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## BDA ENHANCEMENT METHODOLOGY USING SITUATIONAL PARAMETER ADJUSTMENTS

THESIS

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AFIT/GOR/ENS/06-05

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## BDA ENHANCEMENT METHODOLOGY USING SITUATIONAL PARAMETER ADJUSTMENTS

### THESIS

Presented to the Faculty Department of Operational Sciences Graduate School of Engineering and Management Air Force Institute of Technology Air University Air Education and Training Command In Partial Fulfillment of the Requirements for the Degree of Master of Science in Operations Research

> Michael V. Carras Jr, B.S. Chemistry Captain, United States Air Force

> > March 2006

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# BDA ENHANCEMENT METHODOLOGY USING SITUATIONAL PARAMETER ADJUSTMENTS

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### Abstract

In the context of close ground combat, the perception of Battle Damage Assessment (BDA) is closely linked with a soldier's engagement decisions and has significant effects on the battlefield. Perceived BDA is also one of the most complex and uncertain processes facing the soldier in live combat. As a result, the modeling and simulation community has yet to adequately model the perceived BDA process in combat models. This research effort examines the BDA process from a perception standpoint and proposes a methodology to collect the pertinent data and model this perception in the Army's current force-on-force model, CASTFOREM. A subject matter expert survey design and a method to model the BDA process as a Discrete Time Markov Chain are proposed. Bayesian inference is used to update probability distributions at each time step considering the situational parameters available to the soldier at the time of an assessment. Comparisons between the known simulation distributions and those developed from simulated survey responses suggest an adequate number of subject matter experts to be polled.

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# List of Abbreviations

Abbreviation		Page
TRADOC	Training and Doctrine Command	1
TRAC	TRADOC Analysis Center	1
DoD	Department of Defense	1
M&S	Modeling and Simulation	1
BDA	Battle Damage Assessment	1
CASTFORE	MCombined Arms Support Task Force Evaluation Model .	1
AFIT	Air Force Institute of Technology	1
CA	Combat Assessment	2
MEA	Munitions Effectiveness Assessment	2
M-kill	mobility kill	4
F-kill	firepower kill	4
C-kill	communications kill	4
S-kill	sensor kill	4
K-kill	catastrophic kill	4
ND	no damage	5
AMSAA	Army Material Systems Analysis Activity	5
PGM	precision guided munitions	9
SME	Subject Matter Expert	11
PH	Probability of Hit	12
РК	Probability of Kill	12
APC	armored personnel carrier	12
CID	Combat Identification	12
DVO	Direct View Optics	12
TV	television	12
IR	Infrared	12

## Abbreviation

COMBIC	Combined Obscuration Model for Battlefield Induced Con-	
tam	inates	14
LOS	line of sight $\ldots$	14
FOR	field of regard	14
DTMC	Discrete Time Markov Chain	23
iid	independently and identically distributed	44
CLT	Central Limit Theorem	45

# Page

# BDA ENHANCEMENT METHODOLOGY USING

## SITUATIONAL PARAMETER ADJUSTMENTS

### I. Introduction

#### 1.1 Background

The research presented in this thesis is sponsored by the Training and Doctrine Command (TRADOC) Analysis Center (TRAC). TRAC performs analysis to help shape the future of the Army and Department of Defense (DoD) over a five to fifteen year horizon, focusing on such areas as analysis of alternatives, organization and operations, and modeling and simulation (M&S) development and maintenance. During an analysis of alternatives, TRAC found their representation of battle damage assessment (BDA) in force-on-force models inadequate and set to initiate a BDA Project. The primary goal of the TRAC BDA project is to effectively represent the BDA process in combat models. TRAC is also responsible for the Army's main force-on-force model, the Combined Arms Support Task Force Evaluation Model (CASTFOREM), and wished to improve it by employing the Air Force Institute of Technology (AFIT) to develop a new BDA methodology. The goal of this research is to provide a flexible methodology which TRAC can implement not only in CASTFOREM, but also other models such as CombatXXI, the future replacement for CASTFOREM.

This chapter will present an introduction to BDA concepts followed by a discussion of how CASTFOREM models BDA currently. Subsequently, the problem at hand will be formulated and scoped for this research.

#### 1.2 BDA Concepts

Most of the current military doctrine regards BDA as an air-centric warfare component. However, this research specifically deals with BDA using ground weapon systems in real time (i.e. during an engagement). Accordingly, much of the doctrine applies to the problem at hand only in a broad sense. The DoD defines BDA as

The timely and accurate estimate of damage resulting from the application of military force, either lethal or nonlethal, against a predetermined objective. Battle damage assessment can be applied to the employment of all types of weapon systems (air, ground, naval, and special forces weapon systems) throughout the range of military operations... [12]

BDA is part of the combat assessment (CA) process which is, in turn, part of the joint targeting cycle shown in figure 1.1. BDA, munitions effectiveness assessment

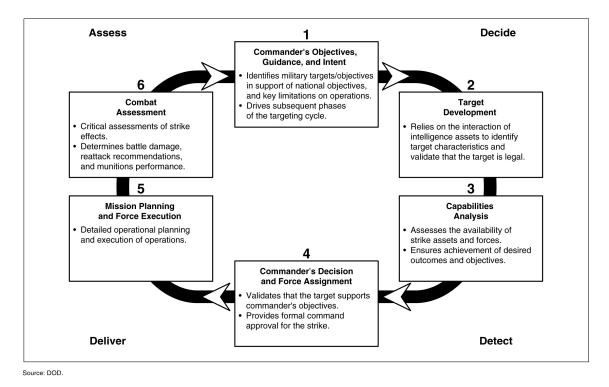


Figure 1.1: Joint Targeting Cycle [3]

(MEA), and future target nominations or re-attack recommendations make up CA. BDA occurs in three phases; physical damage assessment (Phase I), functional damage assessment (Phase II), and target system assessment (phase III). Each phase extends the information from the last phase, to make a further determination of battle damage and its effects. The DoD [12] defines the three phases of BDA as follows:

- Phase I Physical Damage Assessment An estimation of the quantitative extent of physical damage (through the application of military force) to a target element, based on observed or interpreted damage.
- **Phase II Functional Damage Assessment** A continuation of phase I assessments. The estimate of the effect physical damage has on a target's functional or operational capability.
- **Phase III Target System Assessment** An aggregation of phase II effects resulting in a judgement of theater-wide weapons system capabilities and a determination of the enemy's ability to wage war.

The focus of this study is on Phase I and II BDA.

1.2.1 Kill Types. The Joint Munitions Effectiveness Manual (JMEM) defines a list of 45 kill types in combat operations. A list of some possible kill states is presented in Table 1.1.

Aircraft Control kill	Personnel kill
Catastrophic kill (K-kill)	Phase kill
Catastrophic on Ground kill (COG-kill)	Power Supply kill
Communications kill	Prevent Launch kill (PL-kill)
Data Processing kill	Prevent Mission kill (PM-kill)
Expedient Interdiction kill	Prevent Takeoff kill (PTO-kill)
Firepower kill (F-kill)	Short Range Surto-Air Firepower kill
Incapacitation kill	Structural kill
Long Range Surto-Air Firepower kill	Support Functions kill
Mission Control kill	Surface-to-Air Firepower kill
Mission kill (MSN-kill)	Thorough Interdiction kill
Mobility kill (M-kill)	Time Out-of-Action kill(TOA-kill)

Table 1.1: JMEM Kill Types

Many of these kill types are not independent or exclusive of one another (i.e. a target may have more than one kill type at a time). Further, some kill types do not apply to Army (land) engagements or cannot be ascertained visually. Most importantly, however, CASTFOREM only models a subset of these kill types and, as such, will scope the consideration of the research.

CASTFOREM models the following kill types:

- Mobility kill (M-kill) A target is subject to an M-kill if it is incapable of executing controlled movement and the damage is not repairable by the crew on the battlefield. Failure to function may be caused by the incapacitation of the crew or damage to propulsion or control equipment.
- **Firepower kill** (F-kill) A target is subject to an F-kill if it is incapable of delivering controlled fire from the main armament and the damage is not repairable by the crew on the battlefield. The loss of this function may be caused by the incapacitation of the crew or damage to the main armament and its associated equipment.
- **Communications kill** (C-kill) A target is subject to a C-kill if it is incapable of sustained communications with other battlefield entities and the damage is not repairable by the crew on the battlefield. The loss of this function may be cause by crew incapacitation or damage to communications equipment. A Ckill cannot be easily perceived visually and as such will not be considered in this research.
- Sensor kill (S-kill) A target is subject to an S-kill if it is incapable of using its sensors, offensive or defensive, and the damage is not repairable by the crew on the battlefield. The loss of this function may be caused by crew incapacitation or damage to sensors themselves. An S-kill cannot be easily perceived visually and as such will not be considered in this research.
- **Catastrophic kill** (K-kill) A target is subject to a K-kill if it sustains both an Mand F-kill and is damaged to the extent that is not economically repairable. A K-kill is more likely to be apparent to the crew of a weapon system because of the resulting fires/detonation of ammunition.

No-kill If the target has not sustained any kill type and is capable of performing all combat functions it is referred to as No-kill. This is most often referred to as *No Damage* (ND) in CASTFOREM.

Any combination of M-, F-, C-, or S-kills are possible while K-kill and No-kill are singular states. For example, a target can sustain an MF-kill (i.e. the target has mobility and firepower kills only), but cannot have a MK-kill. For the purposes of this research kill type will be referred to as *kill state*.

The Army Material Systems Analysis Activity (AMSAA) provides the data required to derive mutually exclusive probabilities for all feasible combinations of kill types used in the simulation. It is important to note that CASTFOREM does not distinguish between reasons for a kill. For example a vehicle might sustain an M-kill because its tracks are displaced, the engine was damaged, or the soldier driving was killed, but CASTFOREM only knows that the vehicle has an M-kill.

#### 1.3 AMSAA Heuristic

CASTFOREM currently uses a heuristic developed by AMSAA to model BDA. The heuristic is based on the perception of the soldier in combat and is shown in Figure 1.2 on the following page.

The heuristic begins with the firer performing the first shot and an initial evaluation of the target state as K-killed or not K-killed. It assumes that the observer can perceive a K-kill with probability 1. As a result, if at any point in the heuristic the target is assessed as a K-kill, the engagement simulation ends. The firer evaluates non-K-kill targets again with a 0.33 probability of detecting the correct level of damage and 0.67 probability of having *unknown* damage. A second shot is performed and assessed in the same manner with probability of correct detection increased to 0.67. The heuristic ends after three shots where non-K-killed targets are evaluated accurately with probability 1.

The AMSAA heuristic contains several inadequacies that need to be addressed.

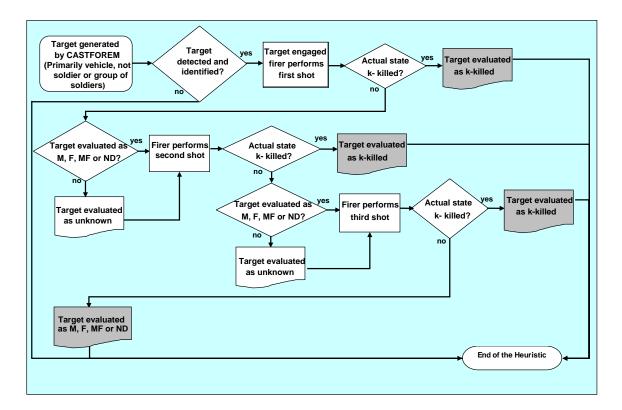


Figure 1.2: Current AMSAA Heuristic

- Assuming that a K-kill is perceived with probability 1, intuitively, does not make sense. Though a K-kill is the easiest kill state to see visually, having no error in this determination trivializes the difficulty of BDA during live combat.
- 2. The assignment of probabilities to detection of the correct kill level (less than K-) as 0.33, 0.67, and 1 for each successive shot, respectively, is rather arbitrary. Realistically, there is no guarantee of detecting the correct kill state after some number of shots.
- 3. The algorithm does not take the firer's perception of the targets actions into account. Situational factors, such as the target's movement or if it is engaging friendly forces, will obviously affect the assignment of a kill state to an enemy target.
- 4. No probabilities are associated with assessing the target to specific kill types (e.g. M, F, MF, K, etc.). Further, an assessment as *unknown* results in the

same action (another shot) as assessing the target as less-than-K. Consequently having an *unknown* assessment may be unnecessary.

- 5. The heuristic lacks any representation of indirect fire, including mortar, missile, or air attacks.
- 6. Environmental factors such as weather, time of day, range, sensor, terrain, and obscurants are not taken into account. Clearly, these factors would affect or degrade the firers ability to make an accurate assessment.

#### 1.4 Research Objectives

The objectives of this research are as follows:

- 1. Develop a methodology to model the BDA process from a perception standpoint that addresses the inadequacies of the current heuristic.
- 2. Develop an efficient SMEs survey instrument that will produce the form of data needed for the proposed methodology and give TRAC an initial situational BDA data set.
- 3. Propose a technique to implement the methodology into a combat model.

#### 1.5 Method of Approach

For the purposes of CASTFOREM, this research focuses on the collection and processing of BDA information during an ongoing engagement. The typical situation involves a dismounted soldier or gunner and his decision to fire again based on sensory and environmental information. The main goal is to develop a mathematical model which can be implemented in CASTFOREM that accurately represents the real time BDA process. It will focus on the firer's perception of the battlefield scenario and his assignment of a kill state based on the information available. To accomplish this, a set of event trees will be built to characterize the possible situations that could occur on the battlefield. Situations (i.e. end nodes of the trees) will then form a set of *parameters* that will frame questionnaires for subject matter experts. The responses will yield an initial data set subsequently used to develop probability distributions for kill types conditioned on the situational parameters.

Since the model will be from the firer's perspective, the kill types that CAST-FOREM models must be reduced to those that can be perceived visually. C-kill and S-kill will not enter consideration in the model because no tractable method exists to visually asses these kill types on the battlefield. This leaves four basic kill types (Mkill, F-kill, K-kill, and ND) and one kill combination (MF-kill). The model will assign probabilities of assessing a target as each of these kill types, based on the scenario facing the firer.

#### 1.6 Organization

This thesis is divided into five chapters. Chapter I presented the research topic, the background behind it, and its motivation. Further, CASTFOREMs current method for modeling BDA and its limitations were discussed and a brief overview of the new approach was discussed.

Chapter II will review the relevant literature on BDA and combat modeling as well as present an overview of the CASTFOREM engagement process. Chapter III details the methodology used for data collection, develops the mathematical foundations for the proposed BDA model, and suggests an strategy for implementation into a combat-simulation model. Chapter IV provides a statistical evaluation of the methodology using survey data. Lastly, Chapter V presents the conclusions and recommendations of this work and suggests future research in this area.

### II. Literature Review

#### 2.1 Introduction

Modeling BDA explicitly in combat models is a relatively young concept. By excluding the BDA process from combat simulations, enemy battle damage was treated as a known quantity. Of course, the BDA process contains a great deal of uncertainty and can heavily influence the flow of an engagement. The effects of the BDA process on a military conflict are significant, and in the arena of close combat the process is both gravely important and largely uncertain. In the heat of battle, BDA is dynamic and the wrong determination may lead to a unit's demise.

While little has been done to explain the BDA process in general, even less exists to describe the intricacies of close combat. Most of the literature addresses the effects of timeliness and accuracy of BDA on an air campaign and its respective targeting process. Though the BDA process for air operations is widely different in time frame (e.g. assessments are generally made after a mission) it shares a similar uncertain nature with close combat situations. This chapter surveys the relevant BDA issues (e.g. information gain, uncertainty) as well as the methodologies proposed to model it in combat simulation models. Further the CASTFOREM methodologies related to engagement and BDA are reviewed.

#### 2.2 BDA Information

The value of BDA information in combat situations has expanded greatly since Operation Desert Storm in the early 1990's. The increased tempo of operations in a new era of warfare along with the increasing use of precision guided munitions (PGMs) make BDA information critical to the efficient application of forces. Yost and Washburn [21] expound on this concept in relation to allocating assets on the modern battlefield.

Baird et al. [1] researched the value of information gain on the battlefield. Their work included a study of how accuracy, timeliness, and completeness of information, including BDA, target type, and target location, affected the number of munitions expended in a simulation. A regression model approach showed intuitive results; the largest gain in effectiveness was obtained from the interaction of high accuracy and more timely data.

Manor and Kress [15] present an algorithm for engaging targets with incomplete BDA information. The results show that engaging the targets using a greedy strategy (i.e. shooting at the least prior engaged target) maximizes the effectiveness per round. Though the greedy approach maximizes this objective, success in actual combat does not depend on effectiveness per round. This differs from the current Army modeling technique by re-targeting after each shot and reflects the differing goals of the models.

Song [17] also investigated the value of BDA information to make ballistic missile defense systems more effective. Though the model dealt with missile defense, it stressed the importance of BDA information for decision making in a time-critical environment, a similar situation to close combat. Additionally, Song notes the role of information in dealing with the uncertainty of a cognisant enemy.

#### 2.3 Information and Uncertainty

The method proposed in this thesis models BDA from a perceptional standpoint in order to capture uncertainty in the process. The uncertainty involved in the BDA process has been stated extensively in outlining the shortcomings of conflicts in recent years [18]. This uncertainty stems not only from the adversary, but also from friendly force miscues. The amount of communications and integration required among coalition forces to execute effective BDA makes the process extremely complex and prone to error, leading to missed (or assumed dead) targets and over-killed targets [18].

Modeling the BDA process is essentially an exercise in modeling perceived information and uncertainty. As such, the method proposed for this research relies on the link between information theory and the human thought process. Jaynes [9] connects human reasoning to Laplace's model of common sense, and in turn, to the concepts of maximum entropy and Bayesian inference. Jaynes [7] [14] [8] has also completed extensive work on maximum entropy as well as its connections to Bayes theorem [10].

Jelinek [11] used Markov chains to model uncertainty in combat operations. BDA is a function of perceived information and its uncertainty. Gaver et al. [6] dealt with the incorporation of uncertainty in perception information into combat models. Combat perceptions were modeled stochastically to capture the inherent uncertainty in combat information.

#### 2.4 BDA Modeling Concepts

Several tchniques for modeling BDA have been developed in recent years, though none specifically for combat simulation models. Franzen [2] created a BDA model for air campaign targeteers based on a Bayesian belief network. The Bayseian net incorporated the addition of information into the BDA process after a target is struck. Subject matter experts (SMEs) estimated initial conditional probabilities, which were updated using the data learning property of Bayesian nets. Though this method is centered around air operations, it offers some parallels to the proposed method in using Bayesian techniques to determine probabilities of damage.

Gaver and Jacobs [4] developed a Shoot-Look-Shoot approach to engaging targets and a simple formulation of the BDA problem. The formulation treated targets simply as alive or dead and gave conditional probability distributions of perceiving the correct state given the ground truth. Tradeoffs between probability of kill  $(p_k)$ and BDA information accuracy were investigated for several tactics including Shoot-Look-Shoot and deterministically shooting two shots. In a piggyback effort, Gaver and Jacobs [5] showed the effects of BDA accuracy in the Shoot-Look-Shoot construct on a service queue of possible targets. This iterative process of engaging a target closely resembles the algorithm used in current Army combat models. Though the BDA problem formulation is simplistic (i.e. targets are either alive or dead), it stands as a good example of a probabilistic modeling technique for the BDA process. The BDA modeling technique proposed in this research uses Markov chains to capture uncertainty in what might happen after firing at a target and Bayesian inference to link perceived information about the target to some probability distribution of kill states. This method will be implemented within the construct of CASTFOREM and as such warrants a brief overview of the pertinent modules within the model.

#### 2.5 CASTFOREM

CASTFOREM is the Army's current force-on-force model intended to simulate conflicts of 60 minutes or less. Conflicts take place between two main forces, *Blue* (friendly), and *Red* (enemy) respectively. It is an agent-based model comprised of organizational entities independently interacting according to their logic set (i.e. intelligence), comprised of orders and decision tables. The model executes interactions at the weapon system level and can simulate complex systems such as communications and logistics networks. Furthermore, CASTFOREM can operate at several levels of fidelity depending on the size of individual unit modeled (e.g. single soldier vs. weapon system with a crew).

During a conflict, entities within the simulation interact in many different ways according to their logic set. The BDA process in CASTFOREM is interdependent with most of these modules, but relies heavily upon only a select few: target search and acquisition, probability of hit (PH) calculations, probability of kill (PK) calculations, and the response algorithms for both firer and target (i.e. the engagement).

2.5.1 Target Search and Acquisition. In order for a blue entity, such as an armored personnel carrier (APC), to engage a target, it must first create a list of targets by searching the battle space. A general flow chart of the search process is given in Figure 2.1 on the next page.

The simulation provides target detection and combat identification (CID) using direct view optics (DVO), image intensifiers, television (TV), and infrared (IR)

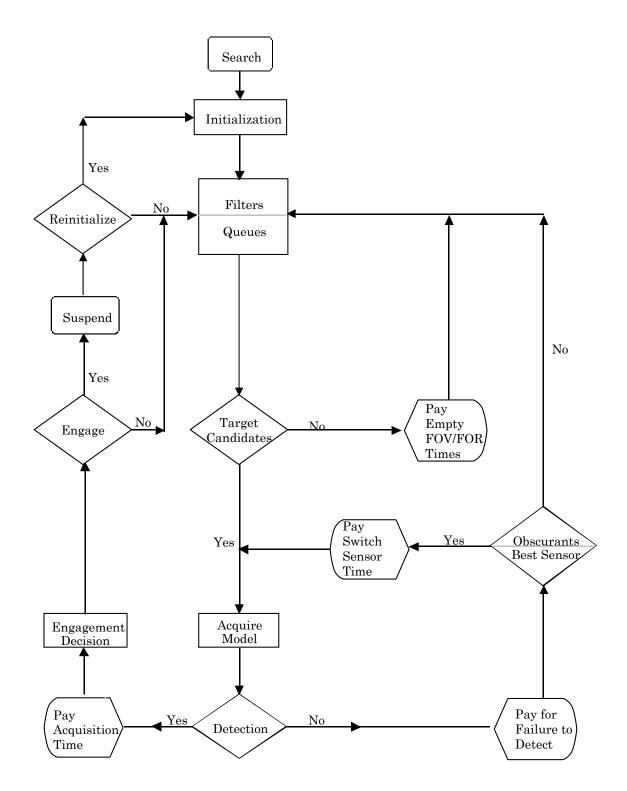


Figure 2.1: Flow Chart of Search Logic [19]

sensors. CASTFOREM handles this search process and CID though the ACQUIRE model.

The ACQUIRE model simulates the physics involved in entities viewing a target. It uses several mathematical models to determine how visible a target is to an observer, taking into account current atmospheric, environmental, and physical conditions. Atmospheric conditions might include weather (e.g. day/night, cloud cover, humidity) or dust and smoke. These conditions are accounted for in the Combined Obscuration Model for Battlefield Induced Contaminates (COMBIC). The environmental conditions represent such things as line of sight (LOS), range to the target, and the nature of the tactical area (forest, desert, urban, etc). Lastly, the observer's field of regard, sensor type, target type, and movement (both observer and target) characterize physical conditions. ACQIURE combines the effects of atmospheric, environmental, and physical conditions on CID of a target and makes a determination.

