BRTRC

Technology Research Corporation

Deception Algorithm

Final Technical Report

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CHAPTER 1

EXECUTIVE SUMMARY

1.1 Overview

Combat modeling has shown that close combat decoys can improve Loss Exchange Ratios by 20-50% and that models that do not realistically address the effects of close combat decoys understate Loss Exchange Ratios by 15-25% when close combat decoys are employed.

This report describes an algorithm that was created to realistically address the effects and operational impacts of deception and close combat decoys in standard Army wargames and analytical models such as Janus, CASTFOREM, and the Semi-Automated Forces module in SIMNET.

Data for the algorithm were obtained from live force-on-force exercises conducted in conjunction with the Multispectral Close Combat Decoy (MCCD) Initial Operational Test and Evaluation (IOTE) conducted at Fort Hunter Liggett during the Spring of 1993. These data reflect the operational impact of the most commonly recognized effects of decoys which includes the detection, identification and engagement of the decoys themselves, and the misidentification and engagement of false targets and non targets by opposing forces.

Use of the Deception Algorithm requires modification to the model's software and database. Appropriate code to accomodate the new target classes (the close combat decoy and false targets) and the transforms to compute the Probabilities of Detection (P_d) adjusted for the presence of decoys and false targets; the Probabilities of Identification (P_{Id}) adjusted for the presence of decoys and false targets, and the Probability of Engagement (P_{eng}) for real targets, decoys and false targets for appropriate sensor and lighting conditions as described in the classified annex to this report must be inserted. The model is then ready to more realistically "play" decoys without further modification to the code or database structure, however the database must be adjusted to include the requisite number and location of decoys and false targets to be played.

The Deception Algorithm constructed by BRTRC was tested in a close combat wargame against MCCD IOTE force-on-force engagement outcomes and was found to produce comparable results within approximately 5% of the actual MCCD IOTE force-on-force engagement Loss Exchange Ratio results.

1.2 Background

The Multispectral Close Combat Decoy (MCCD) Initial Operational Test and Evaluation (IOTE) was conducted in the Spring of 1993 at Fort Hunter Liggett, California.

The IOTE evaluated M1 Abrams Main Battle Tank and M2 Bradley Infantry Fighting Vehicle MCCD visual and infrared fidelity at various ranges and the tactical impact of employing MCCDs during instrumented force-on-force exercises.

In general, the fidelity tests consisted of an array of MCCDs presented to a number of moving and stationary observors positioned at various distances from the array. The observors were equipped with standard US Army visual and infrared target acquisition and engagement devices. The fidelity test was conducted during both day and night without either artificial illumination or obscuration.

The force-on-force exercises were conducted with a friendly M1 tank platoon (BLUFOR) in the defense versus a numerically superior enemy combined arms opposing force (OPFOR) in the attack. BLUFOR was equipped with M1 tanks and with MCCDs part of the time. OPFOR operated standard issue M1 tanks and M2 IFVs configured to represent Threat systems. BLUFOR and OPFOR conducted operations utilizing US and Threat doctrine and tactics as appropriate. Both day and night operations were conducted without artificial illumination or obscurants, although some instances of meteorlogical obscuration occurred.

The results of the force-on-force engagements when BLUFOR employed the MCCDs were compared to the results of the engagements when BLUFOR did not employ the MCCDs. The results of this comparison formed a measure of the potential impact of the use of MCCDs during mechanized close combat.

A comprehensive description of the test conditions, events, and results is presented in References 1 and 2.

The data collected during the IOTE appeared to the MCCD IOTE Test Officer, the Data Authentication Committee, and others to be potentially suitable for use in Army studies, analyses and tactical simulations. The database available for analysis is described in Appendix C. The actual, rather voluminous data is stored on Bernoulli disk (Reference 3).

BRTRC was commissioned to examine the suitability of using these data in Army studies, analyses and simulations of close combat decoys, and to devise a feasible, effective and economical means of utilizing the data in these types of applications. This report presents the findings, conclusions and recommendations derived from that BRTRC effort.

1.3 Program Objective

The objective of this program effort was to create an algorithm for introducing deception and decoys into standard Army wargames and analytical models. The Deception Algorithm was to address the probability of correct identification at close, mid and far ranges.

1.4 Technical Approach

The program effort consisted of four tasks:

(1) Task 1. Examination of the MCCD IOTE data to verify suitability for use in a Deception Algorithm.

(2) Task 2. Construction of a Deception Algorithm for use in standard Army models, conduct trial runs with and without the algorithm, and report findings.

