.86430	321.0718	0.0000000
C2S:EXP	1	3.3891	3.38912	49.7684	0.0000000
Residuals	1898	129.2497	0.06810		

MAIN EFFECTS

	Effects	se
E	0.02685185	0.011911
R	-0.03634259	0.011911
B	0.11111111	0.011911
C2P	0.24282407	0.011911
C2S	-0.10462963	0.011911
EXP	0.24027778	0.011911

TWO-FACTOR INTERACTIONS

	Effects	se
E:R	-0.03518519	0.011911
E:B	0.01087963	0.011911
E:C2P	-0.02361111	0.011911
E:C2S	0.01597222	0.011911
E:EXP	-0.02384259	0.011911
R:B	-0.01481481	0.011911
R:C2P	0.02754630	0.011911
R:C2S	-0.00092593	0.011911
R:EXP	0.02777778	0.011911
B:C2P	-0.09583333	0.011911
B:C2S	0.00208333	0.011911
B:EXP	-0.09606481	0.011911
C2P:C2S	0.10185185	0.011911
C2P:EXP	-0.21342593	0.011911
C2S:EXP	0.08402778	0.011911

BFR

Mean = 0.162

Standard Error = 0.006

CAS PERIOD = 6 HRS

ANOVA

	Df	Sum of Sq	Mean Sq	F Value	Pr(F)
E	1	0.2890	0.28899	4.5840	0.0323990
R	1	1.3021	1.30208	20.6537	0.0000058
B	1	4.2188	4.21875	66.9179	0.0000000
C2P	1	19.3782	19.37819	307.3772	0.0000000
C2S	1	3.8920	3.89200	61.7350	0.0000000
EXP	1	22.0544	22.05442	349.8277	0.0000000
E:R	1	0.0021	0.00208	0.0330	0.8557707
E:B	1	0.0021	0.00208	0.0330	0.8557707
E:C2P	1	0.1408	0.14084	2.2341	0.1351646
E:C2S	1	0.2321	0.23212	3.6820	0.0551539
E:EXP	1	0.1486	0.14856	2.3565	0.1249320
R:B	1	0.0202	0.02016	0.3199	0.5717638
R:C2P	1	0.8803	0.88027	13.9629	0.0001920
R:C2S	1	0.0026	0.00257	0.0408	0.8399512
R:EXP	1	0.7346	0.73459	11.6521	0.0006548
B:C2P	1	2.2994	2.29941	36.4733	0.0000000
B:C2S	1	0.1992	0.19918	3.1593	0.0756534
B:EXP	1	3.1687	3.16875	50.2628	0.0000000
C2P:C2S	1	4.3447	4.34468	68.9153	0.0000000
C2P:EXP	1	14.4676	14.46759	229.4852	0.0000000
C2S:EXP	1	2.9558	2.95579	46.8848	0.0000000
Residuals	1898	119.6569	0.06304		

MAIN EFFECTS

	Effects	se
E	0.0245370	0.01146
R	-0.0520833	0.01146
B	0.0937500	0.01146
C2P	0.2009259	0.01146
C2S	-0.0900463	0.01146
EXP	0.2143519	0.01146

TWO-FACTOR INTERACTIONS

	Effects	se
E:R	-0.0020833	0.01146
E:B	0.0020833	0.01146
E:C2P	-0.0171296	0.01146
E:C2S	0.0219907	0.01146
E:EXP	-0.0175926	0.01146
R:B	-0.0064815	0.01146
R:C2P	0.0428241	0.01146
R:C2S	-0.0023148	0.01146
R:EXP	0.0391204	0.01146
B:C2P	-0.0692130	0.01146
B:C2S	0.0203704	0.01146
B:EXP	-0.0812500	0.01146
C2P:C2S	0.0951389	0.01146
C2P:EXP	-0.1736111	0.01146
C2S:EXP	0.0784722	0.01146