The ACQUIRE model provides an output at one of four levels for target acquisition. The levels are defined in [19] as:

**Detection** A target of military interest has been acquired.

- **Classification** A type of target (e.g. wheeled, tracked, stationary) has been detected and an *aimpoint* can be determined on the detected target.
- **Recognition** The target class (e.g. tank versus APC) can be resolved on the detected target.
- ID Call The observer thinks he has sufficient resolution on the detected target to make an identification, which may or may not be correct (e.g. T-72 tank, M2A3 Bradley).

The entity keeps a list of target candidates and their respective acquisition levels within its field of regard (FOR) at any one time. This list is rank ordered, based on several parameters including proximity, target contrast, and threat. An entity will choose the most logical target for engagement and proceed according to its logic set. It is important to note that an engagement may occur at any of the acquisition levels due to knowledge of which force (Blue or Red) controls the area where the target was detected.

2.5.2 PH/PK Calculation. When shots are exchanged between entities, CASTFOREM must first determine if the target was hit (i.e. PH). If the round impacts the target the model must subsequently determine the appropriate level of damage (i.e. PK). CASTFOREM handles PH and PK in different ways depending on the type of entity involved. A vehicle and its crew are assessed as one in that kills may result from either damage to the vehicle or an injury to its operator. Mounted personnel (i.e. on a vehicle) share PH calculations with their vehicle but assess PK independently. Based on the level of detail in a particular model run, dismounted personnel may be treated as aggregated or individually.

CASTFOREM represents a vehicle as two cell approximations of its turret and hull as depicted in Figure 2.2.  $S_1$  through  $S_4$  are examples of impact points determined

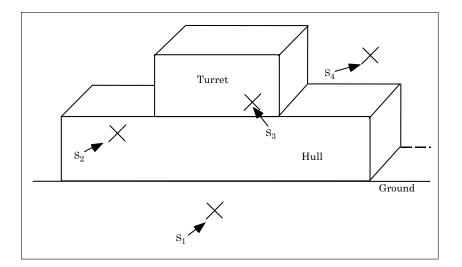


Figure 2.2: Two Cell Approximation of CASTFOREM Unit [19]

using the vehicle silhouette, an aimpoint bias, and round dispersion. Impact points  $S_1$  and  $S_4$  are misses,  $S_2$  is a hull hit, and  $S_3$  is a turret hit.

A vehicle's silhouette is simply the two dimensional projection of the vehicle from a side view, taking cover into account. Generally, the center of mass for the silhouette is the unbiased aimpoint for a particular shot. CASTFOREM biases the aimpoint for the round and then models round dispersion as a bivariate normal distribution, centered on the new biased point. AMSAA provides data for weapon system aimpoint biases and munition specific dispersion information. Figure 2.3 displays an example of this system. So, each round is a draw from its specific bivariate normal

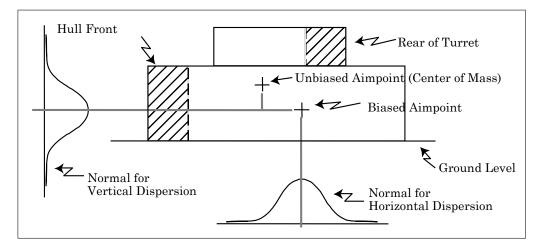


Figure 2.3: Silhouette, Aimpoint Bias, and Dispersion [19]

distribution and hits are recorded for those draws that land on the target silhouette.

After determining that a particular round hits its target, damage must be assigned to the entity through PK calculations. The impact assessment assigns damage to several target systems and evaluates the effects on the targets' combat capabilities. Targets that lose one or more capabilities due to damage will have kill types associated with them. Damage here should be thought of as *Ground Truth* rather than BDA perceptions.

PK determinations are handled in two different ways for dismounted personnel. Determining PK data for aggregated dismounted personnel is a function of the size of the unit, round type, range from the impact, and their tactical posture at the time of the round impact. CASTFOREM can also perform attrition of personnel as individual entities. For this resolution, dismounted soldiers are physically represented as sets of cylinders, depicted in Figure 2.4 and Figure 2.5 on the next page.

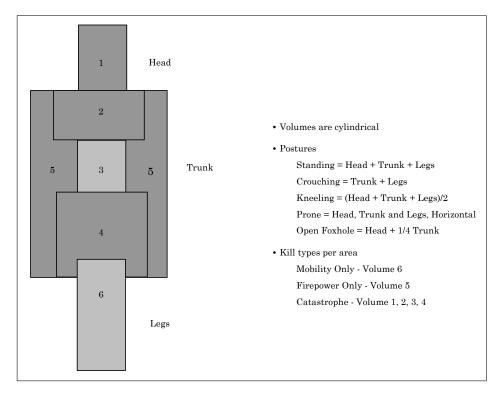


Figure 2.4: Dismounted Soldier Representation (Side View) [19]

If a soldier is hit, the damage depends on exactly where and how the round passes through the *body*. For example, a shot to the trunk may cause a K-kill while a shot in the legs might result in a M-kill. How much of the body is hit (e.g. center of mass vs. graze) also affects how damage is assigned. CASTFOREM uses an incapacitation kill to address the situation where soldiers can perform for a limited time after receiving wounds. Soldiers are allowed combat functionality for one of four time periods before being removed from the simulation: 5 seconds, 30 seconds, 5 minutes, or 30 minutes (depending on the severity of the wounds). In essence, the less body mass a round passes through, the more incapacitation time is given to the soldier.

2.5.3 Firer/Target Response Algorithms. An engagement in CASTFOREM consists of one entity firing a sequence of rounds at an enemy entity. Within each

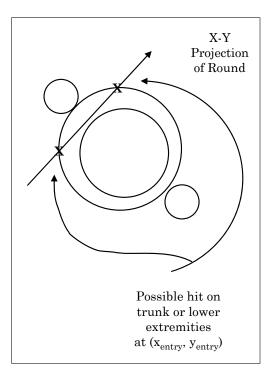


Figure 2.5: Dismounted Soldier Representation (Top View) [19]

engagement, the firer and target have response algorithms to complete the interactions after PH and PK calculations are complete.

The target, upon receiving impact damage as described above, is given the chance to respond to taking fire, unless the target sustained a K-kill. The target uses its response-to-fire decision tables to simulate a response which may include suppressed combat effectiveness. Additionally, other actions may be taken, such as moving, covering, retreating, or a number of other actions.

The firer, after impact of its round, first attempts to perceive the level of damage inflicted on the target. This is where the BDA algorithm is performed. If the desired level of damage is perceived, the firer uses its end-of-engagement decision tables to determine the entity's next action. The next action might consist of engaging another target within the FOR, moving to a collection point, or communicating with command entities. Figure 2.6 on the following page shows an example flow chart of the end-ofengagement logic flow.

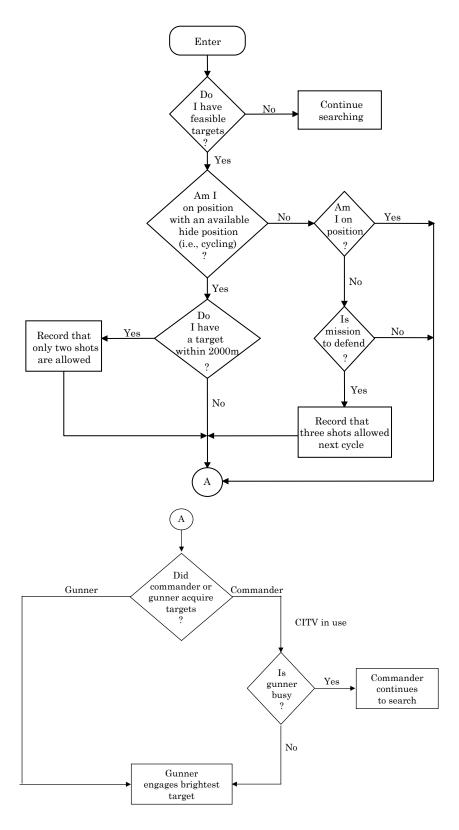


Figure 2.6: Tank Engage Complete Logic Flow [19]

If the desired level of damage is not perceived, the firer may take another shot to achieve its goal, if it is allowed. CASTFOREM allows only up to three shots in succession in any one engagement due to a modeling decision. The model wishes to prevent firing too many rounds at one single target, and therefore expending the available ammunition on a small set of targets.

#### 2.6 conclusion

In this chapter, a brief overview of the concepts related to the BDA process was provided. This research will be the most detailed representation of real time BDA in close combat to date. As a result, the literature is not well established in this area. First, a review of BDA as an information currency was explored. Then, precedents for using information theory and modeling uncertainty as a stochastic process were presented. Additionally, several former techniques for modeling BDA were stated. Lastly, the relevant CASTFOREM engagement methodologies were described in detail.

### III. Methodology

#### 3.1 Introduction

The BDA process has found much difficulty in accurately translating its complexities into a model. As a result, the process has been modeled poorly or completely left out of most combat models. In the following sections, a methodology to effectively model the BDA process will be mapped out from data collection to implementation.

This chapter first presents a method to collect the appropriate data. Second, a methodology for modeling the BDA process as a Markov Process is presented. Then, a method for updating the process based on observed conditions using Bayesian inference is shown. Subsequently, the application and integration of the methodology to the combat model are proposed. Finally, example calculations are completed to illustrate the method.

#### 3.2 Data Collection

Since no precedent exists for real time BDA in combat simulation models, development of an adequate initial data set is needed. To develop an accurate representation of the BDA process, data needs to be from the firer's, (i.e. soldier's) perception. Since the scope of this project is mostly vehicles engaging other vehicles (i.e. tanks, APCs, trucks, etc.), a set of event trees was developed to fully represent the possible actions and physical damage. These trees served to frame a set of survey questions for subject matter experts (SMEs).

3.2.1 Survey Participants. To develop the appropriate data, it is important to survey veterans of live combat as SMEs. The SMEs should include a collection of Army combat veterans from various career fields. The SMEs combat experience is extremely important to understanding the thought process of a shooter (i.e. someone on the trigger) while engaging a target, performing BDA, and subsequently deciding to fire again. Further, their experience in viewing targets having various levels of damage will be integral to collecting the pertinent data. 3.2.2 Survey Design. The SMEs will provide qualitative predictions for actions and visible damage after targets take fire. Before detailing the proposed survey questions and perspective responses, several terms referred to in this section must be defined.

- **Event** More specifically called an *Elementary Event*, it is the particular action or level the target being assessed presents; essentially analogous to an outcome of a chance event.
- **Event Set** A set of mutually exclusive and collectively exhaustive events a target can assume (e.g. Engaging, Not Engaging).
- Situation The particular combination or intersection of events that a target possesses at the time of an assessment.
- Kill State Referred to by DoD as Kill Type, it is the type of kill (ND, M, F, MF, or K) assigned to the target during an assessment. The kill types are both mutually exclusive and collectively exhaustive.

It is important to note, that the form of data collected in survey responses reflects the modeling technique presented in this research. Different methodologies would require different survey structures. In that light, this survey was designed specifically to obtain the data relevant to modeling the BDA process as a Markov chain with Bayesian updates.

Survey participants will be asked to assign qualitative values to several events given a situation which included the target type and its respective kill state. Figure 3.1 on the next page shows an example of a response table (for a tank) that the SME would complete.

Movement, Engaging Targets, Activity, Turret, Hull, and Tracks are all event sets. Movement, Engaging Targets, and Activity refer to observations of the target's tactical responses. The Turret, Hull, and Tracks event sets measure the (visible) physical damage on each component of the tank. The event sets respective events

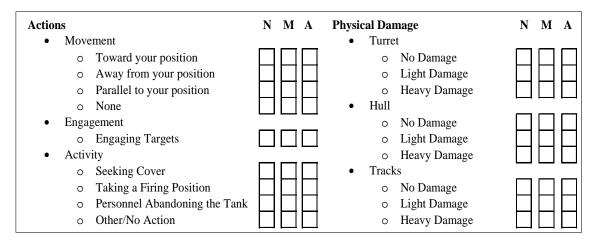


Figure 3.1: Sample Response Table

(e.g. No Damage, Light Damage, or Heavy Damage for Turret) are mutually exclusive and collectively exhaustive, meaning only one of the events in each set may happen to the target at any time.

Within each of the event sets, the SME is required to mark the events with one of three qualitative assessments: events the soldier would never see (N column), ones he might see (M column), or those he would always see (A column).

Response tables differed according to the enemy vehicle type tailored to the appropriate vehicle components. The survey also provided schematic diagrams of the enemy vehicles for soldiers to illustrate specific points of interest and space to add important events or event sets that were excluded from the response tables. A copy of the questionnaire is provided for the reader in appendix A.

#### 3.3 Modeling the BDA Process as a Markov Chain

A system changing randomly over time can be represented as a sequence of random variables,  $X = \{X_n, n \ge 0\}$ , where  $X_n$  denotes the state of the system at time n. If, for all n,  $X_n$  must exist in the finite set,  $S = \{1, 2, ..., m\}$ ,  $\{X_n, n \ge 0\}$ is called a time series stochastic process with state space S. This process can further be modeled as a Discrete Time Markov Chain (DTMC) if it satisfies the following conditions.

- 1. For all  $n \ge 0$ ,  $X_n = i_n \in S$  with probability 1. That is, the system must exist in one of its states (kill types) at all times.
- 2. For all  $n \ge 0$ ,  $X_{n+1} = i_{n+1}, X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_0 = i_0 \in S$ ,

$$P\{X_{n+1} = j | X_n = i_n, X_{n-1} = i_{n-1}, \dots, X_0 = i_0\} = P\{X_{n+1} = j | X_n = i_n\}$$

That is, the probability of a state at time (n + 1) depends only on the  $n^{th}$  state. This is known as the Markovian property.

Further, the DTMC  $\{X_n, n \ge 0\}$  is time homogeneous if the conditional probabilities,  $P\{X_{n+1} = j | X_n = i\}$  do not depend on n. This time homogeneity can be expressed mathematically as

$$p_{ij}(n) = p_{ij} \quad \forall \quad n \ge 0 \quad i, j \in S$$

where  $p_{ij}$  represents  $P\{X_{n+1} = j | X_n = i\}$ . Now, let  $\mathbf{P} = [p_{ij}]$  denote the one step transition probability matrix for the DTMC  $\{X_n, n \ge 0\}$ . For the case where  $S = \{1, 2, ..., m\}$ ,  $\mathbf{P}$  can be represented as

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1,m-1} & p_{1m} \\ p_{21} & p_{22} & p_{2,m-1} & p_{2m} \\ \vdots & & \ddots & & \vdots \\ p_{m-1,1} & p_{m-1,2} & p_{m-1,m-1} & p_{m-1,m} \\ p_{m1} & p_{m2} & \dots & p_{m,m-1} & p_{mm} \end{bmatrix}$$

for which

$$\sum_{j \in S} p_{ij} = 1 \quad \forall \quad i \in S.$$

This means that, since  $\{X_n, n \ge 0\}$  is a DTMC, P is, by definition, stochastic. Modeling the BDA process as a DTMC gives the advantage of using transient analysis to determine shot dependent probability distributions for each assessment. 3.3.1 Transient Analysis of a DTMC. In order to perform transient analysis, the DTMC must be fully characterized with  $\mathbf{P}$  and an initial distribution for  $X_0$ . Let  $\mathbf{a}^{(0)}$  be defined as

$$\mathbf{a}^{(0)} = (a_i^{(0)}) \quad \forall \quad i \in S.$$

That is,  $\mathbf{a}^{(0)}$  represents a row vector of the initial distribution (pmf) of  $X_0$ . Now, with **P** and  $\mathbf{a}^{(0)}$ , the distribution of  $X_n$  at any time *n* can be calculated. First, let

$$a_j^{(n)} = p\{X_n = j\} = \sum_{i \in S} P\{X_n = j | X_0 = i\} P\{X_0 = i\} \quad \forall \quad j \in S$$
(3.1)

be the probability of  $\{X_n, n \ge 0\}$  existing in state j at time n which can be represented in vector form by  $\mathbf{a}^{(n)}$ . Further, let

$$p_{ij}^{(n)} = P\{X_n = j | X_0 = i\} \quad i, j \in S$$

denote the *n* step transition probability from *i* to *j*. Recall that **P** is the one step transition probability matrix. If **P**<sup>2</sup> represents the two step transition matrix, it follows that the case for some *n* steps is

$$\mathbf{P}^{(n)} = [p_{ij}^{(n)}]$$
$$= \mathbf{P}^n.$$

So it follows from Equation 3.1 that

$$\mathbf{a}^{(n)} = \mathbf{a}^{(0)} \mathbf{P}^{(n)}. \tag{3.2}$$

The transient analysis is not limited to conditioning on the initial distribution. The distribution  $\mathbf{a}^{(n)}$  is easily calculated from the distribution at any intermediate time k. The result is an analogue of Equation (3.2).

$$\mathbf{a}^{(n)} = \mathbf{a}^{(k)} \mathbf{P}^{(n-k)}.$$
(3.3)

For a more rigorous demonstration of transient analysis of a DTMC, the reader is directed to [13].

3.3.2 Representation of The BDA Process. Now, this research aims to model the BDA process as a DTMC,  $\{X_n, n \ge 0\}$  where  $X_n$  denotes the assessment after the  $n^{th}$  shot, with state space  $S = \{$  ND,M,F,MF,K $\}$  (i.e. the set of kill states). To determine **P** for this process, consider that only certain state transitions (*is* to *js*) are feasible in reality.

From a ground truth standpoint, assume that within a single engagement (made up of one or more consecutive shots), the target cannot regress in damage due to actions such as repairs. This is a reasonable assumption because major system repairs will not occur (or at least are highly unlikely) in the heat of a battle. This assumption means that once a target sustains one type of kill, the target must have at least that kill state in the next shot iteration. To illustrate, let  $X_n$  be the true state of the target after  $n^{th}$  shot. A target cannot transition from  $X_1 = M$  kill state to  $X_2 = F$ kill state, because  $X_n = F$ -kill implies that the target is F-killed only, and thus could not have transitioned from M-kill at n - 1. If the target sustained F-kill damage at n = 2 it would instead transition to  $X_2 = MF$  kill state to include the M-kill from  $X_1$ . As a result, a target may only transition to a subset of the possible kill states on a second shot from any given kill state on a first shot. For instance, if a target sustains an F-kill on the first shot (n = 1) it may only transition into F-, MF-, or K-kill states after a second shot (n = 2). Table 3.1 shows the possible transitions from each kill state.

 Table 3.1:
 Possible Kill State Transitions

Kill State $(X_n = i)$	Feasible Kill State Transitions $(X_{n+1} = j)$
ND	ND, M, F, MF, K
М	M, MF, K
F	F, MF, K
MF	MF, K
K	К

With no knowledge of what may result from an additional shot on a target, assigning equal probabilities to each feasible transition is justified by the principle of maximum entropy within information theory.

Information entropy was developed by Shannon, who used it as a way to measure the amount of uncertainty in the outcome of a chance event. The entropy, denoted by H, of a random variable X is a function of the set of probabilities,  $p_1, p_2, \ldots, p_r$ , corresponding to the r possible states X can take on. H is stated mathematically in [16] as

$$H = -K \sum_{i=1}^{r} p_i \log p_i$$

where K is a positive constant and  $\log(*)$  is any logarithmic function. H can take on many forms depending on the definition of K to scale entropy and give it a unit of measure. Thus, entropy can be stated without dimensions as  $H = -\sum p_i \log p_i$ . One significant property of Shannon's entropy is that entropy is maximized when a probability distribution is uniform.

Information entropy parallels thermodynamic entropy, where it denotes the amount of randomness in a system. Jaynes [7] proposed that thermodynamics demonstrated only an instance of information theory and entropy. Thus, the principle of maximum entropy was extended from thermodynamics as a mathematical basis for Laplace's principle of insufficient reason. The principle of maximum entropy states that the least biased model is the one that maximizes entropy (uncertainty) while remaining consistent with the prior information.

Now, consider maximizing entropy for the discrete probability distribution above  $(p_1, p_2, \ldots, p_r)$ . Mathematically this problem is stated as

$$\max f(p_1, p_2, \dots, p_r) = -\sum_{k=1}^r p_k \ln p_k$$
  
s.t.  $\sum_{k=1}^r p_k = 1.$  (3.4)

This maximization can be solved by the method of Lagrange multipliers.

$$\frac{\partial}{\partial p_k} (f + \lambda g) = 0$$

$$\frac{\partial}{\partial p_k} \left[ -\sum_{k=1}^r p_k \ln p_k + \lambda \left( \sum_{k=1}^r p_k - 1 \right) \right] = 0$$

$$-(\ln p_k + 1) + \lambda = 0$$

$$p_k = e^{\lambda + 1}$$
(3.5)

Since Equation (3.5) depends only on  $\lambda$ , each  $p_k$  is equal. Consequently, because of the constraint in Equation (3.4),  $p_k = 1/r$ , proving that a uniform distribution maximizes entropy when no prior information is available.

Now by adding prior information, such as the feasible transitions in Table 3.1 on page 26, the distributions with maximum entropy are those that are uniform across these feasible transitions. As a result, the one step transition probability matrix is represented as

$$\mathbf{P} = \begin{array}{cccc} & \text{ND} & \text{M} & \text{F} & \text{MF} & \text{K} \\ & \text{ND} & & \begin{bmatrix} 1/_5 & 1/_5 & 1/_5 & 1/_5 \\ 0 & 1/_3 & 0 & 1/_3 & 1/_3 \\ 0 & 0 & 1/_3 & 1/_3 & 1/_3 \\ 0 & 0 & 0 & 1/_2 & 1/_2 \\ & \text{K} & \begin{bmatrix} 0 & 0 & 0 & 1/_2 & 1/_2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

which is stochastic and time homogeneous because  $\{X_n, n \ge 0\}$  is a DTMC. At the beginning of an engagement, the target is assumed to have kill state ND and as such

$$\mathbf{a}^{(0)} = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}.$$

With the DTMC fully characterized, any  $\mathbf{a}^{(n)}$  may be calculated by transient analysis.

# 3.4 Updating $a^{(n)}$ Using Bayesian Inference

Now suppose  $\mathbf{a}^{(n)}$  is conditioned on situational parameters. Using Bayesian Inference, an updated distribution vector,  $\mathbf{a}^{\prime(n)}$ , can be calculated using the information present at the time of the assessment.

Bayes Theorem can be developed easily, using the definition of conditional probability. In general

$$P\{A \cap B\} = P\{A|B\}P\{B\} = P\{B|A\}P\{A\}$$

Simple algebra yields Bayes Theorem.

$$P\{A|B\} = \frac{P\{B|A\}P\{A\}}{P\{B\}}$$

The Law of Total Probability states that for a set  $\{A_j : j = 1, 2, ...\}$  that are mutually exclusive and collectively exhaustive

$$P\{B\} = \sum_{j} P\{B|A_j\}P\{A_j\}.$$

Combining the Law of Total Probability with Bayes Theorem yields

$$P\{A_i|B\} = \frac{P\{B|A_i\}P\{A_i\}}{\sum_{J} P\{B|A_j\}P\{A_j\}}$$

producing the ability to compute the posterior probability  $P\{A_i|B\}$  for all  $i \in J$ .

For a more in depth review of Bayes' Theorem or the Law of Total Probability, the reader is directed to [20].