(3) Task 3. Extract from the IOTE database and publish the Human Factors Questionnaire files containing Soldier comments and feedback plus comments from the analysts who performed the "ground truth" by analyzing audio and video tapes.

(4) Task 4. Documentation of the Deception Algorithm and IOTE comments/feedback in a Scientific and Technical Report.

1.5 Findings, Conclusions and Recommendations

1.5.1 The Findings of the program effort were:

(1) The MCCD IOTE database was easily accessible, contained data representative of the performance and battlefield impact of close combat decoys, and is of suitable statistical quality to support the development and application of a Deception Algorithm.

(2) An algorithm could be constructed that efficiently utilizes the available data.

(3) Testing of the algorithm in an analytically correct computer simulation showed that the Deception Algorithm closely approximates live force-on-force simulation results.

(4) Analysis of battle outcomes in a computer simulation not otherwise sensitive to decoy effects showed a 15-25% understatement of loss exchange ratios compared to an otherwise identical computer simulation that included the Deception Algorithm.

(5) The scope of the decoy performance database is currently limited to the cases and conditions examined during the MCCD IOTE.

1.5.2 The Conclusions derived from this program effort are:

(1) Standard Army models do not appear currently to be sensitive to the full range of measureable effects of decoys and false targets on the outcome of close combat engagements and understate the impact of close combat decoys on battle outcomes.

(2) Close combat decoys provide significant opportunities to improve Loss Exchange Ratios in typical combat situations.

(3) Currently available data does not address all potential tactical situations and applications for close combat decoys.

1.5.3 The Recommendations derived from this program effort are:

(1) Standard Army wargame methodologies and data structures should be modified to accomodate tactical deception systems and false targets in the manner set forth in this report.

(2) Additional force-on-force exercise data where close combat decoys and false targets are employed should be collected to expand the scope of the database to a wider range of tactical situations and environmental conditions, eliminate current data gaps, and improve the statistical quality of the database.

(3) The findings of this program effort should be validated through experimentation with the Deception Algorithm in applicable standard Army models and wargames.

CHAPTER 2

MCCD IOTE DATA

Task 1 of this program effort was to examine the MCCD IOTE database (Reference 3) to determine whether it contained data that could be suitably employed in Army studies, analyses and wargames involving decoys. Inherent in this examination was three issues:

(1) Could the database be accessed and understood?

(2) Do the data elements in the database address the effects of decoys on tactical engagements?

(3) Is the data of sufficient statistical quality to be suitable for further use?

2.1 Accessing the MCCD IOTE Database

Accessing the MCCD IOTE database was very simple and straightforward. The data on the Bernouilli disk supplied by the MCCD IOTE testors was loaded into a standard IBM PC for further processing. The data files and data structure were contained on the disk and readily accessible. The data structure description (MCCDAPPA) was written in a well organized and well written narrative form in WordPerfect™. The data structure description is presented in Appendix C of this report.

Once the database had been transferred to the IBM PC, BRTRC studied the data structure description, and examined the individual files of interest without any difficulty.

2.2 Database Elements

The next step in the data analysis process was to determine whether the database contained data elements applicable to the use of decoys in tactical environments. BRTRC began by identifying the typical effects of close combat decoys on tactical engagements, and then set forth to determine whether these effects were manifested by the data.

Figure 2-1 presents a table of the typical effects of close combat decoys on tactical engagements. Contained in this table is a column that describes the potential effects of decoys on the enemy during close combat operations, the impact of these effects, and the reason these impacts occur.

As can be seen in the table, there are a number of potentially significant effects of decoys on close combat operations. These include:

(1) ***Alteration of the enemy maneuver plan*** as a consequence of the presence of decoy targets misidentified as real defenders. The impact of such an effect can be an increase in enemy casualties as the enemy force spends more time in the defender's kill zone than it would otherwise, exposes the more thinly armored sides and rear of its vehicles to the defender's weapons, and degrades its target acquisition performance by focusing attention on the area containing decoys rather than the real defense.

(2) ***Premature deployment of the enemy force*** into an assault posture as a consequence of the presence of decoy targets. This can result in additional enemy casualties as a result of additional time spent in the defender's kill zone while the assault force deploys, conducts the assault, and then reconsolidates once the ruse is discovered. In addition, the enemy will tend to present itself to the defender at a slower rate while the decoys are approached and examined. This allows a greater potential number of engagements by the defender and a corresponding increase in enemy casualties.