BFR

Mean = 0.195

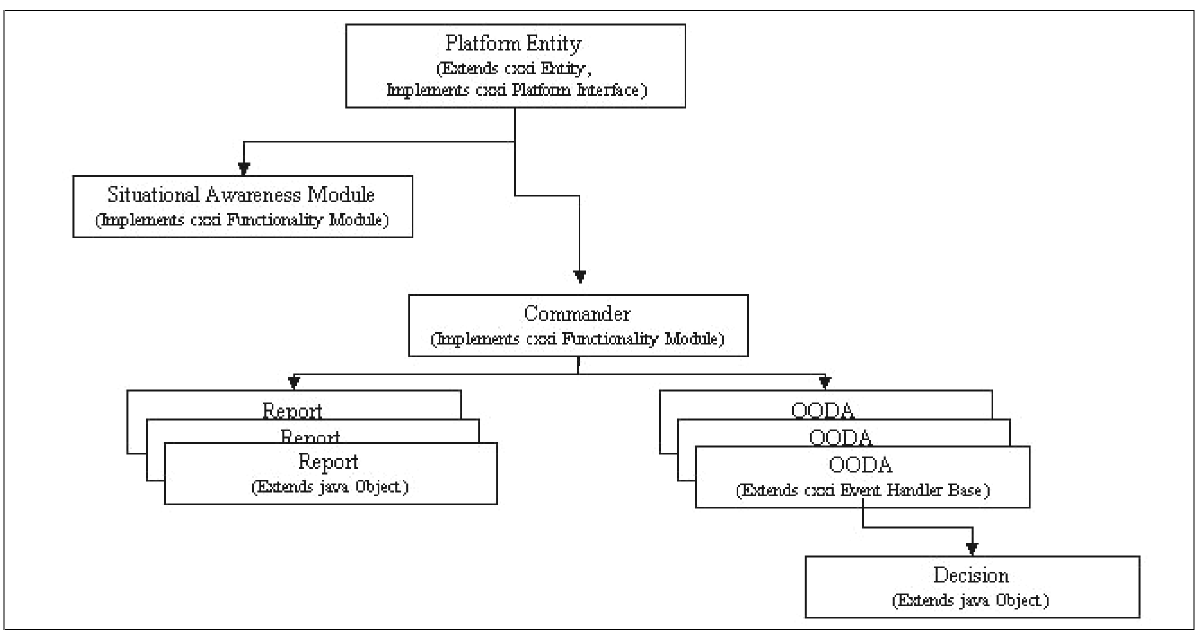
Standard Error = 0.006

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX K. SSIM CODE JAVA CLASSES

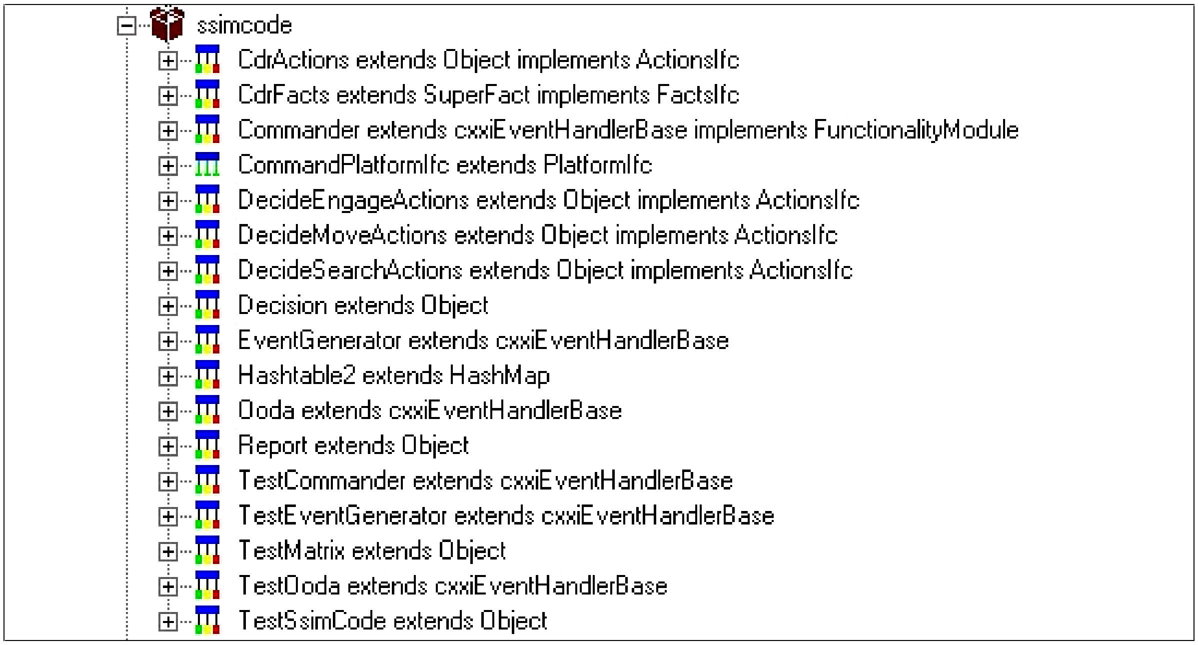
SSIM CODE consists of a base java package with test classes and an evaluation package with test classes. The base package is comprised of over 2,600 lines of Java. Its test classes include over 860 lines of source. The evaluation package contains over 3,100 lines of code, and the corresponding test classes consist of over 2,400 lines of Java. In total, SSIM CODE encompasses approximately 9,120 lines of Java (about half are documentation). The Combat XXI simulation contained over 200,000 lines of code as of February 2001 (version 1.02).

A Combat XXI platform entity contains an SA module, and may contain a SSIM CODE commander module. The SSIM CODE commander module contains a set of OODA loops and a set of reports. Each OODA loop contains a decision. The following figures depict the key classes in SSIM CODE. The methods and attributes for each class are shown.