3.4.1 Calculation of the Updated Vector,  $\mathbf{a}^{(n)}$ . Let  $B_n$  denote that a particular situation (i.e. intersection of events) occurred for the  $n^{th}$  shot and  $\mathbf{a}^{(n)}$  denote the distribution of  $\{X_n|B_n\}$ . Now, the event sets for the  $n^{th}$  shot can be represented

Movement 
$$\equiv M_{nb}$$
  
Engagement  $\equiv E_{nb}$   
Activity  $\equiv A_{nb}$   
Turret  $\equiv T_{nb}$   
Hull  $\equiv H_{nb}$   
Tracks  $\equiv Tr_{nb}$ 

where  $M_{nb}$  denotes the occurrence of b within the Movement event set for shot n. For example, if a soldier perceives that a target that is moving after the first shot it is represented  $M_{1,Yes}$ . So

$$B_n = \{ M_{nb} \cap E_{nb} \cap A_{nb} \cap T_{nb} \cap H_{nb} \cap Tr_{nb} \}.$$

For the update  $P\{B_n\}$  must be calculated. There are several ways to deal with this intersection of events which will be discussed further. For now, assume that  $P\{B_n\}$ , or more specifically  $P\{B_n|X_n\}$ , can be calculated. So the calculation for some  $\mathbf{a'}^{(n)}$  is

$$\mathbf{a}^{\prime(n)} = \begin{bmatrix} P\{X_n = \text{ND}|B_n\} & \dots & P\{X_n = \text{K}|B_n\} \end{bmatrix}$$
$$= \begin{bmatrix} \frac{P\{B_n|X_n = \text{ND}\}P\{X_n = \text{ND}\}}{\sum\limits_{j \in E} P\{B_n|X_n = j\}P\{X_n = j\}} & \dots & \frac{P\{B_n|X_n = \text{K}\}P\{X_n = \text{K}\}}{\sum\limits_{j \in E} P\{B_n|X_n = j\}P\{X_n = j\}} \end{bmatrix}.$$
(3.6)

To develop  $\mathbf{a}^{\prime(n)}$ , the conditional event probabilities,  $P\{B_n|X_n = \text{ND}\}$ , must be obtained from the survey data.

3.4.2 The Calculation of  $P\{B_n\}$ . The calculation of  $P\{B_n\}$  is central to updating  $\mathbf{a}'^{(n)}$ , so the method used to calculate  $P\{B_n\}$  is of utmost importance. Making no assumptions, any intersection probability can be calculated by the chain

rule as

$$P\{A \cap B \cap C\} = P\{A|B \cap C\}P\{B|C\}P\{C\}.$$

Now,  $B_n$  is the intersection of six separate events so calculating  $P\{B_n\}$  with no assumptions makes the problem somewhat intractable. However, several types of assumptions could be made to ease the burden of calculating many conditional probabilities.

The most simplifying assumption would be to assume that each event set is independent of the others. This implies that the occurrence within the Movement event set does not affect the probabilities of events within Engagement, Turret, or any of the other event sets. As a result, the probability of a situation can be calculated

$$P\{B_n\} = P\{M_{nb}\}P\{E_{nb}\}P\{A_{nb}\}P\{T_{nb}\}P\{H_{nb}\}P\{Tr_{nb}\}$$
$$= \prod_{(*)\in B_n} P\{(*)_{nb}\}$$
(3.7)

where  $(*)_{nb}$  is each respective event occurrence in the situation  $B_n$ .

Realistically, the assumption of independence among all event sets does not make sense. The likelihood of certain actions will be affected by physical damage. For example, a soldier is more likely to perceive a target moving, given he perceived the tracks to have no damage. So to avoid extensive calculations, a set of assumptions will be made

- 1. Event sets pertaining to *Physical Damage* are independent of each other.
- 2. Each event set in *Actions* is dependent on all the *Physical Damage* event sets.
- 3. Event sets pertaining to *Actions* are conditionally independent of each other given the physical damage present.

The above assumptions allow the probability of a situation to be calculated as

$$P\{B_n\} = P\{M \cap E \cap A \cap T \cap H \cap Tr\}$$
$$= P\{M \cap E \cap A | T \cap H \cap Tr\}P\{T \cap H \cap Tr\}$$
$$= P\{M \cap E \cap A | T \cap H \cap Tr\}P\{T\}P\{H\}P\{Tr\}$$
$$= P\{M | T \cap H \cap Tr\}P\{E | T \cap H \cap Tr\}P\{A | T \cap H \cap Tr\}P\{T\}P\{H\}P\{Tr\}$$
$$(3.8)$$

where subscripts are excluded for brevity. The conditional probabilities needed for Equation (3.8) can be calculated easily from the survey data.

3.4.3 Numerical Representation of the Data. Using the data available, probabilities of observing events are determined given a target's current kill state. The first task is to assign probability distributions to each of the event sets for all singular SMEs depending on his completed response tables. Mutual exclusivity and collective exhaustiveness of the events within each set allow us to develop numerical distributions. Assigning numerical values to responses marked Always and Never (0 and 1, respectively) is trivial. However, for those event sets where the respondent deems all or some of the events possible (i.e. Might), a different situation arises. Given that each event in this situation is marked similarly as Might, the assignment of equal probabilities to each is the most logical decision by the principle of maximum entropy.

As an example, if a soldier marked the *Activity* event set with the responses displayed in Table 3.2 then the event *Seeking Cover* is assigned 0 probability, while

Event	Response
Seeking Cover	Never
Taking Firing Position	Might
Personnel Abandoning	Might
Other/No Actions	Might

 Table 3.2:
 Example Event Set Response

Taking a Firing Position, Personnel Abandoning, and Other/No Actions would each have a 1/3 probability. This inherently gives a individual's distribution of an event set.

Now, using each individual's responses, a distribution representative of all the survey participants can be developed. The calculation is simply an average across all individual distributions.

To illustrate, let Table 3.2 on the previous page be one soldier's response and Table 3.3 be another soldiers response. This gives two distribution vectors, say  $\mathbf{d}_1$ 

EventResponseSeeking CoverMightTaking Firing PositionMightPersonnel AbandoningNeverOther/No ActionsMight

 Table 3.3:
 Additional Example Event Set Response

and  $\mathbf{d}_2$  respectively.

$$\mathbf{d}_{1} = \begin{bmatrix} 0 & 1/3 & 1/3 & 1/3 \end{bmatrix}$$
$$\mathbf{d}_{2} = \begin{bmatrix} 1/3 & 1/3 & 0 & 1/3 \end{bmatrix}$$

Averaging  $\mathbf{d}_1$  and  $\mathbf{d}_2$  yields the population distribution

$$\bar{\mathbf{d}} = \left[ \begin{array}{ccc} 1/6 & 1/3 & 1/6 & 1/3 \end{array} \right]$$

for the *Activity* event set.

This method can easily be extended across all event sets for multiple survey responses. Now let  $\mathbf{d}_{\eta,i}$ ,  $\eta \in \{1, 2, ..., N\}$ , denote the vector obtained for the  $\eta^{th}$ survey response for the  $i^{th}$  kill state, and  $\mathbf{d}_i$  be the average of the N vectors

$$ar{\mathbf{d}}_i = rac{1}{\mathrm{N}}\sum_{\eta=1}^{\mathrm{N}} \mathbf{d}_{\eta,i}$$

. So the distributions of all event sets for each kill state can be calculated in this manner. and used to determined the  $P\{B_n|X_n = j\}$ s in Equation (3.6).

#### 3.5 Integration with Combat Models

Modeling the BDA process as a DTMC and updating the distribution vectors by Bayesian inference have been shown mathematically in the previous section. Now a procedure to integrate the mathematical representation into a combat model will be developed.

The combat models that concern this research use decision tables. These decision tables use the current values of several parameters in a logical flow to determine the distribution that an entity's next action should be drawn from. In this light, the logic flow for the current representation of the BDA process within an engagement is shown in Figure 3.2.

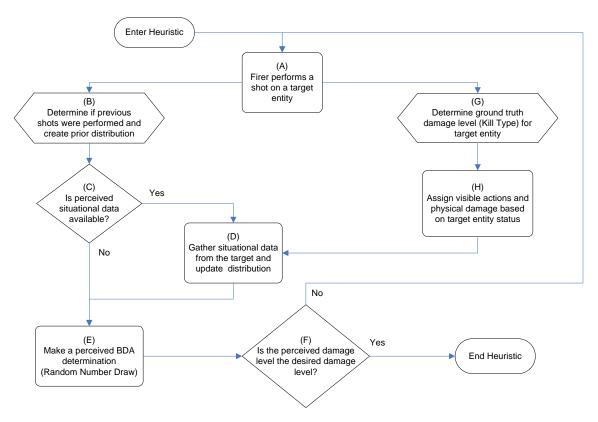


Figure 3.2: Method Integration Logic Flow

The combat model enters the process upon an entity engaging a target which proceeds to fire a shot at the target in node A. From there, two streams of information split off and develop in parallel. Nodes B, C, and D are the firer's perception and nodes G and H represent the target's ground truth. From the ground truth side, the targets damage and true kill state are determined through PH and PK calculations in node G. Node H uses the kill state to generate actions and physical damage for the target. From the firer's perspective, node B takes all the information from any prior shots and calculates the  $\mathbf{a}^{(n)}$  vector. The firer then decides decides whether situational parameter data is available for this shot at node C. If it is, the engaging entity uses its sensors to gather actions and physical damage from the target at node D (generated at node H). From these situational parameters, an updated  $\mathbf{a}^{(n)}$  is calculated. Now, at node E the firer makes a determination of the kill state by drawing a random number and using either  $\mathbf{a}^{(n)}$  or  $\mathbf{a'}^{(n)}$  as a BDA distribution. Finally at node F, if the perceived BDA kill state is more than or equal to the desired BDA kill state, the model exits the heuristic. Otherwise, the firer returns to node A and repeats the process.

### 3.6 Example Calculations

To illustrate the data development, transient analysis of the DTMC, and updating using Bayesian Inference, example calculations will be shown in the context of the logic shown in Figure 3.2 on the preceding page. For the purposes of simplicity, only the event sets pertaining to Actions (i.e. *Movement, Engagement*, and *Activity*) will be considered so that mutual independence can be assumed. Also, for the sake of brevity, the data calculations are based on five survey responses. The scenario will consist of a Blue tank engaging a Red tank.

Survey responses were simulated for five soldiers. As an example, the responses for a tank in kill state ND are shown in Table 3.4 on the next page. The responses are coded A for events the soldier would always see, M for those he might see, and Nfor events he would never see.

	Response N				Jumb	ber
Event Set	Event	1	2	3	4	5
Movement	Yes	M	М	А	Ν	Μ
(M)	No	M	Μ	Ν	А	Μ
Engagement	Yes	М	М	М	Ν	Μ
(E)	No	M	Μ	Μ	А	Μ
Activity	Seeking Cover	N	М	Μ	М	М
(A)	Taking Firing Position	M	Μ	Μ	Μ	Μ
	Personnel Abandoning	N	Μ	Ν	Ν	Ν
	Other/No Actions	M	Μ	М	Μ	Μ

 Table 3.4:
 Simulated Survey Responses for Tank at No Damage

From the responses, distributions  $(\mathbf{d}_{\eta ND})$  are developed for each soldier and averaged across the five responses giving  $\mathbf{d}_{ND}$  following the method described in Section 3.4.3. The distributions created from the data in Table 3.4 are displayed in Table 3.5. Each of the table entries pertain to an element of  $\mathbf{d}_{\eta,\text{ND}}$ . For example

 Table 3.5:
 Probabilities Obtained from Simulated Data in Table 3.4

	Response Number $(\eta)$						
Event Set	Event	1	2	3	4	5	$ar{\mathbf{d}}_{ND}$
Movement	Yes	0.5	0.5	1.0	0.0	0.5	0.5
(M)	No	0.5	0.5	0.0	1.0	0.5	0.5
Engagement	Yes	0.5	0.5	0.5	0.0	0.5	0.4
(E)	No	0.5	0.5	0.5	1.0	0.5	0.6
Activity	Seeking Cover	0.0	0.25	0.33	0.33	0.33	0.25
(A)	Taking Firing Position	0.5	0.25	0.33	0.33	0.33	0.35
	Personnel Abandoning	0.0	0.25	0.0	0.0	0.0	0.05
	Other/No Actions	0.5	0.25	0.33	0.33	0.33	0.35

 $\mathbf{d}_{1,\mathrm{ND}}(A_{SeekingCover}) = 0.$ 

The probabilities displayed in the  $\bar{\mathbf{d}}_{ND}$  column are the conditional distributions of the events given a kill state of ND. The conditional probabilities for the remaining kill states are calculated in the same manner as the ND case and given in Table 3.6 on the next page.

So, imagine a blue tank deems a red tank as a viable target and decides to shoot at it (Node A). As previously stated, without prior knowledge, the red tank is

Event Set	Event	$ar{\mathbf{d}}_{ND}$	$ar{\mathbf{d}}_M$	$ar{\mathbf{d}}_F$	$ar{\mathbf{d}}_{MF}$	$ar{\mathbf{d}}_K$
Movement	Yes	0.500	0.000	0.700	0.000	0.000
(M)	No	0.500	1.000	0.300	1.000	1.000
Engagement	Yes	0.400	0.600	0.000	0.000	0.000
(E)	No	0.600	0.400	1.000	1.000	1.000
Activity	Seeking Cover	0.250	0.066	0.300	0.066	0.100
(A)	Taking Firing Position	0.350	0.367	0.167	0.000	0.000
	Personnel Abandoning	0.050	0.367	0.233	0.567	0.000
	Other/No Actions	0.350	0.200	0.300	0.367	0.900

 Table 3.6:
 Event Probability Vectors for Simulated Data

assumed to have an ND kill state before the engagement, so

$$\mathbf{a}^{(0)} = \left[ \begin{array}{rrrr} 1 & 0 & 0 & 0 \end{array} \right]$$

and as a result (at node B)

$$\mathbf{a}^{(1)} = \mathbf{a}^{(0)} \mathbf{P}$$
  
=  $\begin{bmatrix} 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}$ .

After the shot, the target is assigned damage and a kill state (node G). Consequently actions and physical damage are determined by the model (node H). The intersection of these events makes up the situation,  $B_1$ . In this case

$$B_1 = \{ M_{No} \cap E_{Yes} \cap A_{TakingFiringPosition} \}.$$

If the Blue tank can perceive the situational parameters (node C) then  $\mathbf{a}^{\prime(n)}$  can be calculated (node D). First, calculate the  $P\{B_1|X_1 = i\}$ s for  $i \in S$  by simply multiplying the appropriate conditional probabilities (from Table 3.6) together according to Equation (3.7). The row entitled  $P\{B_1|X_1 = i\}$  in Table 3.7 on the following page shows these intersection probabilities.

		Kill State $(i)$					
Event Set	Event	ND	M-kill	F-kill	MF-kill	K-kill	
Movement	No	0.500	1.000	0.300	1.000	1.000	
Engagement	Yes	0.400	0.600	0.000	0.000	0.000	
Activity	Other/No Actions	0.350	0.200	0.300	0.367	0.900	
	$P\{B_1 X_1=i\}$	0.0778	0.0066	0.0000	0.0000	0.0000	
	$\mathbf{a}^{\prime (1)}$	0.9222	0.0778	0.0000	0.0000	0.0000	

Table 3.7: Calculations for  $\mathbf{a}^{\prime(1)}$ 

Now, using the law of total probability, find  $P\{B_1\}$  by summing the conditional situation probabilities multiplied by its respective kill state probability.

$$\sum_{j \in S} P\{B_1 | X_1 = j\} P\{X_1 = j\} = \sum_{j \in S} P\{B_1 | X_1 = j\} \mathbf{a}_j^{(1)}$$
  
= (0.0778)(0.2) + (0.0066)(0.2) + (0)(0.2)  
+(0)(0.2) + (0)(0.2)  
= 0.0169

Finally, calculate the  $\mathbf{a'}^{(1)}$  using Equation (3.6). Equation (3.9) demonstrates example calculations for the probability of an ND kill state given the situation, and Table 3.7 lists all of the  $\mathbf{a'}^{(1)}$  vector probabilities.

$$P\{X_{1} = \text{ND}|B_{1}\} = \frac{P\{B_{1}|X_{1} = \text{ND}\}P\{X_{1} = \text{ND}\}}{P\{B_{1}\}}$$

$$= \frac{(0.0778)(0.2)}{0.0169}$$

$$= 0.9222$$
(3.9)

At this point (node E), the blue tank gunner has 0.9222 and 0.0778 probabilities of determining the red tank to be in the ND or M kill states, respectively. However, there is zero probability that the target has F, MF, or K kill states. Assume a random draw by the combat model yields the perceived BDA as  $\{X_1 = M\}$ . This would represent an overestimation of battle damage. If the desired BDA is an M-kill (node F) the Blue tank would exit the heuristic. If not, the gunner fires another shot at the red tank (return to node A) and the process is repeated. This time, however, the initial distribution before the second shot,  $\mathbf{a}'^{(1)}$ , is known, so  $\mathbf{a}^{(2)}$  is calculated accordingly.

$$\mathbf{a}^{(2)} = \mathbf{a}^{\prime(1)} \mathbf{P}$$

This process is repeated until the Blue tank perceives adequate BDA for its target or the number of shots exceeds the engagement limit.

3.6.1 Calculating Conditional Probabilities. Now if all event sets were used for the above example, calculating the  $P\{B_n|X_n = i\}$ s would be accomplished using the assumptions in 3.4.2 and the appropriate conditional probabilities needed for this situation would be dictated by the physical damage observed in the situation.

The probabilities for the *Physical Damage* event sets are given in Table 3.8These probabilities are needed explicitly in Equation (3.8). Now suppose for the

Event Set	Event	$ar{\mathbf{d}}_{ND}$	$ar{\mathbf{d}}_M$	$ar{\mathbf{d}}_F$	$ar{\mathbf{d}}_{MF}$	$ar{\mathbf{d}}_K$
Turret	No Damage	0.725	0.717	0.133	0.033	0.100
(T)	Light Damage	0.275	0.267	0.433	0.408	0.425
	Heavy Damage	0.000	0.017	0.433	0.558	0.475
Hull	No Damage	0.408	0.383	0.342	0.358	0.000
(H)	Light Damage	0.358	0.333	0.342	0.358	0.450
	Heavy Damage	0.233	0.283	0.317	0.283	0.550
Tracks	No Damage	0.792	0.083	0.688	0.050	0.067
(Tr)	Light Damage	0.192	0.408	0.288	0.425	0.467
	Heavy Damage	0.017	0.508	0.013	0.525	0.467

 Table 3.8:
 Event Probability Vectors for Simulated Data

previous example,  $B_1$  is instead

$$B_1 = \{ M_{No} \cap E_{Yes} \cap A_{TakingFiringPosition} \cap T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage} \}.$$

As a result, the appropriate conditional probabilities needed to obtain  $P\{B_1|i\}$ 

are

$$P\{M_{No}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\},\$$

$$P\{E_{Yes}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\},\$$
 and
$$P\{A_{TakingFiringPosition}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

for each kill state. Recall that the survey responses are represented in the form of  $\mathbf{d}_{\eta,i}$  vectors containing the  $\eta^{th}$  soldier's event probabilities for kill state *i*. In general, conditional probabilities can be calculated from data in this form by

$$P\{C|D\} = \frac{\sum_{\eta=1}^{N} P\{C\}_{\eta} P\{D\}_{\eta}}{\sum_{\eta=1}^{N} P\{D\}_{\eta}}$$
$$= \frac{\sum_{\eta=1}^{N} \mathbf{d}_{\eta,i}(C) \mathbf{d}_{\eta,i}(D)}{\sum_{\eta=1}^{N} \mathbf{d}_{\eta,i}(D)}$$
(3.10)

where C and D are any event.

As an example,  $P\{M_{No}|Tr_{LightDamage}\}$  will be calculated for the ND kill state. Table 3.9 on the following page is an extension of Table 3.5 used in the above example. Recall that the table entries pertain to elements of  $\mathbf{d}_{\eta,\text{ND}}$ .

Now, following Equation (3.10)

$$P\{M_{No}|Tr_{LightDamage}\} = \frac{\sum_{\eta=1}^{5} \mathbf{d}_{\eta,i}(M_{No})\mathbf{d}_{\eta,i}(Tr_{LightDamage})}{\sum_{\eta=1}^{5} \mathbf{d}_{\eta,i}(Tr_{LightDamage})}$$
$$= \frac{(0.5)(0) + (0.5)(0.5) + (0)(0.5) + (1)(0.5) + (0.5)(0)}{0 + 0.5 + 0.5 + 0.5 + 0}$$
$$= 0.5$$

	Response Number $(\eta)$					(ק
Event Set	Event	1	2	3	4	5
Movement	Yes	0.5	0.5	1	0	0.5
(M)	No	0.5	0.5	0	1	0.5
Engagement	Yes	0.5	0.5	0.5	0	0.5
(E)	No	0.5	0.5	0.5	1	0.5
Activity	Seeking Cover	0	0.25	0.333	0.333	0.333
(A)	Taking Firing Position	0.5	0.25	0.333	0.333	0.333
	Personnel Abandoning	0	0.25	0.000	0.000	0.000
	Other/No Actions	0.5	0.25	0.333	0.333	0.333
Turret	No Damage	0.5	0.5	1	0.5	1
(T)	Light Damage	0.5	0.5	0	0.5	0
	Heavy Damage	0	0	0	0	0
Hull	No Damage	0.5	0.5	0.5	0.5	0.5
(H)	Light Damage	0.5	0.5	0	0.5	0.5
	Heavy Damage	0	0	0.5	0	0
Tracks	No Damage	1	0.5	0.5	0.5	1
(Tr)	Light Damage	0	0.5	0.5	0.5	0
	Heavy Damage	0	0	0	0	0

 Table 3.9:
 Probabilities for Individual Soldiers

so in this very simplistic case  $P\{M_{No}\}$  does not change by adding the condition. With more survey responses, however, the probability will likely change according to the physical damage present.

Recall the situation in this example

$$B_1 = \{ M_{No} \cap E_{Yes} \cap A_{TakingFiringPosition} \cap T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage} \}.$$

Following the above procedure  $P\{B_1\}$  for each kill state and the resulting  $\mathbf{a'}^{(1)}$  vector are displayed in Table 3.10. Adding the physical damage conditions drastically

Table 3.10:  $P\{B_1\}$  and  $\mathbf{a'}^{(1)}$  Using Physical Damage Conditions K: U State (i)

	Kill State $(i)$							
	ND	M-Kill	F-Kill	MF-Kill	K-Kill			
$P\{B_1 i\}$	0.0439	0.2100	0.0000	0.0000	0.0000			
$\mathbf{a}^{\prime (1)}$	0.1731	0.8269	0.0000	0.0000	0.0000			

changes the probabilities in  $\mathbf{a}^{\prime(1)}$ . In the first example the Blue tank gunner had 0.9222 and 0.0778 probabilities of determining the red tank to be in the ND or M kill states, respectively. Now by adding the physical damage conditions, the probabilities are 0.1731 and 0.8269 for ND and M. So, it is easy to see why the dependence of perceived actions on the perceived physical damage is important.