(3) ***Increased target engagement decision time*** can result from the confusion of the enemy as he attempts to sort out real targets from false targets. The net result is an overall decrease in the number of shots taken by the attacker and a

EFFECTS OF CLOSE COMBAT DECOYS ON TACTICAL ENGAGEMENTS

POTENTIAL EFFECT ON ENEMY	IMPACT ON BATTLE	REASON(S)
o ALTER MANEUVER PLAN	o INCREASED ENEMY CASUALTIES	o INCREASED TIME IN KILL ZONE o INCREASED TARGET VULNERABILITY o REDUCTION OF ENEMY TARGET ACQUISITION EFFECTIVENESS
o CAUSE PREMATURE DEPLOYMENT	o INCREASED ENEMY CASUALTIES	o INCREASED TIME IN KILL ZONE o REDUCED TARGET PRESENTATION RATE
o INCREASE TARGET ENGAGEMENT TIME	o INCREASED ENEMY CASUALTIES	o INCREASED ENEMY SIGNATURE
	o REDUCED FRIENDLY CASUALTIES	o REDUCTION OF EFFECTIVE ENEMY RATE OF FIRE
o ENGAGE DECOY TARGETS	o REDUCED FRIENDLY CASUALTIES	o REDUCTION OF EFFECTIVE RATE OF FIRE
o MISIDENTIFY REAL TARGETS	o REDUCED FRIENDLY CASUALTIES	o REDUCTION OF EFFECTIVE RATE OF FIRE

INCREASED ENEMY CASUALTIES + REDUCED FRIENDLY CASUALTIES = BIG LER Δ

Figure 2-1. Effects of Close Combat Decoys on Tactical Engagements potential reduction in the number of casualties sustained by the friendly force.

(4) ***Engagement of decoys*** by the enemy can result in an decrease in friendly losses since every shot fired at a decoy is one less shot fired at a real target.

(5) ***Misidentification of real targets*** by the enemy can result in his not engaging real targets because he believes them to be decoys or other non targets. The result is a reduction in the enemy's effective rate of fire and a potential reduction in the number of friendly casualties.

An examination of the MCCD IOTE database indicated that data was neither explicitly collected for several of these effects nor could be economically inferred from the data that was collected. For example, there was no data available to determine the liklihood of an attacking force changing its maneuver plan and route of advance because of the presence of decoys identified as real opponents. Nor was there a means to determine the increase in target engagement time as a consequence of the confusion that could arise because of the presence of decoy targets.

Nonetheless, data was available for perhaps the most commonly recognized effects of decoys which includes enemy detection, identification and engagement of the decoys themselves, and the misidentification and engagement of targets by the enemy whether they be real targets or decoys.

As a minimum, studies, analysis and simulations of the type of interest here require data expressing the probability of target detection, the probability of target identification, and the probability of target engagement for each element of the analysis or simulation. Only the most sophisticated analyses and simulations employ the probabilities of incorrect target identification given detection, and the probability of engagement given incorrect identification.

The static test data (TD3 in Reference 3) contains information that permits determination of the Probability of Target Detection (P_d) as a function of range, target type, sensor used, and light level (i.e., day versus night). TD3 also permits the determination of the Probabilities of both Correct and Incorrect Target Identification given Detection ($P_{id|d}$) as a function of range, target type, sensor used, and light level. These probabilities were determined based on the number of correct responses compared to the total number of detection/identification opportunities under the various conditions of range, target type, acquisition sensor type and lighting conditions.

The force-on-force exercise data (EA3 in Reference 3) contains information that permits determination of the Probability of Target Engagement (P_{eng}) given correct identification, and the Probability of Target Engagement given incorrect identification. This information is available as a function of engaging weapon, targeting sensor type, target type, and prevailing light conditions. These probabilities were determined on the basis of the number of actual engagements between valid target parings under each set of conditions compared to the number of opportunities to engage under those conditions. There did not appear to be sufficient data to permit a statistically valid determination of some of the other factors that might effect engagement probabilities such as target range, type of shooter, instantaneous force ratio or remaining ammunition available to the shooter.

2.3 Statistical Quality of the Database

The last issue regarding the MCCD IOTE database concerns the statistical quality of the data.

The static test involved collecting between 50 and 100 valid samples at each of several ranges for each of the sensor types and lighting conditions of interest. For statistical analysis purposed, the data was divided into subsets by type of sensor and lighting conditions. For each subset of data, the P_d and $P_{id|d}$ was plotted as a function of range. A polynomial least squares regression analysis with a 95% confidence interval was applied to these probabilities for each subset of data. The polynomial functions produced were generally well behaved and monotonically decreasing as a function of range. All probabilities fell within the 95% range for each subset. As a consequence of these results, the probability data for detection and identification derived from the static tests is considered to be statistically acceptable.