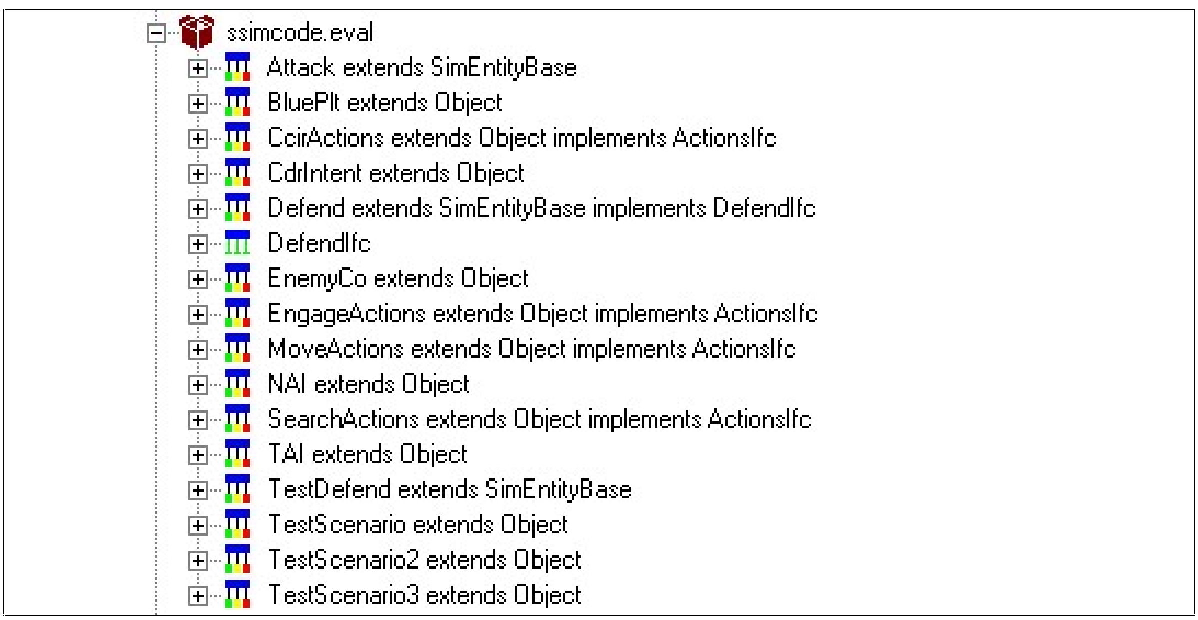


Class Relationships

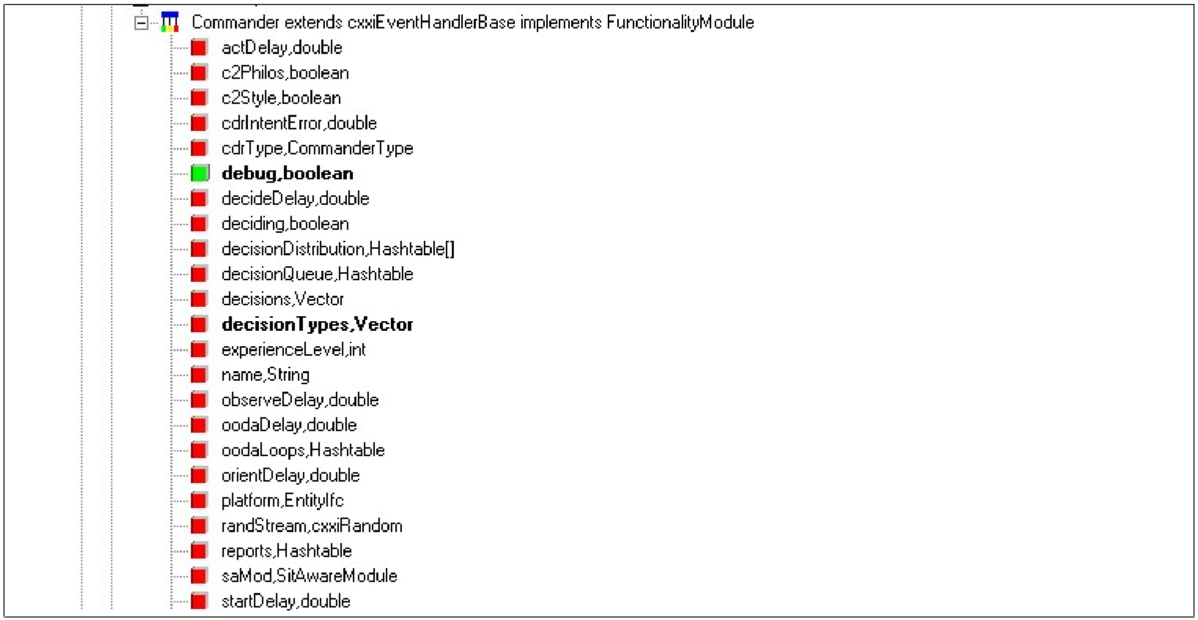
The primary classes in SSIM CODE are: Commander, OODA, Report and Decision.



