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19. ABSTRACT (Continue on reverse if necessary and identify by block number) The TAME report describes a general approach for assessing target unit acquisition in a tactical nuclear scenario, given well-defined input functions representing acquisition and retention conditioned on environment and elapsing time. Input functions suitable for constructing an operational program to execute the methodology are to be generated in an ongoing CAA effort, Target Acquisition Study IV (TAS IV). The methodology supports the Nuclear Fire Planning and Assessment Model III (NUFAM III) at CAA. The TAME approach assesses the acquisition effectiveness of an array of sensors against a target unit. Search and acquisition retention are represented as alternating renewal processes over time. Primary output measures include the steady state probability of unit acquisition and the probability distribution of residual duration of acquisition retention as a valid target.					
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TECHNICAL PAPER
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**TARGET ACQUISITION
METHODOLOGY ENHANCEMENT
(TAME)**

MARCH 1989



**PREPARED BY
FORCE SYSTEMS DIRECTORATE**

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This document was prepared as part of an internal CAA project.



TARGET ACQUISITION METHODOLOGY ENHANCEMENT (TAME)

STUDY
SUMMARY
CAA-TP-89-1

THE REASON FOR PERFORMING THIS WORK is that experience with the Target Detection Routine (TADER) model, used to compute probabilities of operational target acquisition (POTAs) in the Target Acquisition Study III (TAS III), has indicated the need for further methodology enhancement. An improved target acquisition methodology is needed to treat detection perishability and signals intelligence (SIGINT) for improved interface with the Nuclear Fire Planning and Assessment Model III (NUFAM III). The methodology should also be developed to effectively use the updated sensor performance data base to be generated by the Target Acquisition Study IV (TAS IV).

THE PRINCIPAL FINDINGS of the work reported in this paper are:

- (1) A new target acquisition measure, the steady state probability of target acquisition (SPOTA), was developed to better treat acquisition as a function of elapsing time.
- (2) A new target acquisition methodology, denoted herein as the candidate TAME methodology, was designed to apply projected sensor data from TAS IV to generate SPOTAs for target units. The new method is a stochastic simulation which samples acquisition status from dynamically created target acquisition and retention functions. These functions are composites of single environment component acquisition/retention functions generated by TAS IV. The new methodology appears implementable as a computerized process, given that the projected TAS IV products are completely defined.
- (3) The candidate TAME methodology is closely correlated with NUFAM acquisition events and will enhance assessments made with that model.
- (4) The candidate TAME methodology implicitly treats SIGINT through the use of algorithms from TAS IV based on nested results of higher resolution models. The effects of varied scenario environments are explicitly treated in the TAS IV products which are input to the methodology.

THE MAIN ASSUMPTIONS are:

- (1) The order of battle is well known prior to determination of the acquisition probabilities.
- (2) The sensor data catalog of the TAS IV Study will be sufficiently developed to provide information on sensor characteristics and capabilities for methods developed.
- (3) The validity of an acquisition methodology depends on the validity of the input sensor data.

THE PRINCIPAL LIMITATION of this paper is the reliance on the future availability and suitability, for the new methodology, of algorithms from the TAS IV Study.

THE SCOPE OF THE STUDY includes the evaluation, and implementation, where feasible, of methodology for producing target acquisition measures which enhance the use and applicability of NUFAM and other force assessment models.

THE STUDY OBJECTIVES were to assess approaches for, and feasibility of, the following methodological improvements in target acquisition:

(1) Development and use of a single glimpse detection capability and variable search time to represent steady state acquisition probability.

(2) Improved integration with NUFAM at the US Army Concepts Analysis Agency (CAA).

(3) Use of conditional probability distributions to better represent environmental degradation for a scenario.

(4) The automating of computations for methodologies developed.

(5) A SIGINT methodology.

THE BASIC APPROACH was to:

(1) Use a literature search to define the scope and nature of the acquisition modeling problem.

(2) Study acquisition modeling techniques in existing models and research papers.

(3) Select and/or design a "best" methodological approach which:

(a) Reduces assessed deficiencies of the TADER method.

(b) Effectively applies input data to be generated by TAS IV.