The force-on-force exercises resulted in the collection of between 0 and 1000 samples depending on the shooter type, the target type and whether an engagement took place or not. The OPFOR engaged with tank main gun, IFV antitank guided missile, and 30mm cannon. Since the BLUFOR defense consisted solely of M1 tanks, the 30mm cannon engagements can be eliminated as a serious OPFOR engagement system. When the 30mm engagements are eliminated, the number of samples drops to between 0 and 32 for the OPFOR IFVs and between 2 and 60 for the OPFOR tanks. The probabilities of engagement given correct identification was derived from this data excluding the 30mm cannon engagements. A statistical analysis of this data to include an examination of the mean, standard deviation and 95% confidence interval statistics indicated that while the engagements performed visually and thermally by the OPFOR tank crews is statistically acceptable, both the visual and thermal engagements by the OPFOR IFV lacked statistical quality and were thus disregarded for this analysis. The analysis of the tank data indicated that there was a statistically significant difference between the engagement probabilities given correct and incorrect identification of real targets, decoy targets, and unknown targets, and this data was found to be acceptable for futher use.

2.4 Summary

The MCCD IOTE database was easily accessible, contained data representative of the performance and battlefield impact of decoys, and its statistically quality is adequate for the intended purpose.

CHAPTER 3

DECEPTION ALGORITHM

3.1 Introduction

The development of a Deception Algorithm consisted of 4 steps:

(1) Examination of the relevant analytical and modeling attributes of "Standard Army Models",

(2) Assessment of the sensitivity of these models to the factors pertinent to decoys,

(3) Development of the Deception Algorithm, and

(4) Testing the Deception Algorithm.

3.2 Attributes of "Standard Army Models"

"Standard Army Models" consist of three general types:

(1) ***Lanchester square law, differential equation based, closed form analytical treatments of combat situations.*** This type of model is not currently used by the US Army for the analysis of high resolution combat where, for example, individual close combat decoys are deployed in conjunction with small numbers of discrete combat systems (e.g., tanks, IFVs, etc.). The Lanchester type model, when it is used by the US Army, is reserved for highly aggregated, low resolution, theater level campaign analysis. Accordingly, a close combat decoy Deception Algorithm developed under this program effort would be inappropriate for such a model.

(2) ***Man-in-the-loop tactical training simulations.*** These are two-sided, interactive, force-on-force, close combat engagement simulations with actual people operating the

various functional components of tactical systems deployed in a virtual environment. SIMNET is the current manifestation of this type of simulation. Employment of decoys in this type of simulation could be conducted explicitly. Decoy icons would be created that neither move, nor shoot, but would be deployable in accordance with their known or projected transportability and erection attributes. Their physical characteristics would otherwise be identical to the actual, developmental or conceptual decoy being replicated in the simulation. The detectability and identifiability of the decoy icons could be matched to the actual or projected performance of actual, developmental or conceptual decoy systems. This would require a modest experimentation and testing program within the actual simulation environment. While such experimentation and testing is beyond the scope of this current effort, the MCCD IOTE data provides relevant decoy performance criteria appropriate for such an experimentation and testing program.

(3) ***Interactive and non-interactive computerized baysian wargames*** form the last of the general types of "Standard Army Models". These wargames are based on monte-carlo simulations of combat. They utilize conditional probabilities that events may occur given that other, prior events occur (e.g., probability of kill given a hit). These models may include human interaction for scenario, deployment, and manuever decisionmaking (e.g., JANUS) or these elements may be comprehensively scripted in advance and form a part of the model's database (e.g., CASTFOREM). Another example of this type of model is the Semi-Automated Force component of SIMNET. In this application, human interactors operate the BLUFOR tactical systems in a virtual environment otherwise identical to SIMNET, and the SIMNET computer controls and operates the OPFOR without human involvement once the prescripted scenario, deployment and maneuver data for the OPFOR has been generated and installed in the computer's database. The BRTRC model FRED-D is included in this group.

The problem highlighted in the MCCD IOTE is that a large fraction of the engagements recorded were directed against false targets and against decoys, regardless of the ability of the crews to correctly identify real targets from decoys. This is significantly different from the decision-tree, compound probability approach taken by most bayesian models.

The typical bayesian model manipulates only real, defined objects. Because each object defined requires (typically) voluminous data and substantial processing time, most modelers do not attempt to include objects which represent decoys or false targets, nor does their modeling methodology typically include provisions for these types of entities.