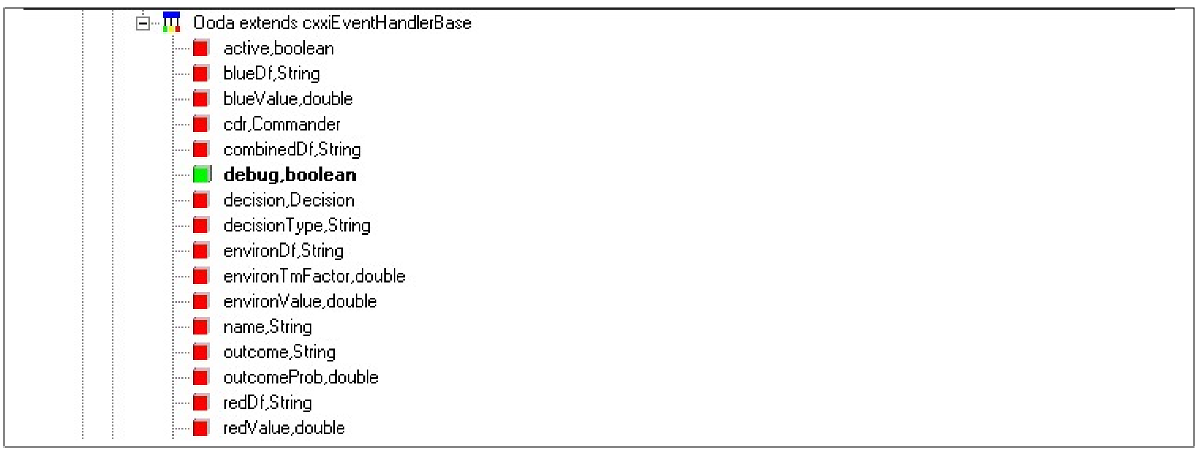
SSIM CODE Base Package and Test Classes



SSIM CODE Evaluation Package and Test Classes



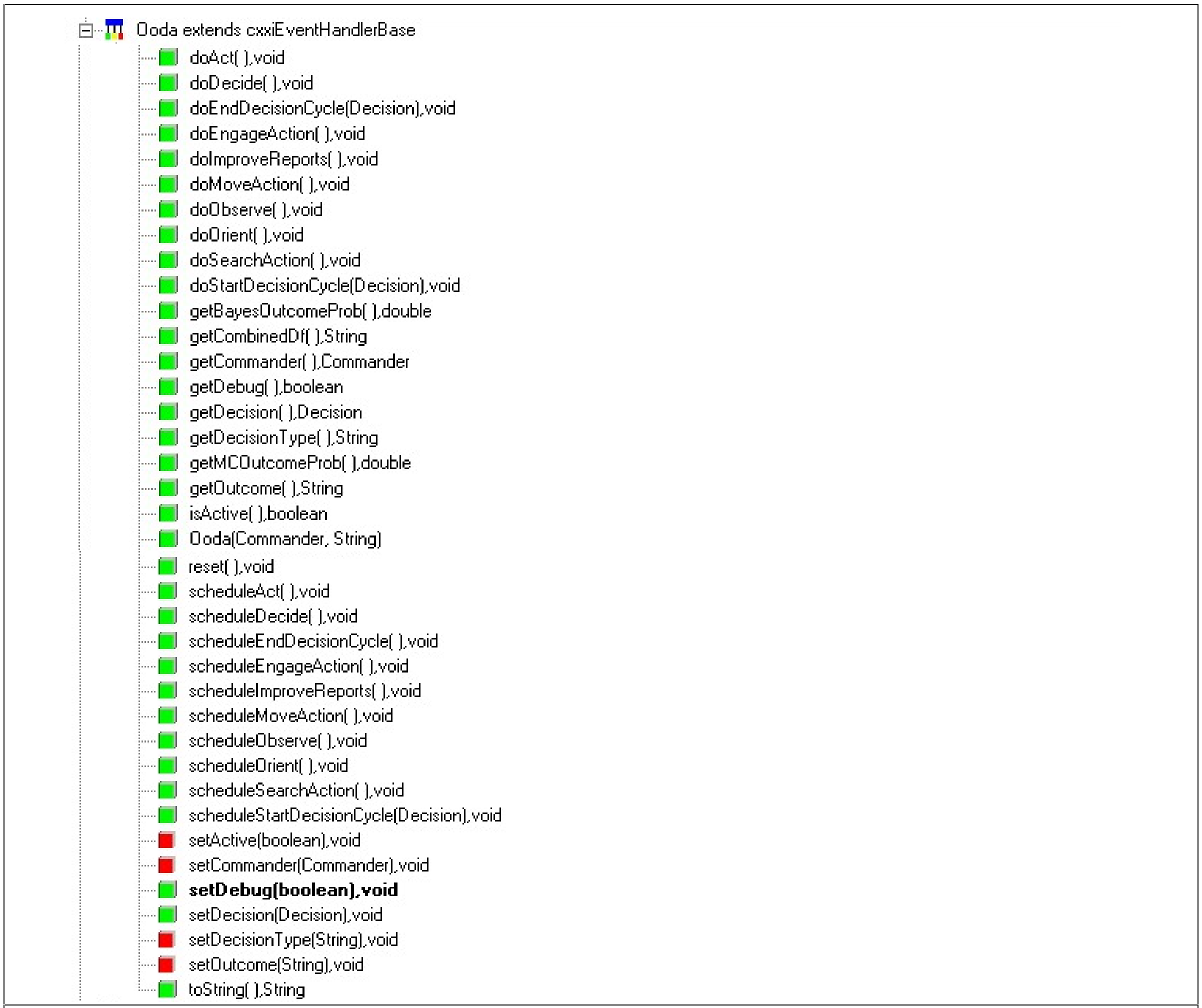
SSIM CODE Commander Attributes



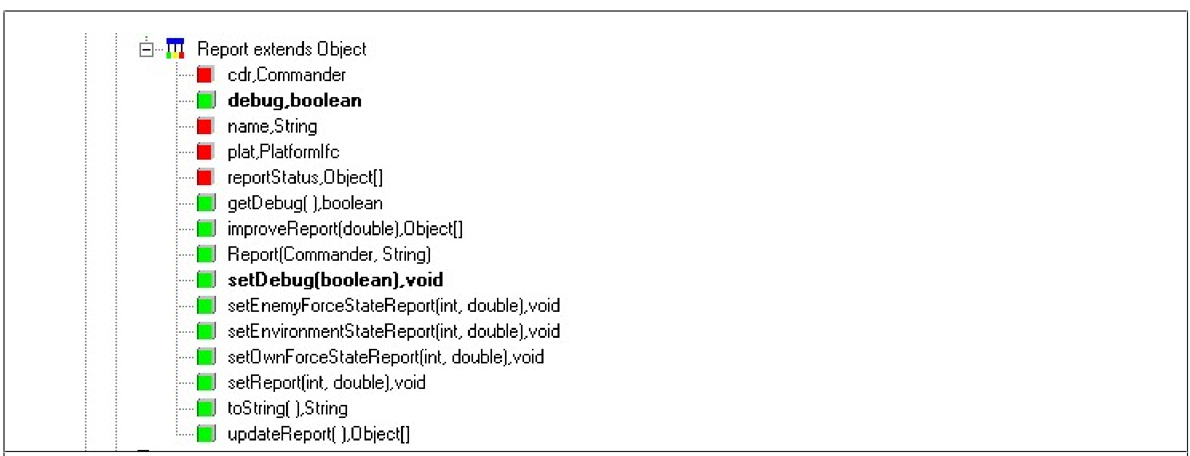
SSIM CODE OODA Attributes

- Commander extends cxxiEventHandlerBase implements FunctionalityModule
  - Commander(String, CommanderType, int, boolean, boolean, FunctionalityModuleHolder)
  - Commander( )
  - Commander(Commander)
  - doEndDecisionCycle(Decision),void
  - doRequestDecision(Object),void
  - doStartDecisionCycle(Decision),void
  - getActDelay( ),double
  - getC2Philos( ),boolean
  - getC2Style( ),boolean
  - getCdrIntentError( ),double
  - getCommanderType( ),CommanderType
  - getDebug( ),boolean
  - getDecideDelay( ),double
  - getDecisionDistribution(String),Hashtable
  - getDecisionEnumeration(String),Enumeration
  - getDecisionProbability(String, String),double
  - getDecisionQueue( ),Hashtable
  - getDecisions( ),Vector
  - getDecisionTypes( ),Vector
  - getDetails( ),String
  - getExperienceLevel( ),int
  - getName( ),String
  - getObserveDelay( ),double
  - getOodaDelay( ),double
  - getOodaLoops( ),Hashtable
  - getOrientDelay( ),double
  - getPlatform( ),EntityIfc
  - getRandStream( ),cxxiRandom
  - getReports( ),Hashtable
  - getSeed( ),long
  - getSitAwareModule( ),SitAwareModule
  - getType( ),int
  - isAggressive( ),boolean
  - isConservative( ),boolean
  - isDeciding( ),boolean
  - isDetailed( ),boolean