(c) Can effectively support current and future versions of NUFAM.

THE STUDY SPONSOR is the Director, US Army Concepts Analysis Agency.

THE STUDY EFFORT was conducted by Mr. Walter J. Bauman, Force Systems Directorate, US Army Concepts Analysis Agency.

COMMENTS AND QUESTIONS may be addressed to the Director, US Army Concepts Analysis Agency, ATTN: CSCA-FSC, 8120 Woodmont Avenue, Bethesda, MD 20814-2797.

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CHAPTER 1

INTRODUCTION

1-1. **CONTEXT.** This study examines the problem of modeling the performance of a comprehensive array of sensors, deployed throughout a large combat force (at least corps level), which seek to acquire units (company, battery, or battalion) of an opposing force for targeting. This modeling problem treats only detecting and detectable entities. The interactive effect with combat and communications is not directly considered. The intention is to assess the susceptibility of a target unit to acquisition in a brief representative period in the combat scenario timeframe. These results may then be used by a combat model to assess the effects of target acquisition in terms of the availability of targets for attack.

1-2. BACKGROUND

a. **Target Acquisition in Nuclear Fire Models at the US Army Concepts Analysis Agency (CAA).** The principal nuclear fire model used at CAA to assess tactical nuclear requirements is the Nuclear Fire Planning and Assessment Model III (NUFAM III). NUFAM III simulates a two-sided exchange at corps level. An offline methodology, the Target Detection Routine (TADER) was created at CAA to analytically calculate the net target acquisition performance of a force of deployed sensors seeking a specified type of target unit. These net performance measures, denoted as probabilities of operational target acquisition (POTAs) are then input to NUFAM in the form of lookup tables. Given a deployed force of sensors observing a specified type of target unit, the POTA for that sensor force against the specified unit is defined as the probability of (at least one sensor of the force) detecting, recognizing, and locating the target unit at (specified) prescribed distances from the forward line of own troops (FLOT) during a random, but limited, period of time in a day of intense combat.

b. **Previous Studies.** The TADER methodology currently used to calculate POTAs for NUFAM III has evolved over three CAA target acquisition studies described in Table 1-1: the Target Acquisition Study (TAS), Target Acquisition Study II (TAS II), and Target Acquisition Study III. Although the concept of a POTA is used in the same way in all of the above studies, each one developed its own method for calculating it. A manual acquisition methodology was used by TAS. TAS II applied a computerized method denoted as the Probability of Operational Target Acquisition Routine (POTAR). The TADER methodology of TAS III is a new method which uses an enhanced TAS II input data set. TADER is a computerized (on the UNISYS 1100/82), analytic model developed at CAA designed to compute the probability of operational target acquisition (POTA) of generic military units scanned by opposing sensor arrays over a fixed search period. TADER assigns lucrativeness threshold inputs to target units to filter out detections not suitable for targeting. The model is documented in CAA-TP-87-9 (Ref. 1) and CAA-D-87-8 (Ref. 2). Summary documentation of TADER is presented in Appendix D. The application of TADER is documented in the TAS III Study Report (Ref. 3).

Table 1-1. Target Acquisition Studies Performed at CAA

Study	Year completed	Scope of forces	Sensor types	Acquisition methodology
TAS I	1976	US divs vs Red tgts 3 Red divs vs Blue tgts	STANO	Manual method
TAS II	1979	US corps vs Red tgts NATO corps vs Red tgts 6 Red divs vs Blue tgts	STANO, SIGINT	Computerized STANO method (POTAR), SIGINT offline
TAS III	1987	US corps vs Red tgts NATO corps vs Red tgts NATO divs vs Red tgts 9 Red divs vs Blue tgts	STANO	Computerized STANO method (TADER)

c. **Assessment of TADER Deficiencies.** Experience with TADER revealed the following shortcomings in model and data attributes.