The result is a distinct insensitiviey in these models to the "fog of war." The models will tend to overstate the capabilities of both sides to attack and engage targets, since crew attention and ammunition is not wasted on things which don't shoot back. Simulated combat proceeds directly and intensely, with little time wasted on confusion and decision making. Actual combat is characterized by a lot of uncertainty, confusion, mistakes, blunders, and delay.

The traditional baysian wargame computes the probabilities that certain entities will detect, identify, engage, hit, and finally kill their opponents (Figure 3-1). These probabilities are expressed as a function of the range from the shooter to the target (as well as other factors such as visibility, intervisibility, ammunition type and availability, optics and sensors used, target hardness, etc.). Each is a compound probability which assumes that all the events prior to it have occurred. For example, the probability of engagement assumes the target has been detected and identified. At any point in the chain of computations, if the target is not detected (or identified, or engaged, or hit, or killed), then it is assumed to have survived the immediate encounter.

If decoys are played in a traditional baysian model, they are represented as entities that do not move (at least not yet) and do not shoot back. Usually they are assigned a low probability of kill given a hit which makes it very difficult for the opposition to kill decoys. The fidelity of the decoys is represented by the assigned P_d (probability of detection) and $P_{id|d}$ (probability of identification given detection) values.

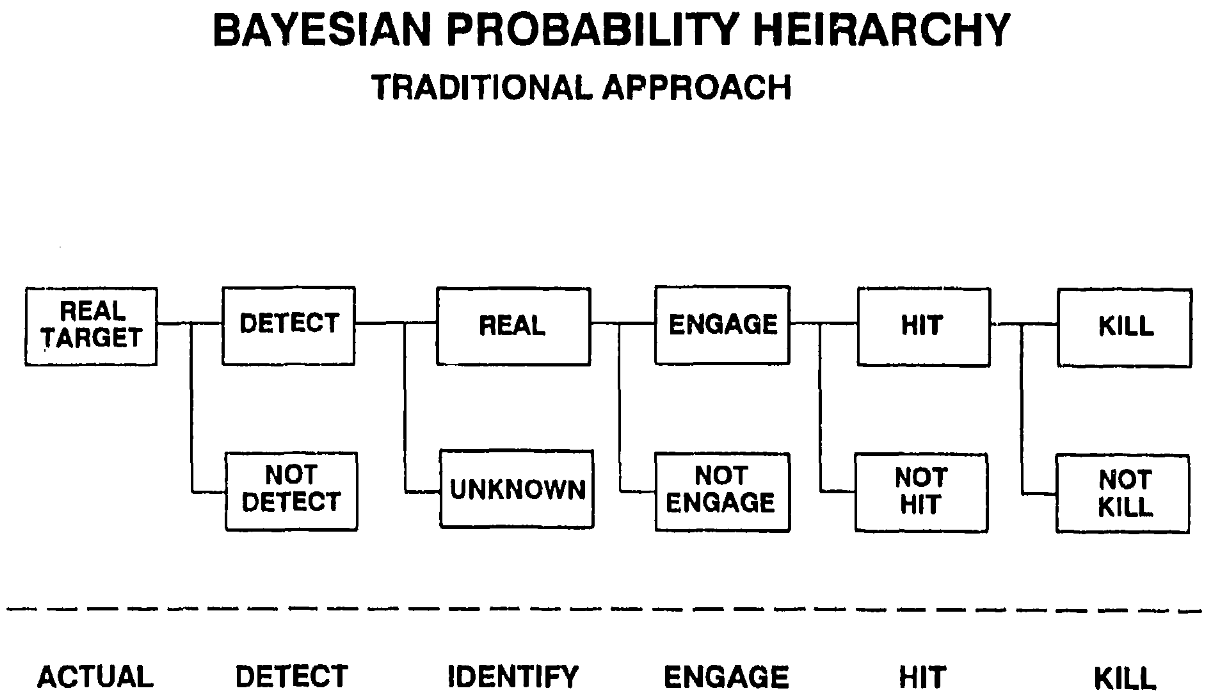

Figure 3-1. Bayesian Probability Hierarchy

Prior to the MCCD IOTE these values had to be estimated and were usually assigned values equal to or somewhat below that of real targets.

If it is assumed that each combatant does not know (and generally cannot know) that there are decoys in the opposing force, then the model only needs the probabilities that the attacker detects and identifies a decoy as a real target. The decoy acts as a bullet sump. If the model is capable of altering the tactical plan based on the disposition of the opposing force, then the decoys can impact that combatant's decision making and maneuver.