### 3.7 Conclusion

The BDA process in real time is a very complex and as such has not been well modeled in the past. This chapter presents a top to bottom approach in developing an adequate BDA representation for direct engagement models. First, a method to collect the adequate data for real time BDA in close combat was proposed. Representation of the BDA process as a Markov Chain was developed and a methodology to update the  $n^{th}$  shot distribution vector was discussed. Next, a strategy to implement the methodology into a combat simulation model was introduced. The chapter concludes by providing calculations for a simple example scenario.

# IV. Results and Analysis

### 4.1 Introduction

Modeling the BDA process as a DTMC with updates by Bayesian inference is an effective way to capture its complicated nature in real time. The most important issue with this model is that the updates are entirely data dependent. The updates are performed directly using the conditional probabilities computed from survey responses and, as a result, are only useful if the probabilities are (relatively) representative of the population.

This chapter will first present an analysis of the number of surveys collected (N) and how it affects singular event probabilities as well as the properties of the updated  $\mathbf{a}^{\prime(n)}$ . From this analysis a sample size will be suggested for an example implementation of the methodology. The example analysis will include calculations of the event probabilities and the update to  $\mathbf{a}^{\prime(n)}$  for a three shot engagement sequence and consider a case where situational information is unavailable.

### 4.2 Effects due to the Number of Survey Responses

The conditioning of some distribution vector  $\mathbf{a}^{(n)}$ , to give  $\mathbf{a}'^{(n)}$ , depends directly on the survey data obtained. This dependence stems from computing the conditional event probabilities (i.e. probabilities of events given a kill state) from the survey responses and using Bayes' Theorem to update the distribution vector. It follows that the updated distribution will vary with the data collected.

The survey responses can be thought of as a sample of N from the population of all soldiers. Calculating the probabilities of events for *Physical Damage* and *Actions* is simply an average across all N responses to obtain

$$\bar{\mathbf{d}}_i = rac{1}{\mathrm{N}}\sum_{\eta=1}^{\mathrm{N}} \mathbf{d}_{\eta,i}$$

The (strong) law of large numbers states that, for any sequence of random independently and identically distributed (iid) random variables  $Y_{\eta}, \eta \in \{1, 2, ..., N\}$  with known and finite mean  $\mu_Y$ 

$$P\left\{\lim_{N\to\infty}\bar{Y}_N=\mu_Y\right\}=1\tag{4.1}$$

where

$$\bar{Y}_N = \frac{1}{N} \sum_{\eta=1}^N Y_\eta.$$

So the analogous case here can be stated

$$P\left\{\lim_{N\to\infty}\bar{\mathbf{d}}_{N,i}=\mathbf{d}_{\mu,i}\right\}=1$$

where  $\mathbf{d}_{\mu,i}$  is the vector of true event probabilities given a kill state *i*. By extension, the updated probability distribution of BDA estimated from N survey responses,  $\hat{\mathbf{a}}^{\prime(n)}$ , will also approach its true values as N approaches  $\infty$ .

The intuitive result here is that more survey responses will yield better estimates of  $\mathbf{d}_{\mu,i}$  and subsequently  $\mathbf{a}'^{(n)}$ . However a practical target number of survey responses required for the modeling methodology is of great interest. Since both  $\mathbf{d}_i$  and the resulting  $\mathbf{\hat{a}}'^{(n)}$  are easily observable, this issue can be handled from two angles. Both estimates will be explored via simulation.

4.2.1 Simulation of Survey Responses. To suggest a target number of survey responses (N), data must be produced to give insight into an adequate number of surveys for which the model will be effective. As such, a simulation technique was developed for this purpose.

To simulate survey responses, underlying probabilities were set to compare random numbers against. Within each *Physical Damage* event set, probabilities of a respondent marking events as possible were determined to give intuitive proportions of survey responses. Probabilities of marking events in the *Action* event sets were conditioned based on how the Physical Damage portion is filled out. The data simulated is meant to be intuitive (e.g.  $P\{M_{Yes}|X_n = M\}$  will be small) to lend credibility to the analysis.

Survey responses were simulated using the Matlab<sup>®</sup> programming language. First, a vector of 17 random numbers was generated. The physical damage portion of the survey is filled by comparing the random numbers to the probabilities of the respondent marking an event possible. The actions are filled depending on the response to the Physical Damage event sets. The result is a vector of 1s and  $\theta$ s which represent the respondent marking events as possible.

The binary vector is transformed into Ns, Ms, and As and further into event probabilities ( $\mathbf{d}_{\eta i}$ s) by placing equal probability into any events marked possible. An event set with only one event marked possible is assigned probability of 1. If two events are marked possible, each receives 0.5 and so on following the principle of maximum entropy. The case where an event set is null (no events marked possible) results in a random draw among the possible distributions.

The set of N total survey responses is used to estimate the probabilities of events given physical damage and further in updating  $\mathbf{a}^{(n)}$  to  $\mathbf{a}^{\prime(n)}$ . The Matlab<sup>®</sup> code used to simulate these responses, perform calculations, and plot data can be found in Appendix B.

4.2.2 Effect of N on the Event Probabilities. The conversion of survey responses into event probabilities and their direct contribution to the calculations of an update has been discussed. Recall that the event probabilities contained in  $\bar{\mathbf{d}}_i$  will approach their true values as the number of survey responses N approaches  $\infty$ .

The Central Limit Theorem (CLT) implies that a standardized sum of random variables will approach a standard normal distribution. For the sequence of iid random

variables,  $Y_{\eta}, \eta = 1, 2, ..., N$ , with known  $\mu_Y$  and  $\sigma_Y$ 

$$\lim_{N \to \infty} P\left\{ \frac{\bar{Y} - \mu_Y}{\sigma_Y / \sqrt{N}} \le z \right\} = \Phi(z)$$
(4.2)

where  $\bar{Y}_{N}$  denotes the sample mean, and  $\Phi(z)$  is the value of the standard normal cumulative distribution function at z.

As a result, the elements of  $\mathbf{\bar{d}}_i(*)$  can be treated with normal distribution theory. One result is that the event probabilities determined by averaging survey data will approach the true values because the standard error of any  $\bar{Y}_N$  has the property

$$\lim_{N \to \infty} \frac{\sigma_Y}{N} = \lim_{N \to \infty} \sigma_{\bar{Y}} = 0.$$
(4.3)

As an example, the true distribution of individual responses for  $\mathbf{d}_{\eta,\mathrm{ND}}(T_{NoDamage})$ (i.e.  $P\{T_{NoDamage}|X_n = \mathrm{ND}\}$ ) is known because the survey responses are simulated. This distribution is

$$P\{\mathbf{d}_{\eta,\text{ND}}(T_{NoDamage}) = *\} = \begin{cases} * = 0: \text{ w.p. } 0.0310\\ * = 1/3: \text{ w.p. } 0.0285\\ * = 1/2: \text{ w.p. } 0.5605\\ * = 1: \text{ w.p. } 0.3800 \end{cases}$$

with known  $\mu_{\mathbf{d}_{\eta,\mathrm{ND}}(T_{NoDamage})} = 0.6695$  and  $\sigma^2_{\mathbf{d}_{\eta,\mathrm{ND}}(T_{NoDamage})} = 0.0747$ . Now,  $\mathbf{\bar{d}}_{\mathrm{ND}}(T_{NoDamage}) \rightarrow 0.6695$  as the number of survey responses,  $\mathbf{N} \rightarrow \infty$  by Equation (4.1). Figure 4.1 on the following page plots the standard error of  $\mathbf{\bar{d}}_{\mathrm{ND}}(T_{NoDamage})$ for this distribution against numbers of survey responses and displays the behavior predicted in Equation (4.3). Technically a target number of survey responses could be calculated for a specified bound(s) on the estimate  $\mathbf{\bar{d}}_{\mathrm{ND}}(T_{NoDamage})$ . Realistically, however, the distribution will not be known in advance and  $\mathbf{\bar{d}}_{\mathrm{ND}}(T_{NoDamage})$  will be the only estimate available for  $\mathbf{d}_{\mu,\mathrm{ND}}(T_{NoDamage})$ .

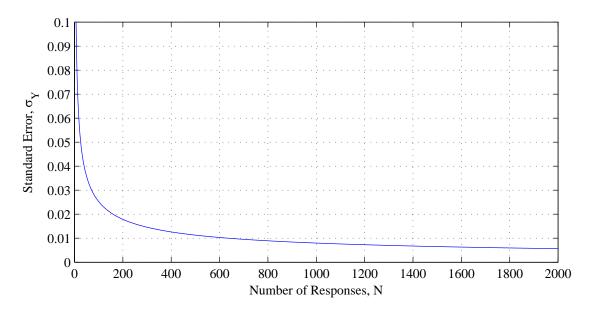


Figure 4.1:  $\sigma_{\bar{\mathbf{d}}_{ND}(T_{NoDamage})}$ , versus number of survey responses, N

A practical solution is to simulate survey responses from this distribution and observe the event probability reach a relatively stable estimate of the true event probability. Figure 4.2 on the next page shows a continuous calculation of  $\bar{\mathbf{d}}_{\text{ND}}(T_{NoDamage})$ as N increases. Because the response distribution is known, a comparison can be made with the true value of  $\mu_{\mathbf{d}_{\eta,\text{ND}}(T_{NoDamage})}$ , 0.6695, denoted by the reference line.

This type of simulation exercise could certainly be performed for each event probability. However, the dependence of *Actions* on *Physical Damage* would indicate the presence of several interactions causing a drastic increase in the number of probabilities that need examination. As a result, such an investigation would prove impractical. Because of the dependence, a more efficient way to observe the effect of N on the model is to compare the estimated and true distributions of  $X_n$ ,  $\hat{\mathbf{a}}'^{(n)}$  and  $\mathbf{a}'^{(n)}$  respectively.

4.2.3 Effect of N on the Moments of  $\mathbf{a}^{\prime(n)}$ . A common method to compare two distributions is to investigate their respective moments. The moments themselves do not specify a distribution, but rather, the characteristic function (a function of the moments) does. Distributions known, or assumed to be of the same form (e.g.

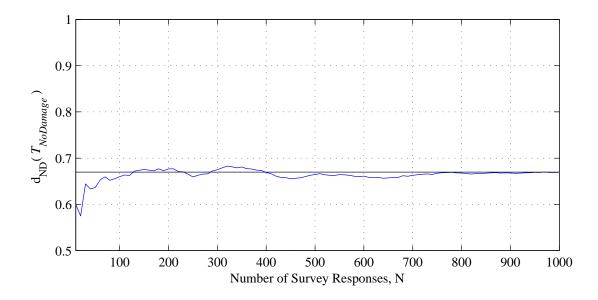


Figure 4.2: Simulated  $\bar{\mathbf{d}}_{ND}(T_{NoDamage})$  versus number of survey responses, N

nominal discrete in this case) may be compared on the basis of moments for this reason. Indeed, many hypothesis tests do just that by estimating parameters from data to draw conclusions about the distribution of a sample.

The two most commonly used moments of a distribution are the mean (i.e. expected value) and the variance. The mean is a raw moment (about the origin) and signifies location. Variance is the second central moment (about the mean) and is a measure of dispersion. The third and fourth order central moments measure skewness (symmetry) and kurtosis (peakedness) respectively.

The methodology is heavily dependent on data, so any variability or biases present in the survey responses will be reflected in the moments of  $\mathbf{a}^{\prime(n)}$ . BDA has a nominal discrete distribution with nominal classes and, as a result, the concepts of a (conditional) expected value and variance of  $X_n$ , given a situation ( $E[X_n|B_n]$ and  $Var[X_n|B_n]$  respectively) do not have intuitive meaning. The nominal nature of the distribution means that the kill states show neither a proportional quantity (cardinality) nor rank (ordinality). To calculate any moments for the distribution, the kill states must be given a cardinal support. An example of a discrete distribution with a cardinal support would be a standard six sided die, for which E[\*] and Var[\*] can be calculated easily.

For the purposes of this demonstration, let the kill states take the following support.

 $ND \equiv 1$  $M \equiv 2$  $F \equiv 3$  $MF \equiv 4$  $K \equiv 5$ 

Since the mapping is completely arbitrary, the expected value and variance of  $\mathbf{a}^{\prime(n)}$  (or  $\hat{\mathbf{a}}^{\prime(n)}$ ) do not have a direct interpretation.

It is well known that for any discrete random variable Y with a known probability distribution, the expected value and variance can be calculated as

$$\begin{split} E[Y] &= \sum_{y} y P\{Y = y\} \\ Var[Y] &= \sum_{y} (y - E[Y])^2 P\{Y = y\} \\ &= E[Y^2] - (E[Y])^2 \end{split}$$

where

$$E[Y^2] = \sum_y y^2 P\{Y = y\}$$

is the second moment of Ya about the origin.

Recall that  $\hat{\mathbf{a}}^{\prime(n)}$  approaches the true distribution for increasing N. A single  $\hat{\mathbf{a}}^{\prime(n)}$  simultaneously reflects the entire body of survey responses for dependent and independent event probabilities alike. Since the survey responses are simulated the true value of any  $\mathbf{a}^{\prime(n)}$  can be calculated and compared against the estimated distribu-

tion. Exploring every possible intersection of events (432) would make the analysis intractable, so a subset of situations  $(B_n s)$  was selected to represent a cross section of the possible intersections.

To see the effect of the number of responses on  $E[X_n|B_n]$  and  $Var[X_n|B_n]$ , survey responses were simulated sequentially. At each new value of N, the distribution after the first shot was updated to give  $\hat{\mathbf{a}}^{\prime(1)}$  for each of the situations.

$$B_{a} = \{M_{No} \cap E_{No} \cap A_{Other/NoAction} \cap T_{NoDamage} \cap H_{NoDamage} \cap Tr_{NoDamage}\}$$

$$B_{b} = \{M_{Yes} \cap E_{Yes} \cap A_{SeekingCover} \cap T_{NoDamage} \cap H_{LightDamage} \cap Tr_{NoDamage}\}$$

$$B_{c} = \{M_{No} \cap E_{No} \cap A_{TakingFiringPosition} \cap T_{NoDamage} \cap H_{LightDamage} \cap Tr_{LightDamage}\}$$

$$B_{d} = \{M_{Yes} \cap E_{No} \cap A_{PersonnelAbandon} \cap T_{HeavyDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

$$B_{e} = \{M_{No} \cap E_{No} \cap A_{Other/NoAction} \cap T_{LightDamage} \cap H_{HeavyDamage} \cap Tr_{HeavyDamage}\}$$

where  $B_*$  represents Situation \* and the numeric subscript (1) is omitted for brevity.

For each of the five situations, the expected value and variance were calculated analytically from  $\hat{\mathbf{a}}^{(1)}$ . Recall, both  $E[X_n|B_n]$  and  $Var[X_n|B_n]$  should approach their true values as the number of survey responses increases by law of large numbers. Figure 4.3 and 4.4 on the following page show the expected value,  $\hat{\mu}$ , and the variance,  $\hat{\sigma}^2$ , plotted against the number of survey responses for  $B_b$  and  $B_e$ . The reference lines indicate the true values of the respective moments. Of the five situations investigated, *Situation b* approaches its true values for the smallest values of N and *Situation e* requires the largest values of N. In Figure 4.3, *Situation b* approaches its true values for  $\mu$  and  $\sigma^2$  to within simulation noise very quickly; just over N = 100 survey responses. Figure 4.4 shows that  $\mu$  and  $\sigma^2$  for *Situation e* approach their reference lines more slowly.  $E[X_n|B_e]$  and  $Var[X_n|B_n]$  reach acceptable levels for N = 700 survey responses. However, a case could certainly be made for N = 1000<sup>+</sup> survey

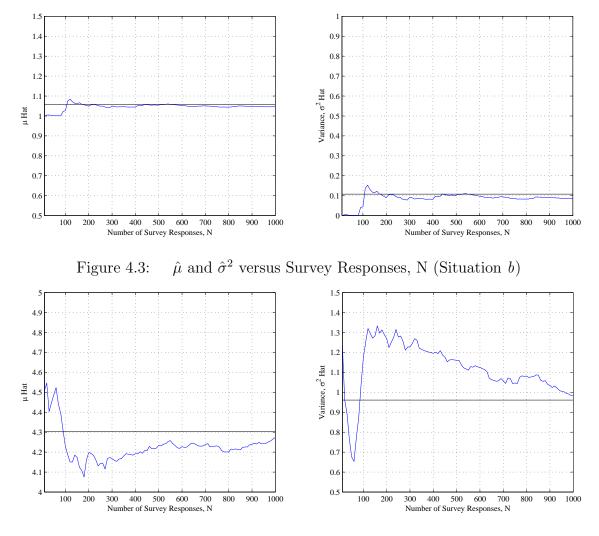


Figure 4.4:  $\hat{\mu}$  and  $\hat{\sigma}^2$  versus Survey Responses, N (Situation e)

lines for N  $\geq$  850. Situations a, c, and d performed somewhere in between Situations b and e. Sample data and plots for all of the situations may be found in Appendix C.

4.2.4 Effect of N on  $\hat{\mathbf{a}}^{\prime(n)}$ . Recall that the moments of  $\hat{\mathbf{a}}^{\prime(n)}$  have no direct interpretation because of the nominal nature of the kill states. To avoid giving kill states an arbitrary support one might think of  $\hat{\mathbf{a}}^{\prime(n)}$  as a point in space, or otherwise stated

$$\hat{\mathbf{a}}^{\prime(n)} \in \mathbb{R}^5.$$

The true distribution also occupies a point in  $\mathbb{R}^5$ , so the distributions may be compared by calculating the distance between the points they represent.

In multidimensional space, different forms of distance from the origin can be calculated by a *p*-norm,  $|| \cdot ||_p$  and represented as

$$||\mathbf{y}||_p = (|y_1|^p + |y_2|^p + \ldots + |y_n|^p)^1/p \quad p \ge 1 \quad \mathbf{y} \in \mathbb{R}^n.$$
(4.4)

The 2-norm is known as the euclidian norm

$$||\mathbf{y}|| = \sqrt{|y_1|^2 + |y_2|^2 + \ldots + |y_n|^2}$$
  
=  $\sqrt{\mathbf{y}^T \mathbf{y}}$  (4.5)

and can be used to measure the straight line distance between points in space. In the case of  $\hat{\mathbf{a}}^{\prime(n)}$  and  $\mathbf{a}^{\prime(n)}$ 

$$||\mathbf{a}^{\prime(1)} - \hat{\mathbf{a}}^{\prime(1)}|| = \sqrt{(a_{\rm ND}^{(n)} - \hat{a}_{\rm ND}^{(n)})^2 + \ldots + (a_{\rm K}^{(n)} - \hat{a}_{\rm K}^{(n)})^2} = \sqrt{\sum_{i \in S} (a_i^{(n)} - \hat{a}_i^{(n)})^2}.$$
(4.6)

The result of Equation (4.6) inherently represents how different the distributions are and captures all of the moment information into a single value. Again, as N becomes large,  $\hat{\mathbf{a}}^{\prime(n)}$  will approach the true distribution and give the result

$$\lim_{\mathbf{N}\to\infty} ||\mathbf{a}^{\prime(n)} - \hat{\mathbf{a}}^{\prime(n)}|| = 0.$$

So to compare distributions  $||\mathbf{a}^{\prime(1)} - \hat{\mathbf{a}}^{\prime(1)}||$  was calculated for increasing values of N. The same set of survey data and situations (a-e) as above were used. Figure 4.5 on the next page display the plots for *Situations b* and *e*, respectively. Both situations show similar results to the moment plots. *Situation b* shows very small values of  $||\mathbf{a}^{\prime(1)} - \hat{\mathbf{a}}^{\prime(1)}||$  for any N > 150. Again, as in the moment plots, *Situation e* displays a

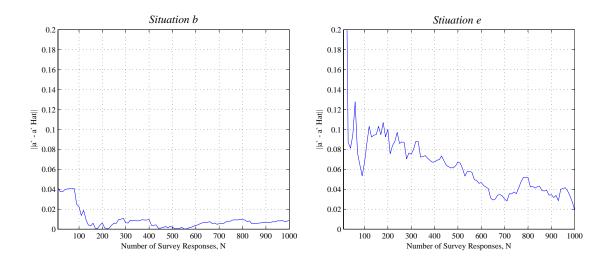


Figure 4.5:  $||\mathbf{a}^{\prime(1)} - \hat{\mathbf{a}}^{\prime(1)}||$  versus Survey Responses, N

much larger difference of  $\hat{\mathbf{a}}^{\prime(n)}$  from  $\mathbf{a}^{\prime(n)}$  and indicates at least N = 700 for acceptable results. *Situations a, c* and *e* show results between those obtained for *Situation b* and *e*. Their plots of  $||\mathbf{a}^{\prime(1)} - \hat{\mathbf{a}}^{\prime(1)}||$  versus N can be seen in Appendix C

Both methods of comparing  $\hat{\mathbf{a}}^{\prime(n)}$  to  $\mathbf{a}^{\prime(n)}$  result in similar proposed values for N. This similarity suggests that either method is adequate to determine a target number of survey responses.

### 4.3 Example Data Analysis

To fully illustrate the methodology, a complete example implementation form data collection to model implementation will be completed. First a data set of survey responses will be obtained (simulated) with N = 700 suggested in the previous section. Next the set of survey responses will be converted to the appropriate event probabilities. Lastly the algorithm will be run for a three shot engagement sequence within a combat simulation model providing the necessary calculations.

4.3.1 Calculation of Conditional Event Probabilities. Now, the qualitative values, contained in the N = 700 survey responses must be transformed into estimates

of the conditional event probabilities, contained in  $\mathbf{d}_i$ . First, the qualitative values (Ns, Ms, and As) marked on the surveys must be mapped to their respective event set probabilities. For each event set within a  $\mathbf{q}_{\eta,i}$ , the most likely distribution is derived from the principle of maximum entropy giving  $\mathbf{d}_{\eta,i}$ . Once all of the  $\mathbf{d}_{\eta,i}$ s are mapped, the  $\mathbf{d}_i$  are calculated by

$$\bar{\mathbf{d}}_i = \frac{1}{N} \sum_{\eta=1}^{N} \mathbf{d}_{\eta,i} \quad \forall \quad i \in S$$

The event probabilities for each kill state,  $\mathbf{d}_{\eta,i}$ , estimated from the N = 700 simulated survey responses are given in Table 4.1. The probabilities in this table are

			K	III State	(i)	
Event Set	Event	ND	M-kill	F-kill	MF-kill	K-kill
Movement	Yes	0.5064	0.0764	0.5071	0.0307	0.0693
(M)	No	0.4936	0.9236	0.4929	0.9693	0.9307
Engagement	Yes	0.5064	0.5014	0.0743	0.0336	0.0579
(E)	No	0.4936	0.4986	0.9257	0.9664	0.9421
Activity	Seeking Cover	0.3575	0.1030	0.3983	0.0675	0.0696
(A)	Taking Firing Position	0.3465	0.3082	0.0669	0.0549	0.0692
	Personnel Abandoning	0.0908	0.3963	0.2831	0.1411	0.4263
	Other/No Actions	0.2051	0.1925	0.2517	0.7365	0.4349
Turret	No Damage	0.6750	0.6590	0.0879	0.0167	0.0448
(T)	Light Damage	0.3014	0.3162	0.4100	0.3974	0.4133
	Heavy Damage	0.0236	0.0248	0.5021	0.5860	0.5419
Hull	No Damage	0.6569	0.5231	0.5493	0.1119	0.2850
(H)	Light Damage	0.3176	0.4045	0.3700	0.3498	0.4014
	Heavy Damage	0.0255	0.0724	0.0807	0.5383	0.3136
Tracks	No Damage	0.6610	0.0336	0.5400	0.0393	0.0543
(Tr)	Light Damage	0.3167	0.4864	0.4407	0.3843	0.4393
	Heavy Damage	0.0224	0.4800	0.0193	0.5764	0.5064

 Table 4.1:
 Conditional Event Probabilities for Simulated Data

 Kill State (i)

the marginal probabilities averaged across all N soldiers. The conditional probabilities for *Actions* given all possible intersections of *Physical Damage* are excluded here for brevity.