(1) **Unavailability of Updated Input Data.** Updated input data is not readily available. TADER input requires a comprehensive set of performance measures (detection probabilities) for a single sensor observing a single target element (e.g., a truck) over a wide spectrum of range and environmental conditions. Degradation factors for sensor-target element pairings for various attenuating environmental and system conditions also have to be constructed. TAS III used an existing data base created for the TAS II Study and, in the absence of new data from higher resolution sources (e.g., field tests), made selected subjective adjustments to perform system updates. The origin of the values in the TAS II data base are not sufficiently well defined to perform an audit trail. Since the TAS II data, created in (or before) 1978, is a decade old, an update is in order. The absence of a comprehensive input data base to TADER limits both the scope and credibility of future products of that model.

(2) **Scenario-restrictive Input Data Base.** Available input data is scenario-restrictive. The input data base available from TAS II, which was also used in TAS III, contains detection probabilities for a single sensor observing a single target element only for a fixed 2-hour duration of search. Output POTAs are therefore constrained by that input to represent effects of only a 2-hour search period. Modeling of a different duration of search requires construction of an input data base configured to that duration. Thus, TADER logic is restrictive in that information accumulation over time must be treated offline during input preparation. As noted above, new input data, and the means (or models) for generating it, are not currently available at CAA.

(3) **No SIGINT Methodology or Data Base.** There is no input data or methodology for assessing signals intelligence (SIGINT). In order to

comprehensively represent the spectrum of target acquisition surveillance assets, a method and data base for assessing SIGINT should be devised and integrated with the assessment methodology for non-SIGINT sensors.

(4) Simplistic Modeling of Environmental Degradation. Environmental and system degradation effects are crudely modeled. In general, degradation from conditions such as weather, crew performance, and smoke are represented as notional "average" factors expressed in terms of the fraction of inherent baseline performance (detection capability) remaining after application of the degradation effect. Thus, a degradation factor in TADER is a multiplier of single sensor or single system performance. Such a simplistic approach ignores the variation in effects which occurs in the real world.

(5) Constraints Imposed on NUFAM Improvements. The rigid structure of TADER limits representation of target acquisition in NUFAM III. NUFAM III, used to assess tactical nuclear requirements at CAA, is undergoing a continual improvement/upgrade process. The scope of feasible improvements is constrained by the inflexibility of the TADER POTAs. NUFAM treats target units as possessing attributes of mobility and acquisition perishability. Acquisition perishability is not addressed in TADER. Acquisition perishability should be incorporated into any target acquisition methodology which supports NUFAM III.

(6) Inadequate Treatment of Elapsing Search Time. Time is not explicitly treated in TADER. As noted above, time is only implicitly considered in the definition of detection input data for a single sensor observing a single target element. These data must be based on the specific search period applicable to the scenario. The TADER methodology is basically an expected value assessment of acquisition status at the end of a predefined (2 hours for TAS III) search period. Sensor detections are not integrated over time. Instead, the TADER single sensor detection input data must have previously been integrated over time. TADER combines single sensor-single element detections by assuming statistical independence of separate detections. Flexibility and credibility of TADER are degraded by the absence of a time-dependent detection methodology in TADER.

d. TAS IV. In order to improve the range and credibility of target acquisition methodology in support of NUFAM III, the Target Acquisition Study IV (TAS IV) was created at CAA. Originally configured to be a combined data base enhancement and model improvement effort, the study scope was subsequently restricted to data base enhancement. Target acquisition methodology improvement is treated as a separate study, the Target Acquisition Methodology Enhancement (TAME) Study. TAS IV has as its primary objective the creation of a comprehensive sensor data catalog for current and future US, non-US NATO (North Atlantic Treaty Organization), and Warsaw Pact (WP) systems. This data base would be applied by the enhanced target acquisition methodology created by TAME.

(1) Responsibilities. The creation of the updated sensor data catalog is a joint effort among CAA, the US Army Materiel Systems Analysis Activity (AMSAA), and a contractor. CAA and AMSAA agreed on data base design requirements. AMSAA will exercise a family of sensor performance models to produce a detailed data base of parametric net assessments over varying search time for a force of sensors seeking a specific unit type under (each of) a wide

variety of scenario conditions. The contractor then will statistically process these data to produce algorithms for direct calculation of the probability of acquisition for each sensor force-target unit combination, as a function of elapsing time and scenario conditions. The contractor will also produce algorithms showing the conditional probability distribution of target retention time, given that the unit has been acquired. CAA will check interim products of TAS IV for correctness and suitability in the enhanced target acquisition methodology developed by the TAME Study.