If the combatants are allowed to consider the possibility of decoys in the opposition force, then the model also needs to consider the probability that the combatant detects and identifies the decoy as a decoy. Then the model must consider whether the identified decoy is engaged or not. Similarly, the model needs to consider the probability that a real target is identified as a decoy. Unless perfect knowledge is assumed by the model, it is unlikely that all attackers will immediately and simultaneously share a common understanding of which opposing targets are decoys and which are real. This level of understanding of the battlefield develops during the course of the engagement at each echelon. The individual combatant chooses his route of advance and targets independently, but in response to guidance from his superiors in the chain of command. The model's ability to simulate the confusion inherent in executing and adjusting the engagement plan based on the disposition of the opposing forces should also include the combinatorial effects of decoys on such decision making.

The addition of false targets into the battlefield mix should be a required element of a combat model regardless of whether decoys are played or not. The attention and ammunition of combatants are wasted on a wide variety of things which are assumed to be real targets until proven otherwise during real combat. The scenario situation, the type of terrain being simulated and the types of sensors used dictate the density of false objects which might be detected and identified as targets. Just as with decoys, these objects act as both bullet sumps and as factors which affect the maneuver and tactical decision making of the combatants. Unfortunately, most models are simply incapable of properly representing the battlefield impact of randomly occuring false targets, non targets (e.g., noncombatants), friendly elements and intentional decoys. Figure 3-2 presents an assessment of the sensitivity of "Standard Army Models" to the effects of decoys. Unless "Standard Army Models" address the effects of decoys as described herein they will not acheve the level of modeling realism that is achievable given available data and methodological techniques.

3.4 The Deception Algorithm

Statistical analysis of the MCCD IOTE data provided the basis for the development of a deception algorithm that permits a "first order" treatment of close combat decoys in "standard Army models," but requires some modification to the model. Figure 3-3 presents the logic tree to implement the Algorithm in a combat model. While the preferred method would be to draw a random variate for each conditional probability shown, and compare the drawn variate to the value for that parameter in the database to determine whether detection, identification, engagement, etc., occurred, these conditional probabilities can be consolidated by using the following expressions and the data provided in the Classified Annex to this report.

$$P_{kreal}=P_{d|real}\times\{[P_{id=real|real}\times P_{engage|id=real}]+[P_{id=decoy|real}\times P_{engage|id=decoy}]+[P_{id=unknown|real}\times P_{engage|id=unknown}]\}\times P_{hit|engaged\ real}\times P_{kill|hit\ real}$$

$$P_{kdecoy}=P_{d|decoy}\times\{[P_{id=real|decoy}\times P_{engage|id=real}]+[P_{id=decoy|decoy}\times P_{engage|id=decoy}]+[P_{id=unknown|decoy}\times P_{engage|id=unknown}]\}\times P_{hit|engaged\ decoy}\times P_{kill|hit\ decoy}$$

$$P_{kfalse}=P_{d|false}\times\{[P_{id=real|false}\times P_{engage|id=real}]+[P_{id=decoy|false}\times P_{engage|id=decoy}]+[P_{id=unknown|false}\times P_{engage|id=unknown}]\}\times P_{hit|engaged\ false}\times P_{kill|hit\ false}$$

3.5 Testing the Algorithm

BRTRC tested the Deception Algorithm by simulating the introduction of the Algorithm into a "standard Army model". The BRTRC FRED-D model was employed to simulate standard Army models.

SENSITIVITY OF "STANDARD ARMY MODELS" TO CLOSE COMBAT DECOYS

DECOY EFFECT	DECOY EFFECT PLAYED IN:					
	CASTFOREM	JANUS	SIMNET (SAF)	SIMNET (MITL)	NTC FOF	FRED-D
o ALTER MANEUVER PLAN	NO	NO	NO	YES	YES	YES
o CAUSE PREMATURE DEPLOYMENT	NO	NO	NO	YES	YES	YES
o INCREASE TARGET ENGAGEMENT TIME	NO	NO	NO	YES	YES	YES
o ENGAGE DECOY TARGETS	YES	YES	YES	YES	YES	YES
o MISIDENTIFY REAL TARGETS	NO	NO	NO	YES	YES	YES