4.3.2 Three Shot Engagement Sequence. To illustrate the transient analysis of the DTMC and updating using Bayesian Inference, the implementation logic will

be followed for a typical engagement in CASTFOREM: a three shot sequence for a blue (friendly) tank firing upon a red (enemy) tank.

So, imagine a blue gunner deems a red tank as a viable target and decides to shoot at it. Recall  $\mathbf{a}^{(n)}$  denotes the probability vector of  $\{X_n, n \ge 0\}$  at time n and the initial distribution (without prior knowledge) is

$$\mathbf{a}^{(0)} = \left[ \begin{array}{rrrr} 1 & 0 & 0 & 0 \end{array} \right]$$

because the red tank is assumed to have an kill state of ND before the engagement. Additionally recall  $\mathbf{P}$  is the transition probability matrix

$$\mathbf{P} = \begin{array}{cccccc} & & & & & & & \\ & & & & & \\ & & & \\ &$$

and as a result

$$\mathbf{a}^{(1)} = \mathbf{a}^{(0)} \mathbf{P}$$
  
=  $\begin{bmatrix} 0.2 & 0.2 & 0.2 & 0.2 & 0.2 \end{bmatrix}$ 

that is, the prior distribution of  $X_1$ .

At this point the model decides (by random number draw) that the Blue tank gunner will perceive situational data. In parallel, the model has determined ground truth kill state to be ND (unknown to the Blue gunner) via PH and PK calculations. Perceived actions and physical damage are determined by the model using a vector of random numbers to draw from the appropriate conditional event set distributions. A simulated random vector yields the the situational data,  $B_1$  given by

$$B_1 = \{ M_{No} \cap E_{No} \cap A_{Other/NoAction} \cap T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage} \}.$$

which the Blue tank gunner will perceive.

The perceived events, along with their respective probabilities are listed in Table 4.2. The probabilities corresponding to the *Actions* in  $B_1$  are conditioned on the

		Kill State $(i)$						
	Events	ND	M-kill	F-kill	MF-kill	K-kill		
Physical	$T_{NoDamage}$	0.6750	0.6590	0.0879	0.0448	0.0167		
Damage	$H_{NoDamage}$	0.6569	0.5231	0.5493	0.2850	0.1119		
	$Tr_{LightDamage}$	0.3167	0.4864	0.4407	0.4393	0.3843		
Actions	$M_{No}$	0.4694	0.9315	0.5587	0.9010	1.0000		
(Conditioned)	$E_{No}$	0.4483	0.4946	0.8691	0.9219	0.8929		
	$A_{Other/NoActions}$	0.2174	0.1911	0.2444	0.4625	0.7500		
-	$P\{B_1 X_1=i\}$	0.00642	0.01476	0.00252	0.00215	0.00048		
	$\mathbf{a}^{\prime (1)}$	0.24379	0.56043	0.09582	0.08173	0.01822		

 Table 4.2:
 Observed Events and Conditional Probabilities (Shot 1)

settings of *Physical Damage*.

First, the conditional probabilities of the situation  $P\{B_1|X_1 = i\}$  are calculated for each kill state using Equation (3.8). This is simply the product of the event probabilities listed in Table 4.2. For example calculate the probability of this situation given  $X_1 = M$ 

$$P\{B_{1}|X_{1} = M\} = P\{M_{No}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

$$\cdot P\{E_{No}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

$$\cdot P\{A_{Other/NoActions}|T_{NoDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

$$\cdot P\{T_{NoDamage}\} \cdot P\{H_{NoDamage}\} \cdot P\{Tr_{LightDamage}\}$$

$$= (0.9315)(0.4946)(0.1911)(0.6590)(0.5231)(0.4864)$$

$$= 0.01476$$

Then by the law of total probability

$$P\{B_1\} = \sum_{j \in S} P\{B_1 | X_1 = j\} P\{X_1 = j\}$$
  
= 
$$\sum_{j \in S} P\{B_1 | X_1 = j\} \mathbf{a}_j^{(1)}$$
  
= 
$$(0.00642)(0.2) + (0.01476)(0.2) + (0.00252)(0.2)$$
$$+ (0.00215)(0.2) + (0.00048)(0.2)$$
  
= 
$$0.00527.$$

Finally, calculate the  $\mathbf{a}^{(1)}$  using Equation (3.6). Equation (4.7) demonstrates example calculations for the probability of an M kill state given the situation, and Table 4.2 on the previous page lists all of the  $\mathbf{a}^{(1)}$  vector probabilities.

$$P\{X_{1} = M|B_{1}\} = \frac{P\{B_{1}|X_{1} = ND\}P\{X_{1} = ND\}}{P\{B_{1}\}}$$

$$= \frac{(0.01476)(0.2)}{0.02364}$$

$$= 0.56043$$
(4.7)

Now the model has an updated distribution for  $X_1$ . Based on the technique

Because this is the second shot, the updated distribution for the first round is known to be  $\mathbf{a}^{\prime(1)}$ , so  $\mathbf{a}^{(2)}$  is calculated using the information available.

$$\mathbf{a}^{(2)} = \mathbf{a}^{\prime(1)} \mathbf{P}$$

$$= \begin{array}{c} \text{ND} & \text{M} & \text{F} & \text{MF} & \text{K} \\ \begin{bmatrix} 0.24379 & 0.56043 & 0.09582 & 0.08173 & 0.01822 \end{bmatrix} \\ \begin{bmatrix} 1/5 & 1/5 & 1/5 & 1/5 \\ 0 & 1/3 & 0 & 1/3 & 1/3 \\ 0 & 0 & 1/3 & 1/3 & 1/3 \\ 0 & 0 & 0 & 1/2 & 1/2 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \\ = \begin{bmatrix} 0.048759 & 0.235568 & 0.080701 & 0.308377 & 0.326596 \end{bmatrix}$$

$$(4.8)$$

Again, the model decides that the gunner can observe the situational data. The model then generates the events associated with the perceived situation,  $B_2$ , from a vector of random numbers. Now

$$B_2 = \{M_{Yes} \cap E_{No} \cap A_{SeekingCover} \cap T_{LightDamage} \cap H_{NoDamage} \cap Tr_{LightDamage}\}$$

and the events are shown in Table 4.3 on the following page with their respective probabilities. The subsequent calculations to obtain  $P\{B_2|X_2 = j\}$ ,  $j \in S$  and  $\mathbf{a'}^{(2)}$  (also displayed in Table 4.3 on the next page) are analogous to those of the first shot.

The prior distribution is calculated similarly to Equation (4.8) as

$$\mathbf{a}^{(3)} = \left[ \begin{array}{cccc} 0.027688 & 0.042012 & 0.283387 & 0.320903 & 0.32601 \end{array} \right].$$

		Kill State						
	Events	ND	M-Kill	F-Kill	MF-Kill	K-Kill		
Physical	$T_{NoDamage}$	0.3014	0.3162	0.4100	0.4133	0.3974		
Damage	$H_{NoDamage}$	0.6569	0.5231	0.5493	0.2850	0.1119		
	$Tr_{LightDamage}$	0.3167	0.4864	0.4407	0.4393	0.3843		
Actions	$M_{No}$	0.4684	0.0785	0.5067	0.0769	0.0238		
(Conditioned)	$E_{No}$	0.5107	0.5026	0.9254	0.9520	0.9667		
	$A_{Other/NoActions}$	0.3684	0.1119	0.3975	0.0773	0.0774		
	$P\{B_2 X_2=i\}$	0.00553	0.00036	0.01850	0.00029	0.00003		
	$\mathbf{a}^{\prime (2)}$	0.13844	0.04297	0.76710	0.04638	0.00511		

 Table 4.3:
 Observed Events and Conditional Probabilities (Shot 2)

As in the previous two shots, the model decides that the Blue tank gunner may perceive situational data. Additionally  $B_3$  is generated by the model.

$$B_3 = \{M_{No} \cap E_{No} \cap A_{PersonnelAbandoning} \cap T_{LightDamage} \cap H_{LightDamage} \cap Tr_{HeavyDamage}\}$$

The events in  $B_3$  and their respective conditional probabilities are displayed in Table 4.4.  $P\{B_3\}$  and  $\mathbf{a}'^{(3)}$  can be calculated in the same manner as for the first and second shots and are also shown in Table 4.4.

 Table 4.4:
 Observed Events and Conditional Probabilities (Shot 3)

TZ:11 01

		Kill State				
	Events	ND	M-Kill	F-Kill	MF-Kill	K-Kill
Physical	$T_{LightDamage}$	0.3014	0.3162	0.4100	0.4133	0.3974
Damage	$H_{LightDamage}$	0.3176	0.4045	0.3700	0.4014	0.3498
	$Tr_{HeavyDamage}$	0.0224	0.4800	0.0193	0.5064	0.5764
Actions	$M_{No}$	0.5698	0.9187	0.5071	0.9394	0.9664
(Conditioned)	$E_{No}$	0.6395	0.5083	0.9574	0.9249	0.9486
	$A_{PersonnelAbandoning}$	0.1105	0.4078	0.2465	0.4153	0.1377
	$P\{B_3 X_3=i\}$	0.00009	0.01169	0.00035	0.03032	0.01011
	$\mathbf{a'}^{(3)}$	0.00018	0.03607	0.00728	0.71437	0.24210

4.3.3 Engagement Sequence with missing information. The result stated in Equation (3.3) from transient analysis allow this methodology to deal with cases where situational parameters cannot be observed. Suppose in the above engagement no perception data was available to the gunner after the second shot, but after the third shot he perceives situational information again.

The values of  $P\{B_3|X_3 = i\}$  do not change for this case but rather the prior distribution shifts. The calculations in this case differ from those in the above sequence only in the way  $\mathbf{a}^{(3)}$  is obtained. With no information gained after the second shot,  $\mathbf{a}^{(3)}$  is calculated from the last known distribution  $\mathbf{a}'^{(1)}$  by

$$\mathbf{a}^{(3)} = \mathbf{a}^{\prime(1)} \mathbf{P}^{(2)}$$
$$= \begin{bmatrix} 0.00975 & 0.08827 & 0.03665 & 0.26936 & 0.59596 \end{bmatrix}$$

to give the prior distribution for Bayes' Theorem.

Now  $\mathbf{a}^{(3)}$  is calculated in the same manner as above in Equation (4.7) and yields

$$\mathbf{a}_{1}^{\prime(3)} = \left[ \begin{array}{cccc} 0.00006 & 0.06772 & 0.00084 & 0.53588 & 0.39551 \end{array} \right].$$

where the subscript (1) indicates  $\mathbf{a}^{\prime(1)}$  as the last distribution updated with situational parameters. The difference between  $\mathbf{a}_1^{\prime(3)}$  and  $\mathbf{a}^{\prime(3)}$  reflects the information lost by not gaining perceptional data on the second shot.

## 4.4 Conclusion

This chapter provides an analysis of the BDA enhancement methodology. First, the issue of how many survey responses are required for the methodology was discussed and a recommendation of sample size determined by simulation using several metrics. Secondly, a full example implementation of the methodology was accomplished using a three shot engagement sequence. Lastly an example calculation with missing information was completed.

### V. Recommendations and Future Research

#### 5.1 Introduction

This thesis deals with the complexity of the BDA process for close combat situations and the difficulties in modeling it. The research has three objectives:

- 1. Develop a new methodology to model the BDA process which addresses the inadequacies of the current heuristic.
- 2. Produce a data collection method (i.e a survey) that will collect the necessary data for the modeling technique.
- 3. Propose a technique to implement the methodology into a combat model.

The first objective was completed by modeling BDA as a stochastic process, more specifically as a discrete time Markov chain (DTMC). The uncertain nature of BDA is captured within the DTMC model. The information gained through battlefield perception was modeled via Bayesian inference, using the result of transient analysis, a pmf kill state vector, as a distribution of prior probabilities.

The second objective was accomplished by designing a survey to collect data pertinent to the proposed methodology. A set of event trees was developed to enumerate those perception events that most affect a determination of BDA. These trees helped to frame the questions that will be asked of combat subject matter experts.

The third objective was completed by developing a logical modeling flow construct of the engagement process and placing the proposed methodology within it. Further, an analysis of how many survey responses will be needed to implement the methodology was performed. The results of the DTMC with Bayesian updating suggest that the number of survey responses should be maximized but that several hundred will give adequate results.

### 5.2 Modeling Issues

There are several modeling decisions that need discussion regarding the representation of the BDA process as a DTMC with Bayesian updating. First, the methodology as presented in this research incorporates more detail than is currently modeled by CASTFOREM and the differences must be considered. Second, during an engagement, the model must make determinations of whether the entity will shoot again or exit the engagement. There are several techniques that the model might use to deal with these problems.

5.2.1 Level of Detail in the Methodology. This methodology was designed with CASTFOREM in mind. However, this research has included a greater level of detail than explicitly modeled in CASTFOREM at this time. This was done to ensure that the model was flexible enough be effective as CASTFOREM evolves, and further to transition into the Army's next generation combat simulaiton model, Combat XXI. The flexibility of this methodology is one of best attributes, since as much or as little information as the user desires can be considered.

Currently, CASTFOREM models very little in the way of perception information. For the BDA enhancement methodology, *Movement* and *Engagement* are the only two event sets modeled by CASTFOREM at this time. As a result, the remaining event sets must be dealt with in one of several ways. First, the *Activity* event set and those pertaining to *Physical Damage* might be ignored. Second, the event sets not explicitly modeled might be selected by a random number generator, based on the *ground truth* state of the target. Probabilities obtained from the survey responses could be used for this purpose. Either way will yield an improved BDA heuristic for CASTFOREM, but the full capabilities of the methodology are achieved using more detail.

5.2.2 Engagement Exit Criterion. The combat model's decision to exit or proceed with an engagement is a very important issue. Overestimation and underestimation of BDA on the battlefield are a result of uncertainty in the model and have effects on the results of a simulated conflict. These effects might include how many targets an entity prosecutes, how quickly a entity runs out of ammunition, or even the survivability of the entity within the simulation. To achieve realism, the model must have adequate exit criteria.

One technique would be to select a BDA goal (e.g. reach K-kill) at the beginning of each engagement. A random number would be drawn after each shot (with update) and the kill state would be determined by the  $\mathbf{a}^{\prime(n)}$  vector. If the selection of  $X_n$ meets or exceeds the BDA goal the model exits the BDA process. This allows for incorrect estimation of a target's kill state due to the uncertainty on the battlefield. For instance, in an engagement sequence, the tank gunner may determine BDA as an MF-kill after the first shot when, in fact, ground truth is an M-kill or perceive an M-kill when ground truth is K-kill.

Another technique would involve having a goal corresponding to threshold of density at or above a kill state (e.g. at least 90% in the M-, MF-, and K-kill states). The gunner would fire until this goal was reached and the target would be presumed as *at least* an M-kill. In the example engagement sequence presented in Section 4.3.2, the gunner would stop after the third shot because > 0.98 of the density in  $\mathbf{a}^{\prime(3)}$  is contained in M-, MF-, and K-kill states. This would likely result in *over-killing* the target, or shooting more rounds than necessary in many engagements. This result actually captures reality quite well, as soldiers are more apt to underestimate BDA due to the (survivability) risks involved.

Yet another technique would create some function to incorporate the tradeoffs between achieving a BDA goal on the current target and engaging another (possibly more important) target. If some critical value was not met during the engagement the entity would exit the process and engage a more critical target. As an example, suppose, in an engagement sequence, that the tank gunner perceives that the target is M-killed after the first shot but would like to achieve a K-kill. However, a new enemy poses an immediate and more serious threat to the tank. The model might decide to move to the higher priority target based on this information. The technique chosen to provide exit criteria for an engagement will certainly shape the implementation of the methodology into a combat simulation model. As a result, this choice is of utmost importance to the decision maker and should be considered carefully.

### 5.3 Model Assumptions and Strengths

The methodology relies on several assumptions that allow a mathematically valid model of the BDA process. The main assumptions that underly the DTMC with updating approach are as follows:

- 1. The event sets contain mutually exclusive events.
- 2. The probability of a situation, or intersection of events can be calculated.
- 3. The probability of the next state depends only on the current state. That is, the Markovian property.
- 4. The conditional probabilities dependent on the current state are time homogeneous. That is, the stationary property.

The strengths of this modeling technique are extensive. Specifically, it addresses several of the shortfalls of the current AMSAA heuristic (reference Section 1.3). An item already discussed is incorporating uncertainty into the model. Allowing the target to jump between any two perceived states and having the assessing soldier perceive incorrect BDA is an important aspect of the model.

Another issue the BDA model resolves is the incorporation of situational factors into an assessment. The model directly makes use of the perception information available to a soldier performing an assessment, providing a realistic representation of the decision process. By using information contained in the situational parameters, meaningful probabilities are assigned to assessing a target at a kill state.

Though not specifically addressed in this research, dealing with indirect fire could be easily accomplished with this approach. Modeling the process as a DTMC provides avenues to deal with missing data, a likely situation for indirect fire. Though the model has numerous strengths and advantages over the previous AMSAA heuristic, it still holds many avenues for improvement and further study.

### 5.4 Recommendations for future research

This thread of research provides numerous continuation and related topics that are of interest. Since this marks the first BDA model of its kind, surely improvement opportunities are available. The most immediate value-added would come from adding a module that captures the degradation of BDA capability due to hindering factors. These factors might include weather, time of day, range to the target, the sensor being used, or obscurants (e.g. dust and smoke). Clearly any of these may affect the quality of the perceived information.

Another improvement would involve an exploration of the dependence relationships among event sets. Through collection of real data from combat SMEs, the assumptions made in the methodology could be challenged and modified if necessary. This would likely occur in conjunction with development of decision tables for use in a combat model.

Additionally, this research has dealt entirely within the construct of Army forceon-force combat models. The incorporation of uncertainty perceived information translates well to the BDA process in any realm (air, sea, or land). As a result, this methodology could prove useful in other DoD simulations with similar decision processes and should be investigated.

Lastly, any number of improvement techniques might be applied to this methodology. The threads above represent just a fraction of the possible topics that can be reached with this research.

# Appendix A. SME Survey Design

The following pages present the proposed data collection method. SMEs will be determined by the Army per their rules and regulations.

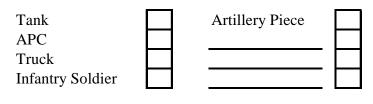
# **Battle Damage Assessment Questionnaire**

Position Code: \_\_\_\_\_ Position Name: \_\_\_\_\_

Years Experience: \_\_\_\_\_

Have you ever performed real time BDA in a combat situation? Yes / No

If yes, on which target types have you performed BDA? (Please check all that apply, adding any not listed.)



## Instructions

For each question you will be presented a scenario and be asked to identify key things that you might see in that situation. There will be three sets of check boxes beside each item labeled "**N**" "**M**" and "**A**". Items that you would *never* or rarely expect to see in the situation should be checked in the "**N**" column. Check items you *might* see in the "**M**" column and finally check critical items that you would *always* expect to see in the "**A**" column. You may also use the space provided to explain your thought process or add items not listed.

You should assume that you are at ID level using the most capable sensor available to you. Try to be as complete as possible.

The following are definitions of battle damage assessment (BDA) kill types that you may be asked to describe. These definitions applicable to vehicles but the concepts extend to dismounted troops as well.

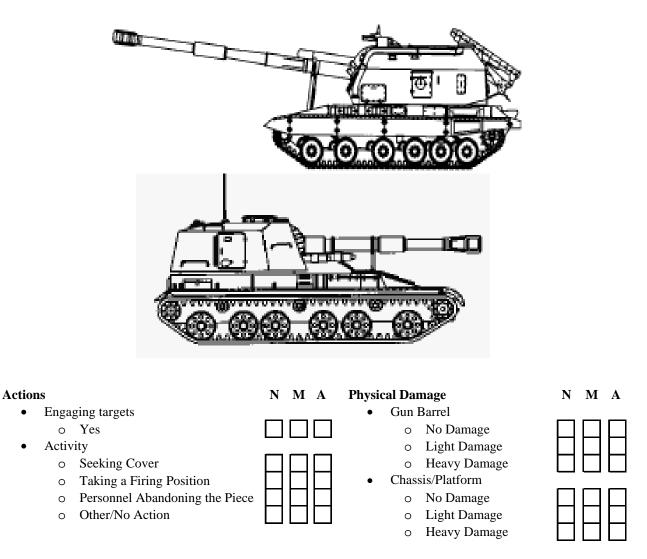
**M-kill (Mobility):** A target is subject to an M-kill if it is incapable of executing controlled movement and the damage is not repairable by the crew on the battlefield. Failure to function may be caused by the incapacitation of the crew or damage to propulsion or control equipment.

**F-kill (Firepower):** A target is subject to an F-kill if it is incapable of delivering controlled fire from the main armament and the damage is not repairable by the crew on the battlefield. The loss of this function may be caused by the incapacitation of the crew or damage to the main armament and its associated equipment.

**K-kill (Catastrophic):** A target is subject to a K-kill if it sustains both an M- and F-kill and is damaged to the extent that is not economically repairable. A K-kill is more likely to be apparent to the crew of a weapon system because of the resulting fires/detonation of ammunition.

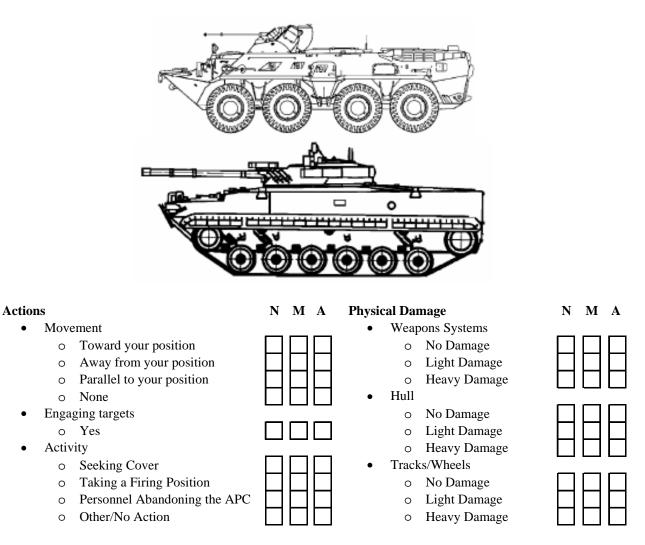
An enemy artillery piece has taken fire and it sustains an F-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the artillery piece is an F-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy artillery that you may use to mark or illustrate your expectations of the assessment.