  - isMission( ),boolean
  - registerDecisionCycles( ),void
  - requestGuidance( ),void
  - reset( ),void
  - resolveDecision( ),void
  - retriveMission( ),void
  - reviewMission( ),void
  - scheduleEndDecisionCycle(Decision),void
  - scheduleRequestDecision(Object),void
  - scheduleRequestDecisionDelay(Object[]),void
  - scheduleStartDecisionCycle(Decision),void
  - setActDelay(double),void
  - setAllDecisionDistributions( ),void
  - setC2Philos(boolean),void
  - setC2Style(boolean),void
  - setCdrIntentError(double),void
  - setCommanderType(CommanderType),void
  - setDebug(boolean),void
  - setDecideDelay(double),void
  - setDeciding(boolean),void
  - setDecisionDistribution(Vector, boolean),void
  - setDecisionProbability(String, String, double),void
  - setDecisionQueue( ),void
  - setExperienceLevel(int),void
  - setName(String),void
  - setObserveDelay(double),void
  - setOodaDelay(double),void
  - setOrientDelay(double),void
  - setPlatform(FunctionalityModuleHolder),void
  - setRandStream(cxxiRandom),void
  - setReports( ),void
  - setSitAwareModule(SitAwareModule),void
  - setStartDelay(double),void
  - startDeciding(String),void
  - toString( ),String

SSIM CODE Commander Methods



SSIM CODE OODA Methods



SSIM CODE Report Attributes and Methods

SSIM CODE Decision Attributes and Methods

SSIM CODE Test Scenario Class

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center 2
   8725 John J. Kingman Road, Suite 0944
   Ft. Belvoir, VA 22060-6218