(2) **Schedule.** Although the initial start of the TAS IV Study was in July 1988, difficulties in securing a contractor commitment delayed award of a contract until March 1989. The study was initially proposed as an 18-month effort. However, the effective schedule depends on contractor resource capability. The TAS IV products are to be delivered incrementally. Receipt of the final items is anticipated 1 year from award of the contract.

The TAME effort was to parallel TAS IV since its methodology must apply TAS IV data products. The unforeseen delay in TAS IV contractor commitment necessitates that TAME be done in phases. The initial phase began in March 1988 and was restricted to a 1-year analysis. Since the TAS IV data products were not defined until late in 1988, this first phase of TAME was limited to a methodology analysis and design effort. A follow-on phase will be defined as the TAS IV data construction gets underway.

1-3. STUDY PURPOSE

a. **Purpose.** The primary purpose of this study is to develop an approach for improved assessment of target acquisition for use in tactical nuclear warfare modeling at the CAA. The methodology developed will address the deficiencies in TADER cited above, viz.:

- Scenario restrictive input data base.
- No consideration of SIGINT.
- Oversimplified representation of sensor degradation factors.
- Limitations imposed on NUFAM improvements.
- Inadequate treatment of elapsing search time.

The emphasis is on supporting NUFAM III though an offline target acquisition methodology. Because of the potentially large number of sensors in a battle-field environment and the complexity of factors affecting detectability, the target detection and acquisition process is not simulated interactively in detail in NUFAM. Instead, the target units in NUFAM III are periodically assessed for acquisition status via a random draw from simple Bernoulli probability distributions with defining parameters (currently the POTA values created by TADER) generated offline.

1-4. **OBJECTIVES.** The TAME study objectives were to assess approaches for and feasibility of the following methodological improvements in target acquisition:

- a. Development and use of a single glimpse detection capability and variable sensor search time to represent steady state acquisition probability.
- b. Improved integration with NUFAM at CAA.
- c. Use of conditional probability distributions to better represent environmental degradation for a scenario.
- d. The automating of computations for methodologies developed.
- e. A SIGINT methodology.

1-5. ELEMENTS OF ANALYSIS. From the study directive, the TAME elements of analysis are:

- a. Should the methodology be modified to take into account, separately and directly, the steady state acquisition capability of each type sensor?
- b. Can the methodology effectively support the NUFAM version current as of 15 December 1988 at CAA?
- c. How can modeling of environmental degradation factors be improved by using conditional probabilities to transform basic environmental data into modifiers for specific scenarios?
- d. To what degree can derived methodologies be automated?
- e. What are the implications to the target acquisition methodology of including SIGINT contributions directly rather than through intelligence preparation of the battlefield, as in TAS III?

1-6. TAS IV/TAME/NUFAM INTERACTION. Figure 1-1 shows the interrelation of data and analytic guidance among three separate projects, TAS IV, TAME, and NUFAM model improvement. The TAME study effort both supports and is supported by the TAS IV Study. The primary objective of the TAS IV Study is, with AMSAA and contractor support, to collect a comprehensive set of new and updated data and data algorithms on sensor capabilities. The new data will be the basis for the TAME methodology. Insights from the TAME methodology in turn will guide the structure of the data collected. At CAA, all TAS studies have had as their primary purpose the production of POTAs for input to NUFAM at CAA. The TAME methodology must be compatible with the current and evolving operational versions of NUFAM. Changes in the application of target acquisition in model improvements to NUFAM are also guiding development of the TAME methodology. The relationship of products in Figure 1-1 is hierarchical in that TAS IV data will be input to TAME, and TAME outputs will be input to NUFAM. Methodological guidance is nested in the reverse order, in that NUFAM application needs are input to TAME, and TAME data requirements are input to TAS IV. From this perspective, the information flow is continuous among the three efforts.