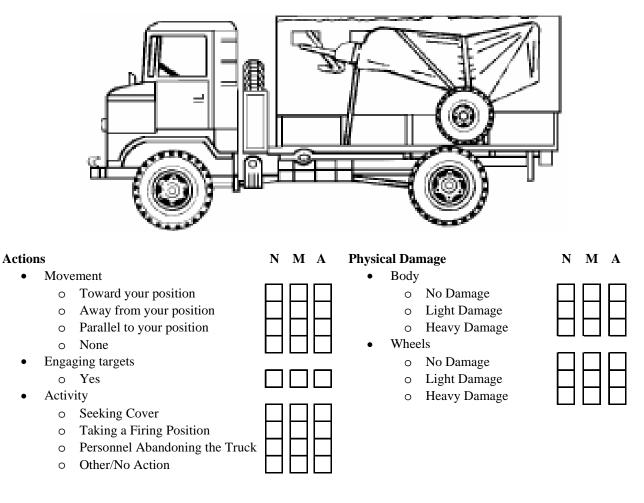
2) An enemy APC has taken fire but it **does not sustain a kill**. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the APC has not sustained a kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy APCs that you may use to mark or illustrate your expectations of the assessment



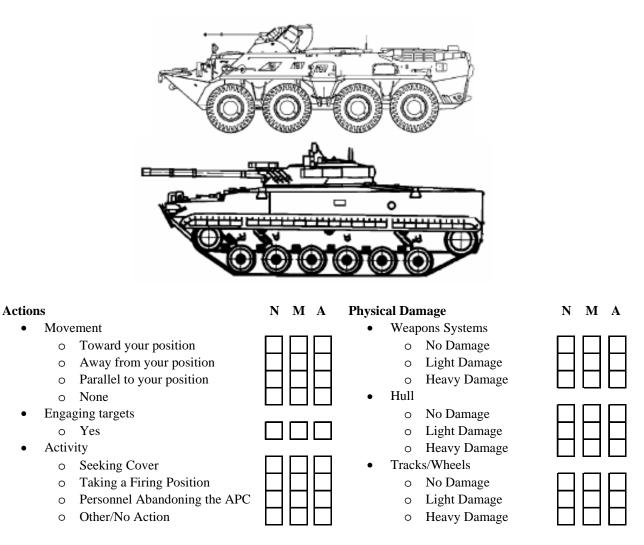
3) An enemy truck has taken fire and it sustains an M-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the truck is an M-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy trucks that you may use to mark or illustrate your expectations of the assessment



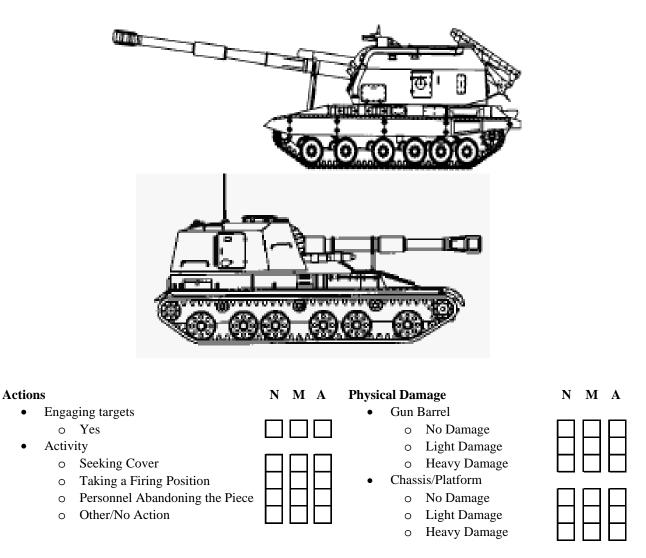
4) An enemy APC has taken fire and it sustains a K-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the APC is a K-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy APCs that you may use to mark or illustrate your expectations of the assessment



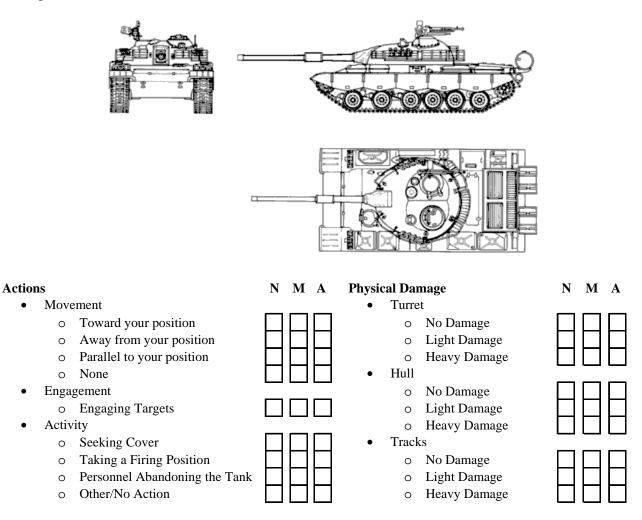
5) An enemy artillery piece has taken fire and it sustains a **K-kill**. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the artillery piece is a **K-kill**, check items you would *never* or rarely see in the "N" column, items you *might* see under the "**M**" column, and items you would *always* see in the "**A**" column.

Below are some pictures of enemy artillery that you may use to mark or illustrate your expectations of the assessment.



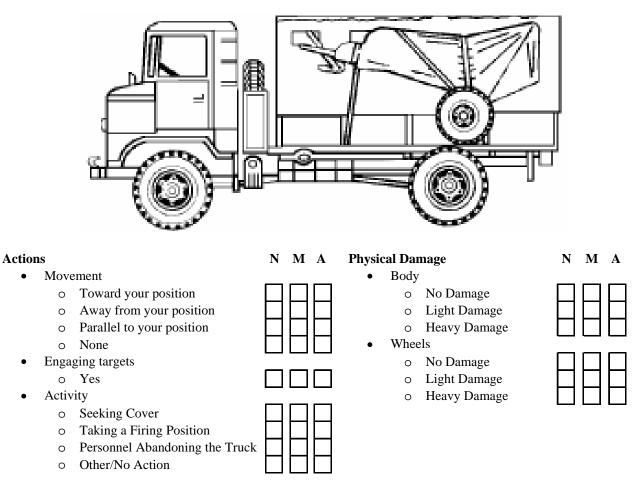
6) An enemy tank has taken fire and it sustains a K-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the tank is a K-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy tanks that you may use to mark or illustrate your expectations of the assessment



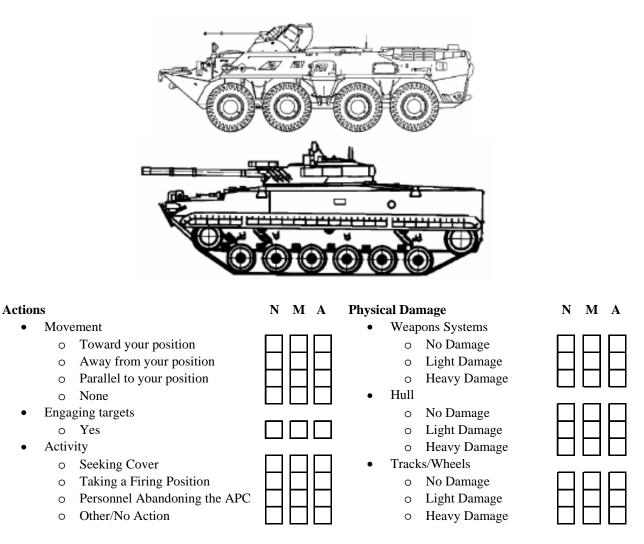
7) An enemy truck has taken fire and it sustains a K-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the truck is a K-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy trucks that you may use to mark or illustrate your expectations of the assessment



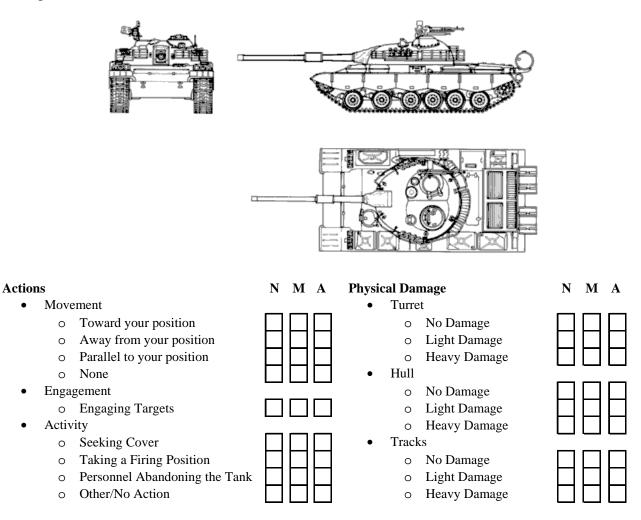
8) An enemy APC has taken fire and it sustains an F-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the APC is an F-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy APCs that you may use to mark or illustrate your expectations of the assessment



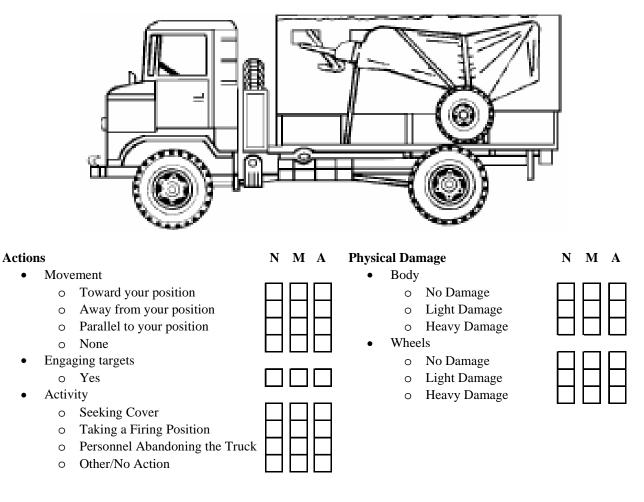
9) An enemy tank has taken fire but it has not sustained a kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the tank did not sustain a kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy tanks that you may use to mark or illustrate your expectations of the assessment



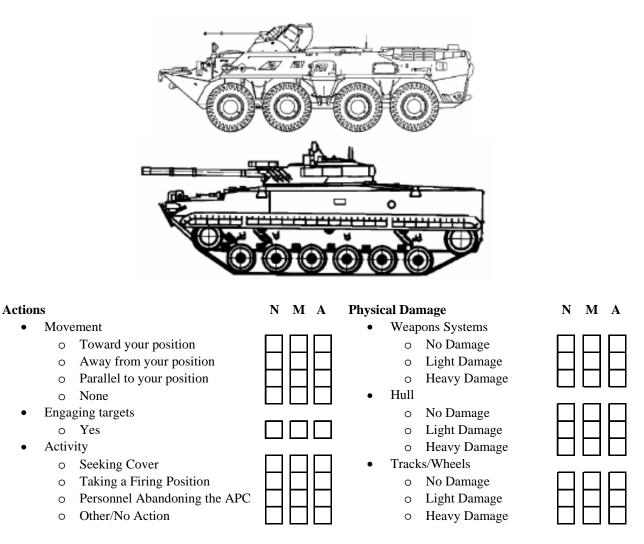
10) An enemy truck has taken fire but **does not sustain a kill**. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the truck has not sustained a kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy trucks that you may use to mark or illustrate your expectations of the assessment



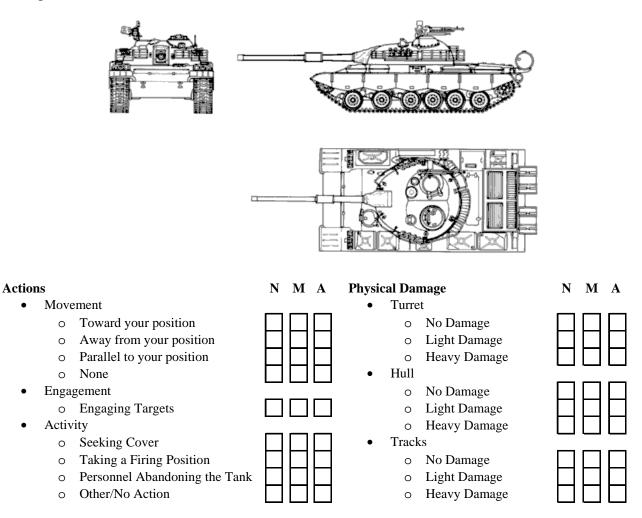
11) An enemy APC has taken fire and it sustains an M-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the APC is an M-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy APCs that you may use to mark or illustrate your expectations of the assessment



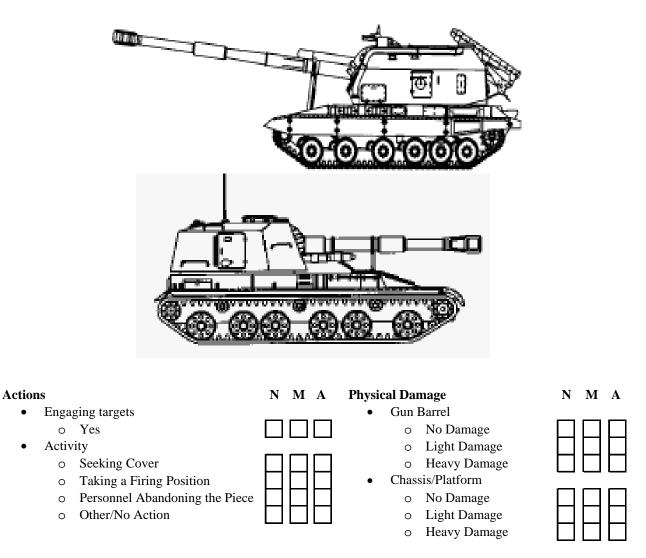
12) An enemy tank has taken fire and it sustains an M-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the tank is an M-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy tanks that you may use to mark or illustrate your expectations of the assessment



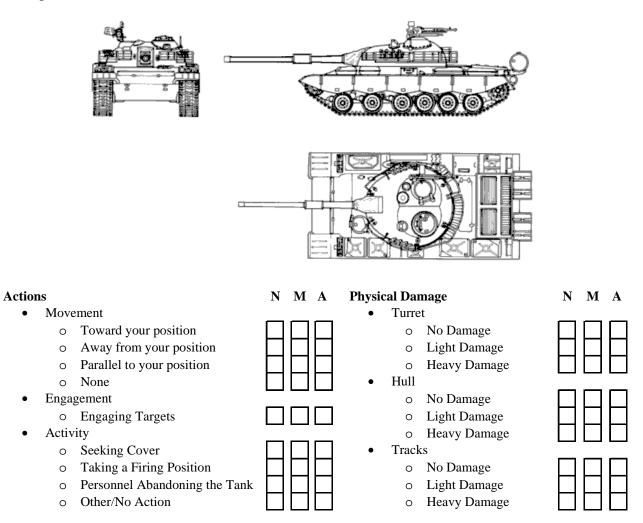
13) An enemy artillery piece has taken fire but **does not sustain a kill**. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the artillery piece did not sustain a kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy artillery that you may use to mark or illustrate your expectations of the assessment.



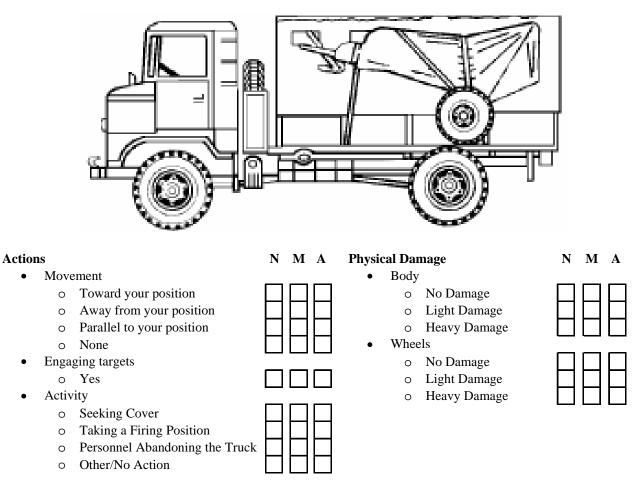
14) An enemy tank has taken fire and it sustains an F-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the tank is an F-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy tanks that you may use to mark or illustrate your expectations of the assessment



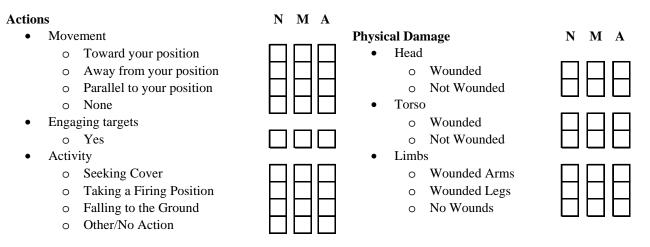
15) An enemy truck has taken fire and it sustains an F-kill. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the truck is an F-kill, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.

Below are some pictures of enemy trucks that you may use to mark or illustrate your expectations of the assessment



For soldiers it does not make sense to use the M-, F- and K-kill types described in the directions at the beginning of this survey. Instead we will classify an enemy soldier as **Incapacitated** if he cannot continue the mission, assault, or defend. **Incapacitation** may include fatality but does not necessarily imply that the enemy is dead.

16) An enemy soldier has taken fire and he sustains an **incapacitation-kill**. Please mark the appropriate box for each of the actions or characteristics that you might see given the situation. If it is true that the soldier is **incapacitated**, check items you would *never* or rarely see in the "N" column, items you *might* see under the "M" column, and items you would *always* see in the "A" column.



## **Degradation Questions**

Now consider making assessments with different sensors. Most likely each sensor is sensitive to different factors that will degrade your ability to see the target and make an assessment. You will be asked to mark how much each factor degrades the given sensor.

Key:
N: No Degradation
H: Half Degradation
F: Full Degradation
Comments: Use the space given to describe how the factor affects the sensor.

Complete the following tables concerning different sensor types. For example if your sensor is unaided visual, ambient light may have a full degradation effect. Comments would include that nighttime (low/no ambient light) impairs your ability to see. If there are additional factors that do not appear on the list, add them and answer in the same manner.

# **IR/Thermal**

Factor	Ν	Н	F	Comments
Ambient Light				
Humidity				
Obscurants				
Range to Target				
Weather				
Movement while Assessing				

# **Unaided Visual**

Factor	Ν	н	F	Comments
Ambient Light				
Humidity				
Obscurants				
Range to Target				
Weather				
Movement while Assessing				

# **TV/Aided Visual**

Factor	Ν	Н	F	Comments
Ambient Light				
Humidity				
Obscurants				
Range to Target				
Weather				
Movement while Assessing				