2. Dudley Knox Library 2
   Naval Postgraduate School
   411 Dyer Road
   Monterey, CA 93943-5101

3. U.S. Army TRADOC Analysis Center 2
   Code WE (Combat XXI)
   White Sands Missile Range, NM 88002

4. Director, Studies and Analysis Division 2
   MCCDC, Code C45
   300 Russell Road
   Quantico, VA 22134-5130

5. Director, Training and Education 1
   MCCDC, Code C46
   1019 Elliot Road
   Quantico, VA 22134-5027

6. Director, Marine Corps Research Center 2
   MCCDC, Code C40RC
   2040 Broadway Street
   Quantico, VA 22134-5107

7. Marine Corps Representative 1
   Naval Postgraduate School
   Code 037, Bldg. 330, Ingersoll Hall, Rm. 116
   555 Dyer Road
   Monterey, CA 93940

8. Marine Corps Tactical Systems Support Activity 1
   Technical Advisory Branch
   Attn: Librarian
   Box 555171
   Camp Pendleton, CA 92055-5080

9. Chairman, Department of Operations Research 1
    Code OR
    Naval Postgraduate School
    Monterey, CA 93943

10. LtCol Greg K. Mislick 1
    Department of Operations Research, Code (OR/MI)
    Naval Postgraduate School
    Monterey, CA 93943

11. LtCol Eugene P. Paulo 1
    Department of Operations Research, Code (OR/PE)
    Naval Postgraduate School
    Monterey, CA 93943

12. Professor Tom W. Lucas 1
    Department of Operations Research, Code (OR/LT)
    Naval Postgraduate School
    Monterey, CA 93943

13. Maj Sergio Posadas 2
    U.S. Army TRADOC Analysis Center
    Code WE (Combat XXI)
    White Sands Missile Range, NM 88002