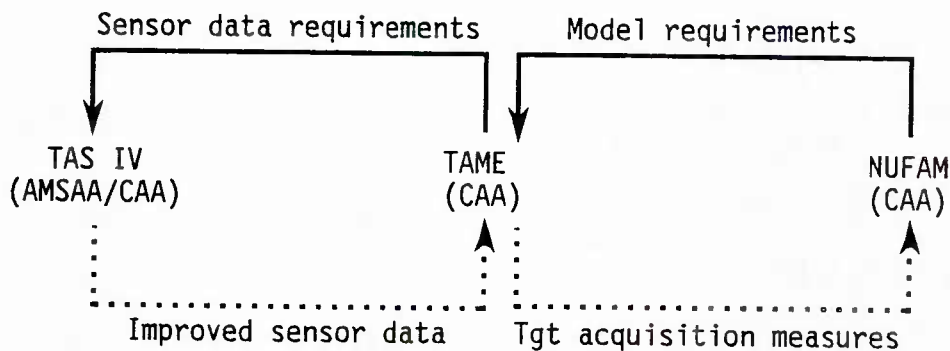


Figure 1-1. TAS IV/TAME/NUFAM Interaction

1-7. **APPROACH.** The study approach is diagrammed in Figure 1-2. Starting with a literature search of approaches to the modeling of target acquisition, the scope and nature of the modeling problem were defined. Parallel to this, existing techniques for modeling aspects of the target acquisition problem were identified as candidate tools for the TAME methodology. These tools included, but were not limited to, the TADER methodology of TAS III. The incorporation of selected candidate methods into a best unified TAME methodology was based on the extent to which:

- Assessed TADER deficiencies were reduced.
- Input data requirements were satisfied by the products of the TAS IV study.
- The unified methodology supports current and projected versions of NUFAM.