Appendix B. MATLAB Code for Simulation of Survey Responses

function [] = MasterSimulation() 1  $\mathbf{2}$ % MasterSimulation: a function to simulate survey responses, calculate estimated and true a'(n) vectors, record data, and % 3 % 4create plots 5% % Calls: ReadSimulationProbabilities, ReadTrueProbabilities, 6 % SurveyResponseMatrix, PlotDataConvergence, DTMC, GetSituation, 7 % DataCalcuations, GetStats, N\_Plots, EngageSequence 8 % 9 10 % Author: Michael Carras 11 % michael.carras@afit.edu 12%-----13 % Created: 2006 1415% Last Modified: 9 March 2006 16 % 17% VARIABLES (Global/Main)------18 % Pio\_PhysicalDamage - Simulation probabilities for binary response 19 vector of physical damage % 20% CondPio\_Actions - Conditional simulation probabilities for binary 21% response vector of actions given phys damage 22 % Ptrue\_All - True marginal event probabilities 2324 % CondPtrue\_Actions - True conditional "Action" Probabilities % NumResponse - Number of survey responses 2526% ResponseMatrix - Matrix containing all survey responses % aPnTrue - True a' vector 2728 % a\_nTrue - True a vector 29% Situation - Matrix of situations tested % sit - Current situation counter 30 % B\_n - Current siutation 31 - Pointer to correct row of conditional action % Bn\_pd 32 33 % probabilities % P\_BnaTrue - True conditional probabilities for current 34% situation 35 - True marginal probabilities for current situation 36 % P\_BnTrue 37 % temp - temporary vector holding intersection probs 38 % tempSum - sum of temp 39 % PlotData - Matrix with data for plots 40 % Mean - Mean BDA based on a' - Variance of BDA based on a' 41 % Var 42% SD - Standard Deviation of BDA based on a' - Coefficint of variation based on a' 43 % CV % ------44

```
45
46 % Closes all open plots and turns warning displays off
47
   warning off all
   close all
^{48}
49
   % Read simulation Probabilities and True Probabilities
50
   [Pio_PhysicalDamage,CondPio_Actions] = ReadSimulationProbabilities();
51
52
   [Ptrue_All,CondPtrue_Actions] = ReadTrueProbabilities();
53
   % Set the number of responses here
54
   NumResponse = 1000;
55
56
57 % generate survey responses
   [ResponseMatrix] = SurveyResponseMatrix(NumResponse,...
58
       Pio_PhysicalDamage,CondPio_Actions,0);
59
60
61
   % Plot convergence of data
62 PlotDataConvergence(ResponseMatrix,NumResponse);
63
   % initialize variables
64
   aPnTrue = [1 \ 0 \ 0 \ 0];
65
66
   a_nTrue = DTMC(aPnTrue);
67
68 % retrieve B_n's
   [Situation] = GetSituations();
69
70
  % create data for plots
71
72 for sit = 1:5
73
74
       B_n = Situation(sit,:);
75
       Bn_pd = 1+(B_n(4)-9)+3*(B_n(5)-12)+9*(B_n(6)-15);
76
       P_BnaTrue = squeeze([CondPtrue_Actions(Bn_pd,B_n(1),:),...
77
           CondPtrue_Actions(Bn_pd,B_n(2),:),...
78
79
           CondPtrue_Actions(Bn_pd,B_n(3),:)]);
80
       P_BnTrue = [P_BnaTrue; ...
81
           Ptrue_All(:,B_n(4))'; ...
82
           Ptrue_All(:,B_n(5))';...
83
           Ptrue_All(:,B_n(6))'];
84
85
       temp = prod(P_BnTrue,1).*a_nTrue;
86
       tempSum = sum(temp);
87
88
       aPnTrue = temp/tempSum;
```

```
89
       [PlotData] = DataCalculations(NumResponse,B_n,ResponseMatrix,aPnTrue);
90
91
       [Mean,Var,SD,CV] = GetStats(aPnTrue);
       PlotData = [PlotData; [1,aPnTrue,Mean,Var,SD,CV,0]] ;
92
       xlswrite('Ch4PlotData.xls',PlotData,sit,'b2');
93
94
       N_Plots(PlotData,sit,NumResponse);
95
96
97
   end
98
   EngageSequence(ResponseMatrix,Ptrue_All,CondPtrue_Actions)
99
100
   end
   101
102
103
104
   % Sub functions
   105
   function[Pio_PhysicalDamage,CondPio_Actions]=ReadSimulationProbabilities()
106
   \% ReadSimulationProbabilities: a function to read in the probabilities of
107
                      simulated surevey responses from an excel spreadsheet
108
   %
109
110
   Pio_PhysicalDamage = xlsread('SurveyProbs.xls', 'p_0', 'b2:j6');
111
   CondPio_Actions(:,:,1) = xlsread('SurveyProbs.xls','p_0','b18:i44');
112
   CondPio_Actions(:,:,2) = xlsread('SurveyProbs.xls','p_0','b46:i72');
113
   CondPio_Actions(:,:,3) = xlsread('SurveyProbs.xls','p_0','b74:i100');
114
   CondPio_Actions(:,:,4) = xlsread('SurveyProbs.xls','p_0','b102:i128');
115
   CondPio_Actions(:,:,5) = xlsread('SurveyProbs.xls','p_0','b130:i156');
116
117
118
   end
119
120
   *****
121
122
   function [Ptrue_All,CondPtrue_Actions] = ReadTrueProbabilities();
   \% ReadSimulationProbabilities: a function to read in true probabilities of
123
   %
124
                      events from and excel spreadsheet
125
   Ptrue_All = xlsread('SurveyProbs.xls', 'p_0', 'b11:r15');
126
127
   CondPtrue_Actions(:,:,1) = xlsread('SurveyProbs.xls','p_0','k18:r44');
128
   CondPtrue_Actions(:,:,2) = xlsread('SurveyProbs.xls','p_0','k46:r72');
129
   CondPtrue_Actions(:,:,3) = xlsread('SurveyProbs.xls', 'p_0', 'k74:r100');
130
   CondPtrue_Actions(:,:,4) = xlsread('SurveyProbs.xls', 'p_0', 'k102:r128');
131
   CondPtrue_Actions(:,:,5) = xlsread('SurveyProbs.xls', 'p_0', 'k130:r156');
132
```

```
133
134
   end
135
136
   137
   function [ResponseMatrix] = SurveyResponseMatrix(NumResponse,...
138
       Pio_PhysicalDamage,CondPio_Actions,Ex)
139
140
   % SurveyResponseMatrix: a function to simulate (NumResponse) number of
   %
                      survey responses by rendom numer draws
141
   %
142
       Calls: DamageCondition, ConvertActions
143
   %
144
   %
   % LOCAL VARIABLES -----
145
   % i
                          - kill state counter
146
   % iResponseMatrix
                          - placeholder for ith layer of ResponseMatrix
147
   % Rnd_io_pd
                          - matrix of random numbers for physical damage
148
149
   % Rnd_io_a
                          - matrix of random numbers for actions
150 % n
                          - Number of responses counter
   % etaRnd_io_pd
                          - nth row of Rnd_io_pd
151
   % etaRnd_io_a
                          - nth row of Rnd_io_a
152
   % TempPio_pd
                          - appropriate row of simulation probabilities
153
154
   % Rsp_io_pd
                          - binary vector of physical damage responses
   % Rsp_num_pd
                          - physical damage response in numerical form
155
   % Weight_pd
                          - Weight vector for actions to condition on
156
   %
                              physical damage
157
                          - appropriate simulation probabilities for actions
   % TempPio_a
158
                          - binary vector of action responses
159
   % Rsp_io_a
   % Rsp_num_a
                          - action response in numerical distribution form
160
   % etaRsp_num
                          - concatenation of action and pysical damage
161
   % ------
162
163
   % Initialize ResponseMatrix
164
   ResponseMatrix = zeros(NumResponse,17,5);
165
166
   % Iterate thorough kill states
167
   for i = 1:5
168
       \% initialize the response matrix for this kill state and generate
169
       % random numbers
170
       iResponseMatrix = zeros(NumResponse, 17);
171
172
       Rnd_io_pd = rand(NumResponse,9);
       Rnd_io_a = rand(NumResponse,8);
173
174
175
       for n = 1:NumResponse
176
           % Get the random numbers for this reponse
```

```
89
```

```
177
            etaRnd_io_pd = Rnd_io_pd(n,:);
178
            etaRnd_io_a = Rnd_io_a(n,:);
179
            % Get the appropriate kill state physical damage event
180
            % probabilities and compare against random numbers
181
            TempPio_pd = Pio_PhysicalDamage(i,:);
182
            Rsp_io_pd = etaRnd_io_pd <= TempPio_pd;</pre>
183
184
            % convert the binary physical damage to numerical probability
185
            % distributions and get the weight vector for action responses
186
            [Rsp_num_pd,Weight_pd] = DamageCondition(Rsp_io_pd,i);
187
188
            % Get appropriate kill state conditional probabilities and ocmpare
189
            % them against random numbers
190
            TempPio_a = squeeze(CondPio_Actions(:,:,i));
191
            TempPio_a = Weight_pd*TempPio_a;
192
193
            Rsp_io_a = etaRnd_io_a <= TempPio_a;</pre>
194
195
            % convert the binary actions to numerical probability
            % distributions
196
            [Rsp_num_a] = ConvertActions(Rsp_io_a,i);
197
198
            % place this reponse in the iResponseMatrix
199
            etaRsp_num = [Rsp_num_a, Rsp_num_pd];
200
            iResponseMatrix(n,:) = etaRsp_num;
201
        end
202
203
        % place the ith layer into ResponseMatrix
204
        ResponseMatrix(:,:,i) = iResponseMatrix;
205
206
        % write data to spreadsheet
207
        if Ex == 0
208
            xlswrite('Ch4SimData.xls',iResponseMatrix,i,'b2');
209
        elseif Ex == 1
210
211
            xlswrite('Ch4ExSimData.xls',iResponseMatrix,i,'b2');
212
        end
    end
213
214
    end
215
216
217 %
    function [Rsp_num_pd,Weight_pd] = DamageCondition(Rsp_io_pd,i);
218
    % DamageCondition: function to convert binary rsponses to numerical ones
219
220 %
                            and produce a conditioning weight vector for
```

```
221 %
                          actions
222 %
223
   % LOCAL VARIABLES ------
224
   % tur_io, hul_io, trk_io - binary response pieces for turret, hull, tracks
   % tur_num, hul_num, trk_num - numerical responses for turret, hull, tracks
225
226
   % ------
227
228
   % break logical vectors into turret, hull, track pieces
   tur_io = [Rsp_io_pd(1),Rsp_io_pd(2),Rsp_io_pd(3)];
229
   hul_io = [Rsp_io_pd(4), Rsp_io_pd(5), Rsp_io_pd(6)];
230
   trk_io = [Rsp_io_pd(7),Rsp_io_pd(8),Rsp_io_pd(9)];
231
232
   tur_num = []; hul_num = []; trk_num = [];
233
   % assign distribution to turret
234
   tur_num(~tur_io)= 0;
235
   switch sum(tur_io)
236
       case(0)
237
           switch i
238
               case(1)
239
                   if rand < .75 \text{ tur_num} = [1,0,0];
240
                   else tur_num = [.5,.5,0]; end
241
242
               case(2)
                   if rand < .75 tur_num = [0,.5,.5];
243
                   else tur_num = [1/3,1/3,1/3]; end
244
               case{3,4,5}
245
                   if rand < .75 tur_num = [0,0,1];
246
                   else tur_num = [0,.5,.5]; end
247
248
           end
       case(1)
249
250
           tur_num(tur_io) = 1;
       case(1)
251
           tur_num(tur_io) = 1;
252
       case{2}
253
           tur_num(tur_io) = .5;
254
255
       case{3}
           tur_num(tur_io) = 1/3;
256
   end
257
258
   % assign distribution to hull
259
   hul_num(~hul_io)= 0;
260
   switch sum(hul_io)
261
       case(0)
262
263
           switch i
264
               case{1,2,3}
```

```
if rand < .75 hul_num = [1,0,0];
265
                     else hul_num = [.5,.5,0]; end
266
267
                 case(4)
                     if rand < .75 hul_num = [.5,.5,0];
268
                     else hul_num = [1/3,1/3,1/3];
                                                        end
269
                 case(5)
270
271
                     if rand < .75 hul_num = [0,0,1];
                     else hul_num = [0,.5,.5]; end
272
273
            end
        case(1)
274
            hul_num(hul_io) = 1;
275
        case{2}
276
            hul_num(hul_io) = .5;
277
        case{3}
278
            hul_num(hul_io) = 1/3;
279
280
    end
281
    %assign distribution to tracks
282
    trk_num(~trk_io)= 0;
283
    switch sum(trk_io)
284
        case(0)
285
286
            switch i
                 case{1,3}
287
                     if rand < .75 trk_num = [1,0,0];
288
                     else trk_num = [.5,.5,0]; end
289
                 case{2,4}
290
                     if rand < .75 trk_num = [0,0,1];
291
                     else trk_num = [0,.5,.5]; end
292
                 case(5)
293
294
                     if rand < .75 trk_num = [1/3,1/3,1/3];
                     else trk_num = [0, .5, .5]; end
295
296
            end
        case(1)
297
            trk_num(trk_io) = 1;
298
299
        case{2}
            trk_num(trk_io) = .5;
300
        case{3}
301
            trk_num(trk_io) = 1/3;
302
    end
303
304
305 % assign output 1 (d_eta,i)
    Rsp_num_pd = [tur_num, hul_num, trk_num];
306
307
308 % assign output 2 (weight vector)
```

```
Weight_pd = zeros(1,27);
309
   for k = 1:3
310
311
       for h = 1:3
          for t = 1:3
312
              wt_pd = tur_num(t)*hul_num(h)*trk_num(k);
313
              TempPos = t + 3*(h-1) + 9*(k-1);
314
              Weight_pd(TempPos) = wt_pd;
315
316
          end
       end
317
   end
318
319
320
   end
321
   322
   function [Rsp_num_a] = ConvertActions(Rsp_io_a,i);
323
   % ConverActions: function to convert binary rsponses to numerical ones
324
325
   %
   % LOCAL VARIABLES -----
326
327
   % mov_io, eng_io, act_io - binary response pieces for movement, engagement,
   %
                            activity
328
   \% mov_num, eng_num, act_num - numerical responses for movement, engagement,
329
330
   %
                            activity
   % -----
331
332
333 % break logical vectors into movement, engagement, activity
   mov_io = [Rsp_io_a(1),Rsp_io_a(2)];
334
   eng_io = [Rsp_io_a(3),Rsp_io_a(4)];
335
336 act_io = [Rsp_io_a(5),Rsp_io_a(6),Rsp_io_a(7),Rsp_io_a(8)];
   mov_num = [];eng_num = []; act_num = [];
337
338
339 % assign distribution to movementn
   mov_num(~mov_io) = 0;
340
   switch sum(mov_io)
341
       case(0)
342
          switch i
343
              case{1,3}
344
                 mov_num = [.5,.5];
345
346
              otherwise
                 mov_num = [0, 1];
347
348
          end
       case(1)
349
          mov_num(mov_io) = 1;
350
351
       case(2)
352
          mov_num(mov_io) = .5;
```

```
353
    end
354
355
    % assign distribution to engagement
    eng_num(~eng_io) = 0;
356
    switch sum(eng_io)
357
        case(0)
358
             switch i
359
                 case{1,2}
360
                     eng_num = [.5,.5];
361
                 otherwise
362
                     eng_num = [0,1];
363
364
             end
        case(1)
365
             eng_num(eng_io) = 1;
366
        case(2)
367
             eng_num(eng_io) = .5;
368
369
    end
370
    % assign distribution to activity
371
    act_num(~act_io)= 0;
372
    switch sum(act_io)
373
        case(0)
374
             switch i
375
                 case(1)
376
377
                     if rand < .75 act_num = [.25,.25,.25,.25];
                     else act_num = [1/3,1/3,0,1/3]; end
378
                 case{2,4}
379
                     if rand < .75 act_num = [0,0,.5,.5];
380
                     else act_num = [0,0,1,0]; end
381
382
                 case(3)
                     if rand < .75 act_num = [1/3,0,1/3,1/3];
383
                     else act_num = [.5,0,.5,0]; end
384
                 case(5)
385
                     act_num = [0,0,0,1];
386
387
             end
        case(1)
388
             act_num(act_io) = 1;
389
        case{2}
390
             act_num(act_io) = .5;
391
        case{3}
392
             act_num(act_io) = 1/3;
393
        case{4}
394
             act_num(act_io) = .25;
395
396 end
```

```
397
   % assign output (d_eta,i)
398
399
   Rsp_num_a = [mov_num, eng_num, act_num];
400
401
   end
402
403
   404
   function [] = PlotDataConvergence(ResponseMatrix,NumResponse);
405
   % PlotDataConvergence: function to plot how an event probability converges
406
   %
                            to its ''true'' probability
407
408
   %
   % LOCAL VARIABLES ------
409
   % P_Tnd
                         - Probability of turret with no damage from
410
   %
                            ResponseMatrix
411
   % pTrue_Tnd
                         - True probability of turret with no damage
412
   % -----
413
414
415
   % get responses for turret no damage
   P_Tnd = squeeze(ResponseMatrix(:,9,1));
416
417
418
   % create data points every 10 responses
   for N = 10:10:NumResponse
419
       d_Tnd(N/10) = mean(P_Tnd(1:N));
420
   end
421
422
423
   % set x axis support
   x = 10:10:NumResponse;
424
425
   pTrue_Tnd = ones(length(x),1)*0.66975;
426
427
   % draw figure and set properties
428
   figure(1)
429
       plot(x,d_Tnd)
430
431
       hold on
       plot(x,pTrue_Tnd,'-k')
432
       hold off
433
434
       ax1 = gca;
       set(get(ax1,'XLabel'),'String','Number of Survey Responses, N',...
435
              'FontName', 'times new roman');
436
       set(get(ax1,'YLabel'),'String','d_{ND}( {\itT_{NoDamage}} ) ',...
437
              'FontName', 'times new roman');
438
       set(ax1,'FontName','times new roman',...
439
440
              'YLim',[0 1],...
```

```
'XLim',[10 NumResponse])
441
442
      grid on
443
   end
444
445
446
   447
448
   function [an] = DTMC(aPn)
   \% DTMC: function to multiply aPn and the transition probability matrix
449
450
   % transition probability matrix, P
451
452
   P=[.2, .2, .2, .2, .2;...
          1/3, 0, 1/3, 1/3;...
453
      0,
              1/3, 1/3, 1/3;...
      0,
          0,
454
              0, .5, .5;...
      0,
          Ο,
455
          0,
              0, 0, 1];
456
      0,
457
   an = aPn*P;
458
459
   end
460
461
462
   463
   function [Situation] = GetSituations()
464
   \% GetSituations: function to retrieve the correct actions and physical
465
                         damage for plots
466
   %
467
   %
   % LOCAL VARIABLES -----
468
   % ObsAct
                      - matrix of all possible action combinations
469
   % ObsPhysDam
                      - matrix of all possible physical damage combos
470
   % ------
471
472
   ObsAct = [1,3,5; ...1
473
      2,3,5;...2
474
475
      1,4,5;...3
      2,4,5;...4
476
      1,3,6;...5
477
      2,3,6;...6
478
      1,4,6;...7
479
      2,4,6;...8
480
      1,3,7;...9
481
      2,3,7;...10
482
      1,4,7;...11
483
      2,4,7;...12
484
```

485	1,3,8;13
486	2,3,8;14
487	1,4,8;15
488	2,4,8;];%16
489	ObsPhysDam = [9,12,15;1
490	10,12,15;2
491	11,12,15;3
492	9,13,15;4
493	10,13,15;5
494	11,13,15;6
495	9,14,15;7
496	10,14,15;8
497	11,14,15;9
498	9,12,16;10
499	10,12,16;11
500	11,12,16;12
501	9,13,16;13
502	10,13,16;14
503	11,13,16;15
504	9,14,16;16
505	10,14,16;17
506	11,14,16;18
507	9,12,17;19
508	10,12,17;20
509	11,12,17;21
510	9,13,17;22
511	10,13,17;23
512	11,13,17;24
513	9,14,17;25
514	10,14,17;26
515	11,14,17;];%27
516	
517	% set matrix of current situations
518	Situation = [ ObsAct(16,:) ,ObsPhysDam(1,:) ;
519	ObsAct(1,:) ,ObsPhysDam(4,:) ;
520	ObsAct(8,:) ,ObsPhysDam(13,:) ;
521	<pre>ObsAct(11,:) ,ObsPhysDam(12,:) ;</pre>
522	<pre>ObsAct(8,:) ,ObsPhysDam(26,:) ];</pre>
523	
524	end
525	
526	
527	%**************************************
528	<pre>function [PlotData] = DataCalculations(NumResponse,B_n,ResponseMatrix,aPnTrue)</pre>

```
\% DataCalcuations : function to calculate statistics for the survey
529
   %
530
                                responses
531
   %
       Calls: DTMC, aPrimeCalc, GetStats
   %
532
   %
533
   % LOCAL VARIABLES ------
534
   % N
                         - The numbefr of responses that stats are based on
535
536
   % Nrm2
                         - 2-norm of the difference between a'true and a'
   % ------
537
538
   % initialize variables
539
   aPn = [1 \ 0 \ 0 \ 0];
540
   a_n = DTMC(aPn);
541
   PlotData = [];
542
543
   % create data points for every 10 responses
544
545
   for N = 10:10:NumResponse
546
547
       \% calcuate the updated a' vector for each situation
       [aPn] = aPrimeCalc(ResponseMatrix,a_n,N,B_n);
548
549
550
       % calculate stats of the a' vector
       [Mean, Var, SD, CV] = GetStats(aPn);
551
       Nrm2 = norm(aPn-aPnTrue);
552
553
       % concatenate data
554
       PlotData = [PlotData; [N, aPn, Mean, Var, SD, CV, Nrm2]] ;
555
   end
556
557
558
   end
559
   560
   function[aP] = aPrimeCalc(ResponseMatrix,an,N,B_n)
561
   \% aPrimeCalc: function to calculate the updated a' vector based on the
562
   %
                            situation
563
   %
564
565 % LOCAL VARIABLES ------
566 % Psim_N
                         - Simulated probabilities from N responses
567 % P Bn
                         - Probability of the situation B_n
568 % Prod_pd
                         - product of the physical damage probabilities
569 % Sum_pd
                        - sum of the physical damage products
570 % i
                        - counter
571 % P_aNaN
                         - probabilities of actions that are NaN
572 % Pcond_a
                        - probabilities of actions conditioned on physical
```

```
%
573
                           damage
574
   % aP
                        - a' vector
575
   %
     _____
576
   \% get the appropriate probabilities for the calculations
577
   Psim_N = squeeze(sum(ResponseMatrix(1:N,:,:),1)/N);
578
   P_Bn = [Psim_N(B_n(1),:);Psim_N(B_n(2),:);Psim_N(B_n(3),:);...
579
      Psim_N(B_n(4),:);Psim_N(B_n(5),:);Psim_N(B_n(6),:)];
580
   Prod_pd = squeeze(ResponseMatrix(1:N,B_n(4),:)...
581
       .*ResponseMatrix(1:N,B_n(5),:)...
582
       .*ResponseMatrix(1:N,B_n(6),:));
583
   Sum_pd = sum(Prod_pd);
584
585
   \% cacluate the conditional probabilities of actions and make sure all are
586
   % numbers
587
   for i = 1:3
588
589
       Pcond_a(i,:) = (sum(squeeze(ResponseMatrix(1:N,B_n(i),:))...
          .*Prod_pd))./Sum_pd;
590
591
   end
   P_aNaN = isnan(Pcond_a);
592
   Pcond_a(P_aNaN) = eps;
593
594
   \% calculate a' (define temp and tempsum are same as in main)
595
   temp = prod(Pcond_a,1).*an.*prod(P_Bn(4:6,:),1);
596
   tempSum = sum(temp);
597
   aP = temp/tempSum;
598
599
   end
600
601
602
   603
   function [Mean,Var,SD,CV] = GetStats(aP)
604
   % GetStats: function to calculate analytical stats from the a' vector
605
   %
606
   % LOCAL VARIABLES -----
607
   % SupportX_n
                        - The support for BDA so mean, var, etc may be
608
   %
                           calculated
609
   % -----
610
611
612 % calculations
613 SupportX_n = [1 2 3 4 5];
614 Mean = aP*SupportX_n';
615 Ebda2 = aP*SupportX_n'.^2;
616 Var = Ebda2 - Mean^2;
```

```
617 SD = Var<sup>1</sup>.5;
   CV = SD/Mean;
618
619
   end
620
621
622
   623
624
   function N_Plots(PlotData,sit,NumResponse)
   % N_Plots: function to plot statistics of the a' vector and compare them
625
   %
                            against the true values
626
   %
627
628 % LOCAL VARIABLES -----
629 % MnV
                         - true mean plot data
630 % VarV
                         - true variance plot data
631 % tit
                         - title of the plots
632 % MnMin, MnMax
                        - Plot limits of the mean
633
   % VarMin, VarMax
                         - plot limits of the variance
   % ax1, ax2, ax3
634
                         - axes handles
   % ------
635
636
637
638
   MnV = ones(length(PlotData)-1,1)*PlotData(length(PlotData),7);
   VarV = ones(length(PlotData)-1,1)*PlotData(length(PlotData),8);
639
640
641
   if sit == 1
642
      tit = 'Situation \ita';
643
      MnMin = 0.5; MnMax = 2;
644
       VarMin = 0; VarMax = 1;
645
   elseif sit == 2
646
       tit = 'Situation \itb';
647
      MnMin = 0.5; MnMax = 1.5;
648
       VarMin = 0; VarMax = 0.5;
649
   elseif sit == 3
650
651
       tit = 'Situation \itc';
       MnMin = 1.5; MnMax = 2.5;
652
       VarMin = 0; VarMax = 1;
653
   elseif sit == 4
654
       tit = 'Situation \itd';
655
       MnMin = 2.5; MnMax = 3.5;
656
       VarMin = 0; VarMax = 0.5;
657
   else
658
659
       tit = 'Situation \ite';
660
       MnMin = 3.5; MnMax = 5;
```

```
VarMin = 0.2; VarMax = 1.8;
661
    end
662
663
    PlotData(length(PlotData),:)=[];
664
665
    figure(2*sit)
666
667
668
        subplot(1,2,1)
669
            plot(PlotData(:,1),PlotData(:,7))
            hold on
670
            plot(PlotData(:,1),MnV,'-k')
671
            hold off
672
            ax2 = gca;
673
            set(get(ax2,'XLabel'),'String','Number of Survey Responses, N',...
674
                     'FontName', 'times new roman');
675
            set(get(ax2,'YLabel'),'String','\mu Hat',...
676
677
                     'FontName', 'times new roman');
            set(ax2,'FontName','times new roman',...
678
                     'YTick',0:.1:5,...
679
                     'YLim',[MnMin MnMax],...
680
                     'XLim',[10 NumResponse])
681
682
            grid on
683
684
        subplot(1,2,2)
685
            plot(PlotData(:,1),PlotData(:,8))
686
            hold on
687
            plot(PlotData(:,1),VarV,'-k')
688
            hold off
689
690
            ax3 = gca;
            set(get(ax3,'XLabel'),'String','Number of Survey Responses, N',...
691
                     'FontName', 'times new roman');
692
            set(get(ax3,'YLabel'),'String','Variance, \sigma^2 Hat',...
693
                     'FontName','times new roman');
694
695
            set(ax3,'FontName','times new roman',...
                 'YTick',0:.1:2,...
696
                 'YLim',[VarMin VarMax],...
697
                 'XLim',[10 NumResponse])%
698
                 %
699
700
            grid on
            propertyeditor('on')
701
702
703
    figure(1+2*sit)
704
```

```
705
       plot(PlotData(:,1),PlotData(:,11))
706
       ax1 = gca;
707
       set(get(ax1,'XLabel'),'String','Number of Survey Responses, N',...
               'FontName', 'times new roman');
708
       set(get(ax1,'YLabel'),'String','||a' - a' Hat||',...
709
               'FontName', 'times new roman');
710
       set(ax1,'FontName','times new roman',...
711
712
              'YLim',[0 .2],...
              'XLim',[10 NumResponse])
713
714
715
       grid on
716
717
   end
718
   719
   function [] = EngageSequence(ResponseMatrix,Ptrue_All,CondPtrue_Actions)
720
721
   % EngageSequence: function to run through 3 shot engagement sequence
   %
722
723
   %
      Calls: DTMC, aPrimeCalc, GetStats
   %
724
   |% LOCAL VARIABLES -----
725
726
   % Etas
                         - N values of interest
   % Seq_a, Seq_pd
                         - sequence of actions and physical damage
727
                         - matrix of a' and stats for output
728
   % Engagement Data
   % ------
729
730
731
   % ensure the porper number of arguments
   if nargin < 3
732
       for i = 1:5
733
           ResponseMatrix(:,:,i) = xlsread('Ch4SimData.xls',i);
734
735
       end
       Ptrue_All = xlsread('SurveyProbs.xls', 'p_0', 'b11:r15');
736
737
       CondPtrue_Actions(:,:,1) = xlsread('SurveyProbs.xls','p_0','k18:r44');
738
       CondPtrue_Actions(:,:,2) = xlsread('SurveyProbs.xls','p_0','k46:r72');
739
       CondPtrue_Actions(:,:,3) = xlsread('SurveyProbs.xls', 'p_0', 'k74:r100');
740
       CondPtrue_Actions(:,:,4) = xlsread('SurveyProbs.xls', 'p_0', 'k102:r128');
741
       CondPtrue_Actions(:,:,5) = xlsread('SurveyProbs.xls', 'p_0', 'k130:r156');
742
   end
743
744
745 % initialize variables
746 aPn = [1 \ 0 \ 0 \ 0];
747 aPnTrue = [1 0 0 0 0];
748 Seq_a = [2,4,8; 2,3,7;2,4,8];
```

```
749 Seq_pd = [10,14,17;9,13,16;10,14,17];
750 Etas = [25, 50, 100, 250, 500, 1000];
751
   % iterate through situations
752
753 for sit = 1:3
754
755
        EngagementData = [];
756
        % calculate a vector true values
757
        if sit > 1
758
            aPnTrue = aPnMatrix(length(aPnMatrix),:);
759
760
        end
        a_nTrue = DTMC(aPnTrue);
761
762
        % define the situation
763
        B_n = [Seq_a(sit,:), Seq_pd(sit,:)] ;
764
765
        Bn_pd = 1+(B_n(4)-9)+3*(B_n(5)-12)+9*(B_n(6)-15);
766
        % get the true probabilities
767
        P_BnaTrue = squeeze([CondPtrue_Actions(Bn_pd,B_n(1),:),...
768
            CondPtrue_Actions(Bn_pd,B_n(2),:),...
769
770
            CondPtrue_Actions(Bn_pd,B_n(3),:)]);
        P_BnTrue = [P_BnaTrue; ...
771
            Ptrue_All(:,B_n(4))'; ...
772
773
            Ptrue_All(:,B_n(5))';...
            Ptrue_All(:,B_n(6))'];
774
775
        % calculate a' true
776
        temp = prod(P_BnTrue,1).*a_nTrue;
777
778
        tempSum = sum(temp);
        aPnTrue = temp/tempSum;
779
780
        \% iterate through N of interest
781
        for i = 1:length(Etas)
782
783
            if sit > 1
                 aPn = aPnMatrix(i,:);
784
            end
785
            a_n = DTMC(aPn);
786
787
            \% calculate a' and stats for n of interest
788
            N = Etas(i);
789
            [aPn] = aPrimeCalc(ResponseMatrix,a_n,N,B_n);
790
            [Mean,Var,SD,CV] = GetStats(aPn);
791
792
            Nrm2 = norm(aPn-aPnTrue);
```

```
793
            % concatenate data
794
            EngagementData = [EngagementData; [N,aPn,Mean,Var,SD,CV,Nrm2]] ;
795
796
        end
797
        % calculate stats for a' true
798
        [Mean,Var,SD,CV] = GetStats(aPnTrue);
799
800
        \% gather all data and write to excel spreadsheet
801
        EngagementData = [EngagementData;[1,aPnTrue,Mean,Var,SD,CV,0]] ;
802
        xlswrite('Ch4EngagementData.xls',EngagementData,sit,'b2');
803
804
        aPnMatrix = EngagementData(:,2:6);
805
806
    end
807
808
    end
809 %EOF
```