Figure 3-2. Sensitivity of "Standard Army Models" to Close Combat Decoys

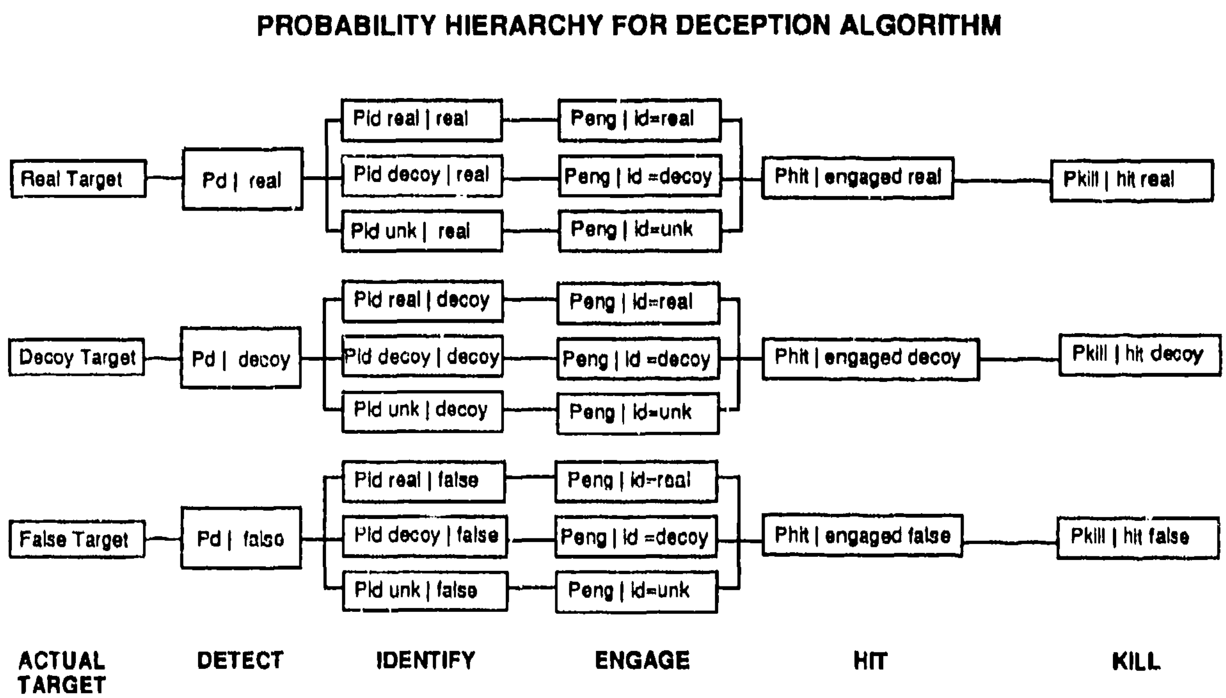

Figure 3-3. Probability Hierarchy for Deception Algorithm

FRED-D is a force-on-force, stochastic, close combat computer simulation featuring video animation. FRED-D was developed to provide an expeditious and economical means to readily study the detailed interactions of armor and mechanized infantry combat, and to examine the potential impact of different equipment, tactics, terrain, and environmental conditions on the outcome of small unit battlefield engagements.

FRED-D realistically models opposing force interactions at the individual item level through rigorous simulation of target acquisition systems, targeting decisions, maneuver decisions, the engagement process and the effects of weapons against battlefield targets.

FRED-D inputs are drawn from theoretical, analytical and empirical sources to include military field exercises. FRED-D output includes mean and standard deviation statistics for force attrition, types of damage, loss exchange ratios and shots fired by combatant type. The dynamic video display of the in-process simulation permits the analyst to easily verify input data and immediately assimilate results.

FRED-D results have been compared to the following wargames and models: ADEA; BAT90; BBS; CMTC; SIMNET; CASTFOREM and JANUS. For comparable simulation exercises, FRED-D results fall within 5-10% of CASTFOREM.

FRED-D analyses are performed on a 386/486 personnel computer. Input data file preparation requires approximately 1-2 hours for a new base case analysis and approximately 2-10 minutes for variations about the base case. FRED-D requires 20 minutes to an hour to run a statistically valid number of trials. Output interpretation requires 30 seconds to approximately 5 minutes.

Since FRED-D was originally constructed to realistically address decoys and false targets, several FRED-D features had to be disabled to properly simulate the performance of "standard Army models" during the testing of the Deception Algorithm. Figure 3-4 presents the results of FRED-D testing of the Deception Algorithm.