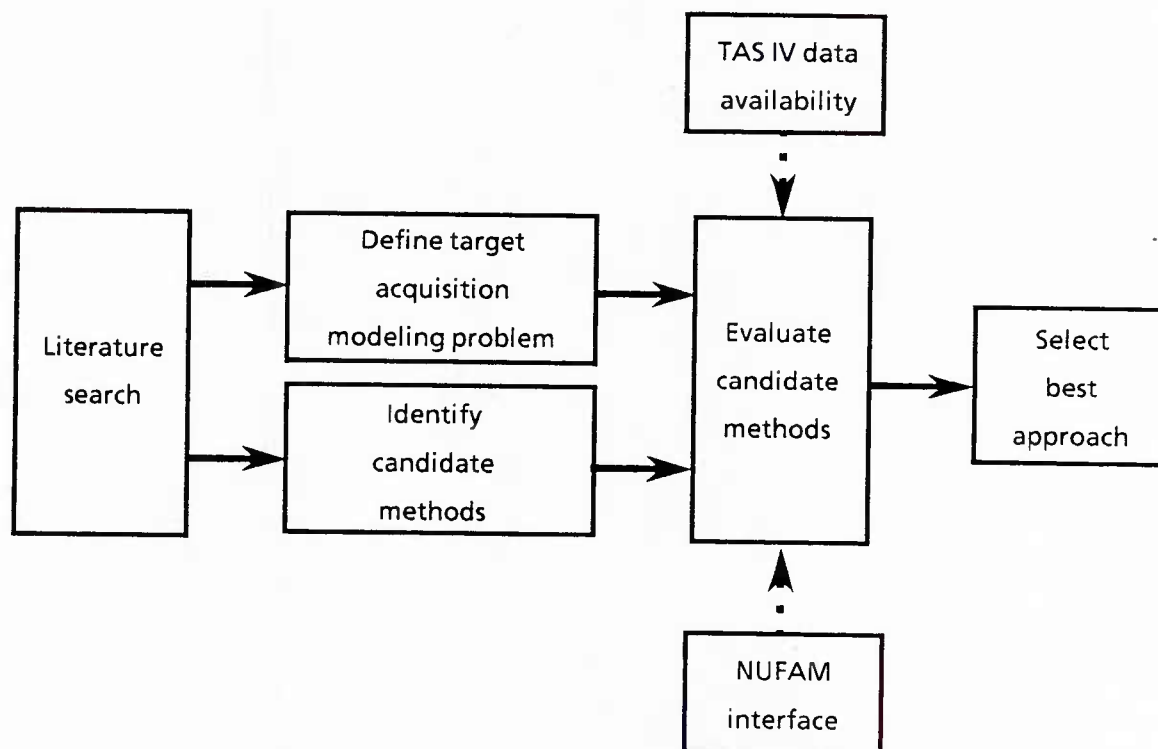


Figure 1-2. TAME Study Approach

1-8. **STRUCTURE OF REPORT.** This paper is organized around the elements of analysis stated in paragraph 1-5. Chapter 2 summarizes the analytic nature of the target acquisition modeling problem and describes past modeling approaches. Chapters 3 and 4 develop a new modified steady state measure and methodology for target acquisition. This new method is denoted as the candidate TAS IV methodology and is the preferred TAME approach. Chapter 5 describes the appropriateness of the new method for supporting NUFAM. Chapter 6 describes considerations in modeling environmental degradation effects on acquisition. Chapter 7 describes approaches to SIGINT detection modeling. Chapter 8 summarizes findings and describes the preferred (TAME) acquisition methodology. Appendixes A, B, and C show the study contributors, study directive, and references respectively. Appendixes D, E, F, and G provide additional detail on modeling approaches summarized in the main report. Appendix H provides additional detail on the use of statistical independence assumptions in modeling.

CHAPTER 2

STRUCTURE OF THE TARGET ACQUISITION MODELING PROBLEM

2-1. TYPES OF SYSTEMS. The generic types of target acquisition systems are summarized in Table 2-1. These have been subcategorized into types primarily used to acquire targets for direct fire attack and those primarily used to acquire target information for indirect fire attack and for an intelligence/surveillance data base. Further characteristics of these classes are:

a. Direct Fire. Direct fire sensor systems are primarily handheld or vehicular mounted electro-optical devices for acquiring and attacking individual target elements, e.g., a vehicle. Small clusters of target elements might also be acquired. Targets acquired by these systems are at relatively close (direct fire) range. An acquisition event is generally rapidly processed for attack or evasion because the sensor carrier is frequently also the attacker and is itself subject to attack if the target has equivalent detection capability. Therefore, separate detection events are seldom stored and fused into a broader intelligence estimate. The deployment of direct fire sensor assets is generally dictated by the combat priorities of their carriers. Therefore, they often seek targets of opportunity rather than confirmation of targets cued by prior sources. Detailed modeling of direct fire combat and acquisition events in a force is usually done via stochastic simulation. The scope of such a simulation is generally limited to at most a division-size slice, due to the large time and memory requirements for processing generated by the many events in a battle.

b. Indirect Fire/Surveillance. Indirect fire/surveillance sensor systems are generally on either ground-based or airborne carriers. Surveillance systems are usually organic to units whose primary function is collection of target acquisition information which is then transmitted to another unit which acts on the information. Intelligence centers receiving surveillance reports will attempt to fuse separate reports in time and space into a schematic of the enemy order of battle. Surveillance systems seek targets within a much greater range spectrum than direct fire systems. By design, they are usually sited to have unobstructed line of sight over a wide search area. Indirect fire target acquisition systems, e.g., counterfire radars, rapidly process a (firing) target for attack because of the tactically dictated high perishability of a firing unit. Counterfire systems can also be used to build a surveillance picture of the battlefield. The deployment of sensor systems for indirect fire and surveillance is often preplanned as part of an overall battlefield intelligence collection plan designed to acquire information on high priority targets in critical battlefield sectors.