## Appendix C. Simulation Data for Sample Size Plots

		Updated	l Distribut					
N	ND	Μ	F	$\mathbf{MF}$	Κ	$\hat{\mu}$	$\hat{\sigma}^2$	$  \mathbf{a}^{\prime(n)}-\hat{\mathbf{a}}^{\prime(n)}   $
10	1.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.25743
50	0.88289	0.03237	0.08474	0.00000	0.00000	1.20184	0.33058	0.10968
100	0.83915	0.05715	0.10370	0.00000	0.00000	1.26455	0.40197	0.06094
150	0.80473	0.05210	0.14317	0.00000	0.00000	1.33845	0.51025	0.01602
200	0.79899	0.06039	0.14061	0.00000	0.00000	1.34162	0.50614	0.01280
250	0.80286	0.05300	0.13897	0.00516	0.00000	1.34644	0.53534	0.01219
300	0.81353	0.04812	0.13310	0.00525	0.00000	1.33006	0.51881	0.02439
350	0.80166	0.05821	0.13135	0.00717	0.00161	1.34886	0.55220	0.01435
400	0.81159	0.05568	0.12343	0.00791	0.00140	1.33186	0.53282	0.02651
450	0.82666	0.05009	0.11356	0.00772	0.00197	1.30824	0.51028	0.04458
500	0.81776	0.05093	0.12194	0.00727	0.00210	1.32501	0.53204	0.03241
550	0.81790	0.04834	0.12549	0.00626	0.00201	1.32613	0.53242	0.03106
600	0.81661	0.04646	0.12804	0.00677	0.00213	1.33135	0.54378	0.02917
650	0.81392	0.04893	0.12748	0.00705	0.00262	1.33553	0.55167	0.02653
700	0.80695	0.05426	0.12848	0.00769	0.00262	1.34477	0.56043	0.01963
750	0.80686	0.05160	0.13138	0.00744	0.00271	1.34754	0.56674	0.01811
800	0.81159	0.05127	0.12700	0.00724	0.00291	1.33860	0.55624	0.02445
850	0.80723	0.05193	0.13080	0.00736	0.00268	1.34632	0.56429	0.01868
900	0.80638	0.04897	0.13508	0.00704	0.00254	1.35039	0.57046	0.01674
950	0.79842	0.05251	0.14099	0.00555	0.00252	1.36124	0.57629	0.00746
1000	0.79244	0.05535	0.14393	0.00580	0.00248	1.37054	0.58565	0.00402
True	0.79203	0.05482	0.14118	0.00848	0.00349	1.37656	0.60983	

Table C.1: Sample Points of  $\hat{\mathbf{a}}^{\prime(n)}$  and Metrics for Situation a

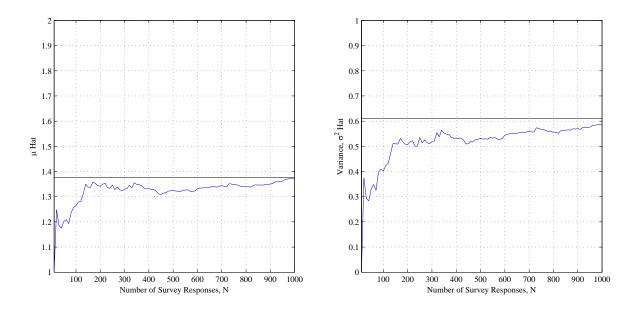


Figure C.1: Situation *a* Moments

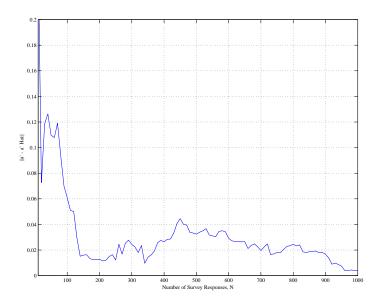


Figure C.2: Situation *a* Norm

		Updated	l Distribut					
N	ND	М	F	MF	Κ	$\hat{\mu}$	$\hat{\sigma}^2$	$  \mathbf{a}^{\prime(n)} - \hat{\mathbf{a}}^{\prime(n)}  $
10	1.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.00000	0.04125
50	0.99891	0.00109	0.00000	0.00000	0.00000	1.00109	0.00109	0.04032
100	0.98266	0.00826	0.00907	0.00000	0.00000	1.02641	0.04386	0.02260
150	0.96622	0.00534	0.02844	0.00000	0.00000	1.06221	0.11521	0.00324
200	0.97280	0.00535	0.02185	0.00000	0.00000	1.04904	0.09033	0.00622
250	0.97300	0.00472	0.02228	0.00000	0.00000	1.04928	0.09141	0.00600
300	0.97332	0.00457	0.02212	0.00000	0.00000	1.04880	0.09065	0.00635
350	0.97463	0.00464	0.02074	0.00000	0.00000	1.04611	0.08546	0.00824
400	0.97525	0.00542	0.01933	0.00000	0.00000	1.04408	0.08079	0.00972
450	0.96947	0.00483	0.02569	0.00000	0.00000	1.05622	0.10444	0.00111
500	0.97022	0.00465	0.02513	0.00000	0.00000	1.05491	0.10216	0.00202
550	0.96875	0.00488	0.02637	0.00000	0.00000	1.05762	0.10704	0.00024
600	0.97149	0.00463	0.02386	0.00003	0.00000	1.05242	0.09755	0.00382
650	0.97364	0.00472	0.02161	0.00003	0.00000	1.04803	0.08911	0.00693
700	0.97276	0.00429	0.02292	0.00003	0.00000	1.05021	0.09370	0.00541
750	0.97456	0.00466	0.02076	0.00003	0.00000	1.04626	0.08580	0.00818
800	0.97565	0.00422	0.02011	0.00003	0.00000	1.04451	0.08290	0.00943
850	0.97273	0.00458	0.02265	0.00003	0.00000	1.04998	0.09296	0.00555
900	0.97339	0.00459	0.02199	0.00003	0.00000	1.04866	0.09044	0.00648
950	0.97484	0.00437	0.02076	0.00003	0.00000	1.04597	0.08555	0.00839
1000	0.97533	0.00408	0.02056	0.00003	0.00000	1.04529	0.08454	0.00890
True	0.96875	0.00469	0.02652	0.00003	0.00000	1.05785	0.10781	

Table C.2: Sample Points of  $\hat{\mathbf{a}}^{\prime(n)}$  and Metrics for Situation b

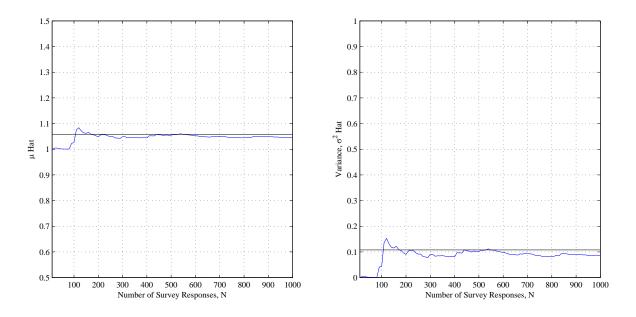


Figure C.3: Situation *b* Moments

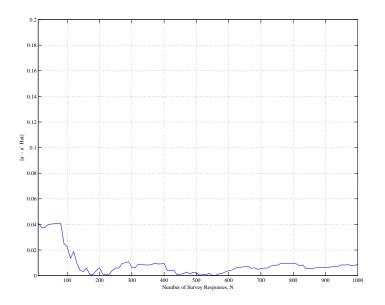


Figure C.4: Situation *b* Norm

		Updated	l Distribut					
N	ND	Μ	F	MF	Κ	$\hat{\mu}$	$\hat{\sigma}^2$	$  \mathbf{a}^{\prime(n)} - \hat{\mathbf{a}}^{\prime(n)}  $
10	0.34637	0.65363	0.00000	0.00000	0.00000	1.65363	0.22640	0.12213
50	0.21363	0.78203	0.00434	0.00000	0.00000	1.79070	0.17416	0.08089
100	0.22342	0.76945	0.00713	0.00000	0.00000	1.78372	0.18377	0.06616
150	0.27891	0.69748	0.00763	0.01598	0.00000	1.76069	0.29320	0.04126
200	0.27286	0.69868	0.00847	0.01230	0.00769	1.78327	0.35273	0.03534
250	0.27243	0.68326	0.01223	0.01923	0.01285	1.81683	0.44371	0.04179
300	0.27918	0.68459	0.01009	0.01762	0.00853	1.79174	0.39315	0.04617
350	0.28189	0.67436	0.01134	0.01970	0.01271	1.80697	0.44914	0.05465
400	0.27356	0.68706	0.00994	0.01805	0.01139	1.80664	0.42080	0.04054
450	0.26431	0.69615	0.01155	0.01407	0.01392	1.81714	0.42400	0.02897
500	0.24744	0.71487	0.01065	0.01415	0.01290	1.83019	0.40192	0.01334
550	0.25725	0.70378	0.00906	0.01852	0.01139	1.82303	0.41160	0.01963
600	0.25559	0.70598	0.00892	0.01922	0.01029	1.82263	0.40253	0.01742
650	0.25389	0.70829	0.00887	0.02003	0.00893	1.82182	0.39146	0.01536
700	0.25565	0.70557	0.00882	0.02152	0.00844	1.82152	0.39464	0.01737
750	0.25887	0.70049	0.01117	0.02100	0.00847	1.81971	0.39778	0.02092
800	0.25199	0.70939	0.01229	0.01850	0.00784	1.82081	0.37668	0.01174
850	0.25668	0.70234	0.01576	0.01659	0.00863	1.81815	0.38341	0.01746
900	0.25198	0.70461	0.01741	0.01570	0.01030	1.82772	0.39520	0.01298
950	0.25315	0.70065	0.01843	0.01806	0.00970	1.83051	0.40243	0.01538
1000	0.25319	0.69944	0.01738	0.02082	0.00918	1.83336	0.40867	0.01601
True	0.24252	0.71112	0.01860	0.02068	0.00708	1.83869	0.38156	

Table C.3: Sample Points of  $\hat{\mathbf{a}}^{\prime(n)}$  and Metrics for Situation c

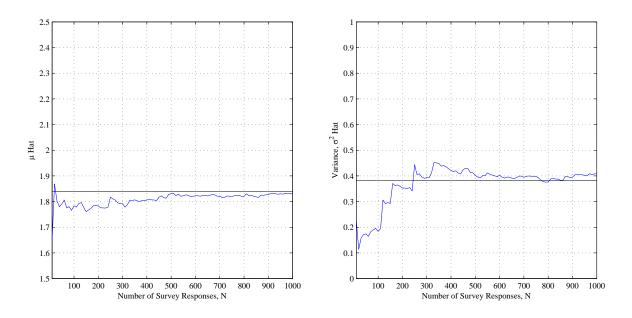


Figure C.5: Situation c Moments

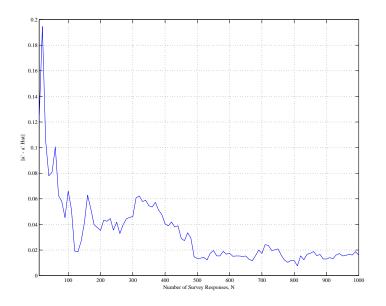


Figure C.6: Situation c Norm

		Updated	l Distribut					
N	ND	М	F	MF	Κ	$\hat{\mu}$	$\hat{\sigma}^2$	$  \mathbf{a}^{\prime(n)}-\hat{\mathbf{a}}^{\prime(n)}   $
10	0.00000	0.00000	0.93185	0.06815	0.00000	3.06815	0.06350	0.07507
50	0.00000	0.01401	0.91413	0.07186	0.00000	3.05785	0.08253	0.05937
100	0.00758	0.00639	0.88333	0.10269	0.00000	3.08113	0.13284	0.01631
150	0.00479	0.00599	0.87692	0.11230	0.00000	3.09672	0.12811	0.00976
200	0.00315	0.00501	0.89344	0.09840	0.00000	3.08709	0.10843	0.02680
250	0.00526	0.00371	0.90327	0.08361	0.00414	3.07765	0.11890	0.04223
300	0.00447	0.00372	0.90384	0.08513	0.00284	3.07814	0.11198	0.04188
350	0.00901	0.00637	0.89129	0.08920	0.00414	3.07310	0.14281	0.02967
400	0.00878	0.00823	0.88588	0.09225	0.00486	3.07619	0.14925	0.02387
450	0.00701	0.00688	0.87253	0.10985	0.00374	3.09644	0.15042	0.00396
500	0.00674	0.00622	0.87242	0.11084	0.00378	3.09870	0.14938	0.00372
550	0.00710	0.00593	0.88227	0.10054	0.00415	3.08871	0.14360	0.01536
600	0.00665	0.00709	0.87284	0.10868	0.00473	3.09775	0.15175	0.00380
650	0.00575	0.00670	0.86063	0.12071	0.00621	3.11492	0.16206	0.01463
700	0.00552	0.00615	0.85742	0.12466	0.00624	3.11995	0.16349	0.01967
750	0.00617	0.00604	0.85546	0.12611	0.00622	3.12017	0.16729	0.02203
800	0.00580	0.00570	0.85742	0.12528	0.00581	3.11959	0.16310	0.02012
850	0.00561	0.00546	0.85137	0.13111	0.00645	3.12732	0.16860	0.02848
900	0.00522	0.00539	0.84874	0.13450	0.00615	3.13098	0.16822	0.03277
950	0.00509	0.00496	0.84582	0.13680	0.00733	3.13632	0.17287	0.03644
1000	0.00605	0.00468	0.84803	0.13427	0.00697	3.13142	0.17375	0.03305
True	0.00675	0.00546	0.87067	0.11021	0.00691	3.10506	0.15926	

Table C.4: Sample Points of  $\hat{\mathbf{a}}^{\prime(n)}$  and Metrics for Situation d

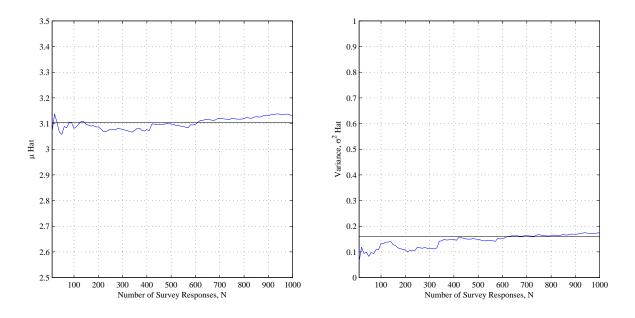


Figure C.7: Situation *d* Moments

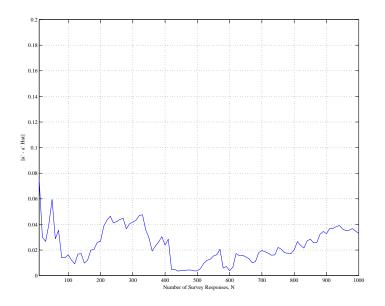


Figure C.8: Situation *d* Norm

		Updated	l Distribut					
N	ND	М	F	MF	Κ	$\hat{\mu}$	$\hat{\sigma}^2$	$  \mathbf{a}^{\prime(n)} - \hat{\mathbf{a}}^{\prime(n)}  $
10	0.00000	0.16416	0.00000	0.00000	0.83584	4.50751	1.23492	0.43192
50	0.00000	0.07093	0.00000	0.30101	0.62806	4.48620	0.67540	0.09430
100	0.00000	0.16643	0.00000	0.27351	0.56006	4.22720	1.17415	0.06679
150	0.00000	0.19009	0.00000	0.25672	0.55319	4.17300	1.28363	0.09481
200	0.00000	0.18495	0.00000	0.24670	0.56836	4.19846	1.26876	0.10005
250	0.00000	0.19229	0.00000	0.27936	0.52835	4.14376	1.27685	0.08585
300	0.00000	0.17693	0.01290	0.27574	0.53443	4.16766	1.22695	0.07518
350	0.00000	0.17401	0.01138	0.27405	0.54057	4.18118	1.21514	0.07275
400	0.00000	0.16971	0.01087	0.27694	0.54248	4.19220	1.19524	0.06739
450	0.00000	0.16524	0.01020	0.27626	0.54830	4.20761	1.17637	0.06412
500	0.00000	0.16126	0.00703	0.26923	0.56248	4.23293	1.16031	0.06739
550	0.00000	0.15074	0.00745	0.27497	0.56685	4.25793	1.11071	0.05798
600	0.00000	0.15590	0.00673	0.29146	0.54591	4.22738	1.12455	0.04675
650	0.00000	0.14393	0.00754	0.30937	0.53916	4.24377	1.06300	0.02924
700	0.00000	0.14338	0.00768	0.31642	0.53252	4.23808	1.05706	0.03012
750	0.00000	0.14233	0.00757	0.32659	0.52351	4.23128	1.04691	0.03560
800	0.00000	0.15099	0.00747	0.33144	0.51009	4.20063	1.08129	0.05192
850	0.00000	0.15081	0.00737	0.32116	0.52066	4.21168	1.08646	0.04287
900	0.00000	0.14057	0.00418	0.33116	0.52409	4.23876	1.03356	0.03455
950	0.00000	0.13527	0.00410	0.34215	0.51847	4.24383	1.00420	0.04093
1000	0.00000	0.12981	0.00291	0.33089	0.53639	4.27386	0.98354	0.01922
True	0.00107	0.12224	0.00173	0.32290	0.55206	4.30264	0.96079	

Table C.5: Sample Points of  $\hat{\mathbf{a}}^{\prime(n)}$  and Metrics for Situation e

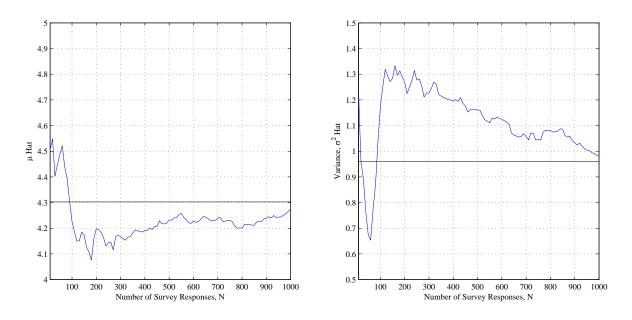


Figure C.9: Situation e Moments

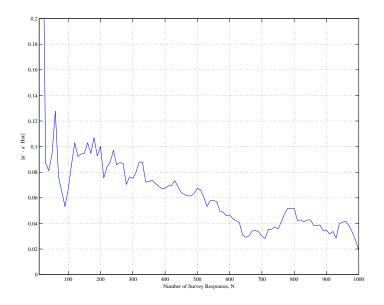


Figure C.10: Situation e Norm

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## **REPORT DOCUMENTATION PAGE**

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						research effort examines the BDA			
						pertinent data and model this			
						matter expert survey design and a			
						ed. Bayesian inference is used to update			
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