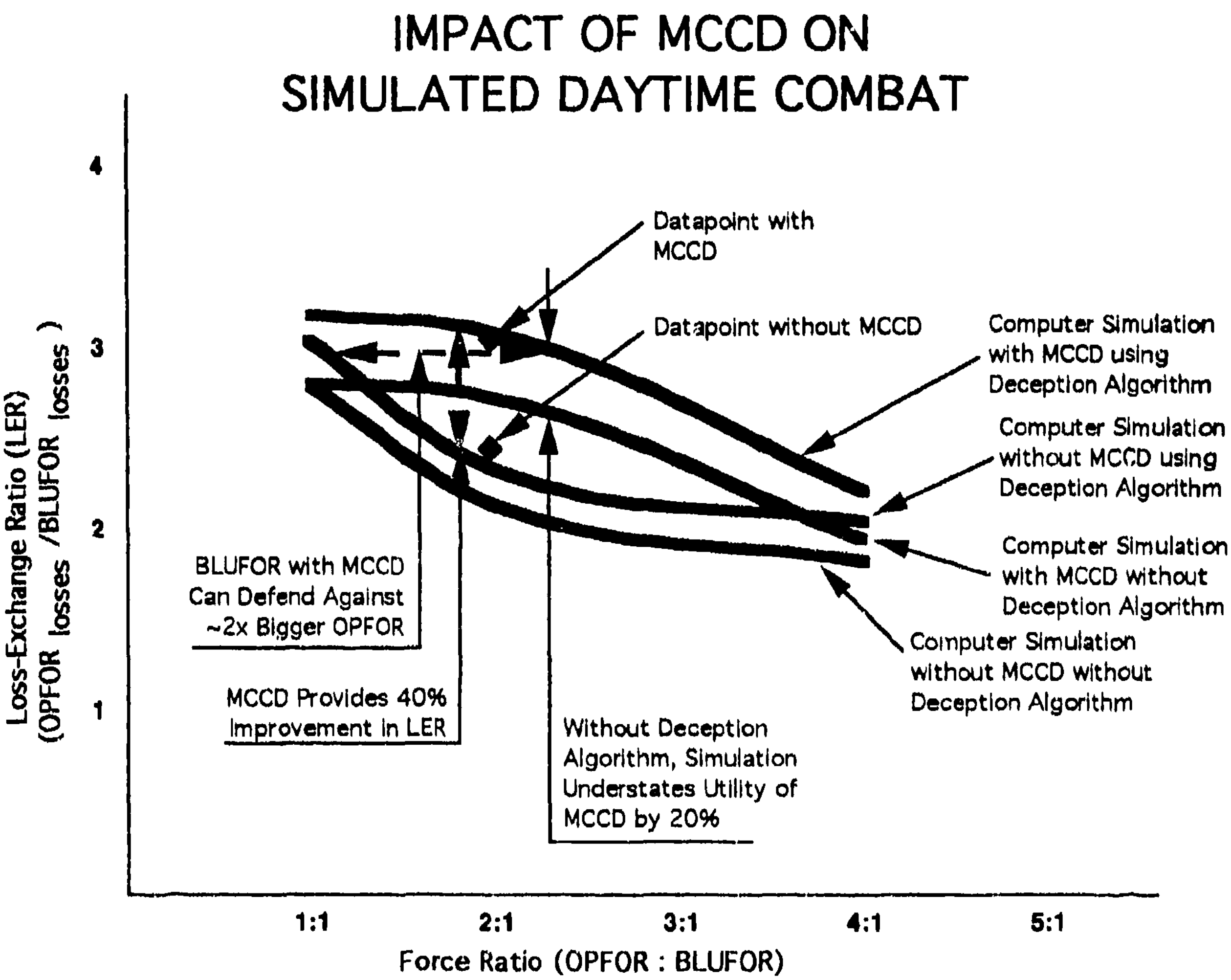

Figure 3-4. Impact of MCCD on Simulated Combat

CHAPTER 4

HUMAN FACTORS DATA FILES

The Human Factors Data Files and Audio/Video Tape Analyst Comment Files were extracted from Reference 3, were converted to a readable format, and are reproduced in Appendix A and B of this report.

There is ample annecdotal evidence from the comments of the participants and observors that decoys had a profound impact on OPFOR actions during the force-on-force exercises.

BRTRC was not commissioned to undertake a detailed examination or analysis of these files.

REFERENCES

1. (U) Independent Assessment Report for the M1 and M2 Multispectral Close Combat Decoy Type Classification - Standard, TECOM Project Number 1-ES-035-BDS-001/002, November 1993 (Secret)

2. (U) Multispectral Close Combat Decoy Initial Operational Test and Evaluation, TEXCOM Number 1993-OT-TXEC-1377B (Secret)

3. (U) MCCD IOTE Deliverable Data Files (Secret)