Table 2-1. Sensor System Types

Direct fire	Indirect fire/surveillance
Electro-optic (EO) sights - visual - image intensifier	Ground-based eye, EO, IR, image intensifier Ground-based counterfire radar (countermortar/ counterbattery (CM/CB)) Ground-based surveillance radar (MTI (moving target indicator))
Television (TV)	Ground-based electronic intelligence (ELINT) system
Unaided eye	Ground-based communications intelligence (COMINT) system
Infrared (IR) imager	Airborne eye, EO, IR, image intensifier, photo
Millimeter wave radar	Airborne MTI
Laser rangefinder	Unattended acoustic/seismic sensors Flash ranging systems Airborne ELINT Airborne COMINT

2-2. TIMELINES. As noted above, target acquisition is part of a dynamic process, the ultimate purpose of which is usually to select targets for attack. The sensor, target, and intelligence processing center all interact in the sequence of activity states shown in Figure 2-1. The sensor is in a search state until it acquires the target. At that point, it may transmit intelligence to a processing center while it tracks the target. The target acquisition itself is valid only as long as its position is known, or assumed known, to the sensor. The period of time after acquisition that an acquired target remains valid is denoted as the retention time of the target. This retention time may be greater than the duration of time after acquisition that the sensor tracks the target. Thus, the target retention time is a measure of the perishability of a target acquisition. Targeting can usefully be initiated only against a valid target (i.e., one that is retained). The interacting effects of these activity timelines create resolution difficulties in modeling. The following approaches are possible, depending on scenario assumptions and assessment objectives.

a. Stochastic Model. All of the entities and event states in Figure 2-1 could be represented in a stochastic model, possibly through a simulation. However, the usefulness of such a model depends on the completeness of the model representation of sensors and targets. The large number of sensors of different types on the battlefield can easily generate unwieldy computer time and resource requirements. In addition, a comprehensive input data base for assessing one-on-one sensor performance is not readily available. Activities supporting the Joint Tactical Fusion Program (JTFF) simulate reports from a full sensor spectrum, but the inclusion of certain national systems produces a data base and algorithms that are releasable only as special compartmented information (SCI).

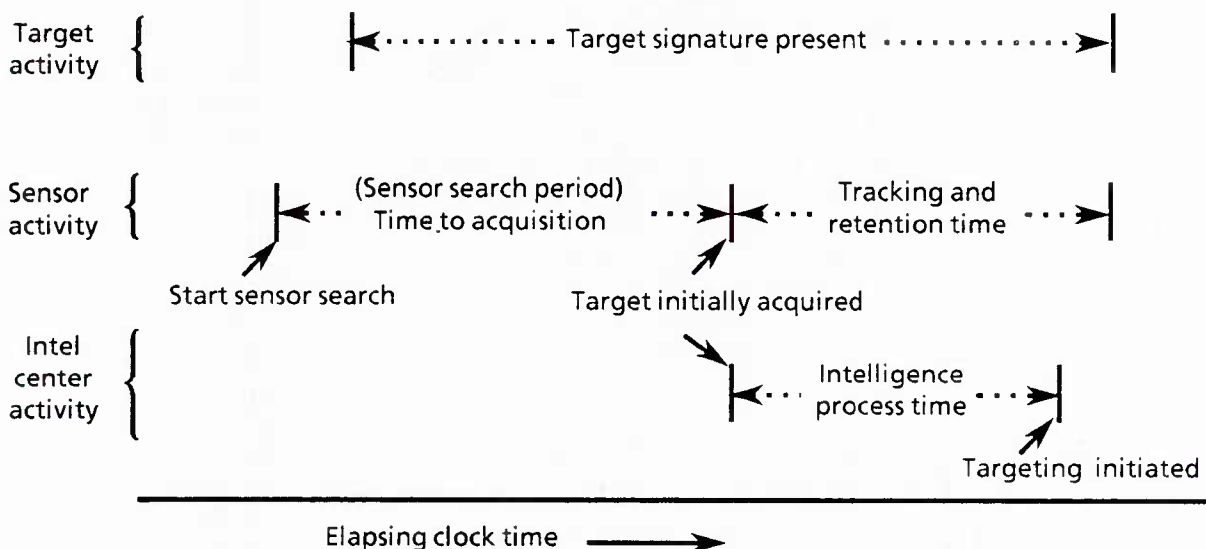


Figure 2-1. Activity Timelines in Target Acquisition

b. Expected Value Model. An expected value approach will combine closed form algorithms representing many processes to yield a deterministic state of events. Time dependence is very difficult to treat, since time would then have to be a parameter of a closed form algorithm representing a process. A deterministic expected value assessment could then be made only by integrating the process over time. Typically, a time-dependent process (e.g., detection, over time, of a target by a sensor) must be assumed to be a steady state process over time, and a closed form algorithm (i.e., a formula or equation) must be defined to represent that process. If there are several processes occurring simultaneously, then a means of combining single process algorithms into a joint process algorithm must be found. If such a combined function can be found, the result would still have to be integrated over time to yield an expected value. Because detection depends on distance from the sensor, expected value assessment of target acquisition also requires integration over space (distance). The large number of interacting sensor-target processes in the force-on-force target acquisition scenario can easily make treatment of time and space extremely complex. If one dimension, time or space, is fixed, the expected value problem is easier. For example, an "interval snapshot" of target acquisition probability at a fixed point in scenario time might be done analytically by integrating instantaneous detection functions over space (coverage area).

2-3. HIERARCHY OF MODELING

a. Introduction. As stated previously, the large number of sensors and target elements in a force-on-force combat scenario makes high resolution modeling of acquisition processes unwieldy or intractable as the scope of the scenario enlarges. The apparent solution is to model a large problem with a nested set of models. A high-resolution model for a small force problem would generate output which provides algorithm processes (or even process results) as input to a model of large scope that has been partitioned into "small force problems." These "small force" components of the larger problem are then processed independently over the attributes treated in the high-resolution model. This solution does assume statistical independence between entities and processes in separate small force problems modeled with high resolution. Appendix H discusses the use and appropriateness of independence assumptions in modeling.

b. Definition of Terms. The following nomenclature applies to components of target and sensor groupings:

(1) **Target Elements.** In terms of resolution, a target unit, treated as a military unit (e.g., a tank company), is defined in this paper as being composed of target elements, i.e., physical objects like tanks or trucks. A target element possesses one or more signatures which are detectable attributes. For example, a howitzer may have a visual shape signature and, when firing, an audio and flash signature. Sensors technically detect signatures rather than elements, but when a sensor-target interaction involves only one signature (as is often the case), then target element detection may equate to target signature detection.

(2) **Sensor Aggregations.** In terms of resolution, individual ground sensors with identical characteristics, but deployed over an area, are denoted herein as a sensor suite of a single sensor type. Airborne sensors are generally deployed in missions. The entire spectrum of active sensors and sensor missions in a scenario is denoted herein as the scenario sensor suite.

c. Model Hierarchy Categories. A nesting hierarchy for sensor models can be defined by the following three categories, described in order from highest resolution to lowest resolution: one-on-one models, one-on-many models, and many-on-many models. Their definitions are as follows:

(1) **One-on-one Model.** This type of model computes the acquisition probability of a single target element by a single sensor under a specific set of conditions. The basic acquisition probability, or time to acquisition, for a single sensor observing a single target element is the end result and, if done in parallel, is not fused or combined with other sensor-target interactions. Most one-on-one models apply formulas from engineering and physics to target elements with very detailed characteristics. A one-on-one model is often only a set of mathematical formulae and may not even comprise a labeled computer software package "model." A well-known example of a one-on-one model is the electro-optic search model created by the US Army Center for Night Vision and Electro-optics (CNVEO) as described in Institute for Defense Analysis (IDA) Paper P-2022 (Ref 4.). Inputs include field of view, target size, target contrast level, sensor resolution, and atmospheric

The one-on-one model is suited for assessment for direct fire acquisition, since acquisition information is generally not fused at that level.

(2) **One-on-many Model.** This type of model computes the acquisition probability of a target unit by a single sensor through the fusion of single sensor-single target element acquisition probabilities comprising a scan of the target unit. In one sense, a one-on-many model integrates the results of one-on-one models over target elements in a unit. Most one-on-many models are integrated into many-on-many models.

(3) **Many-on-many Model.** This type of model computes the acquisition probability of a target unit by a suite of sensors in a given timeframe or as a function of time. Such a model can be thought of as combining the results of many one-on-many models over sensors in a suite. TADER is an example of a many-on-many model. Figure 2-2 illustrates the interacting entities in each type model.

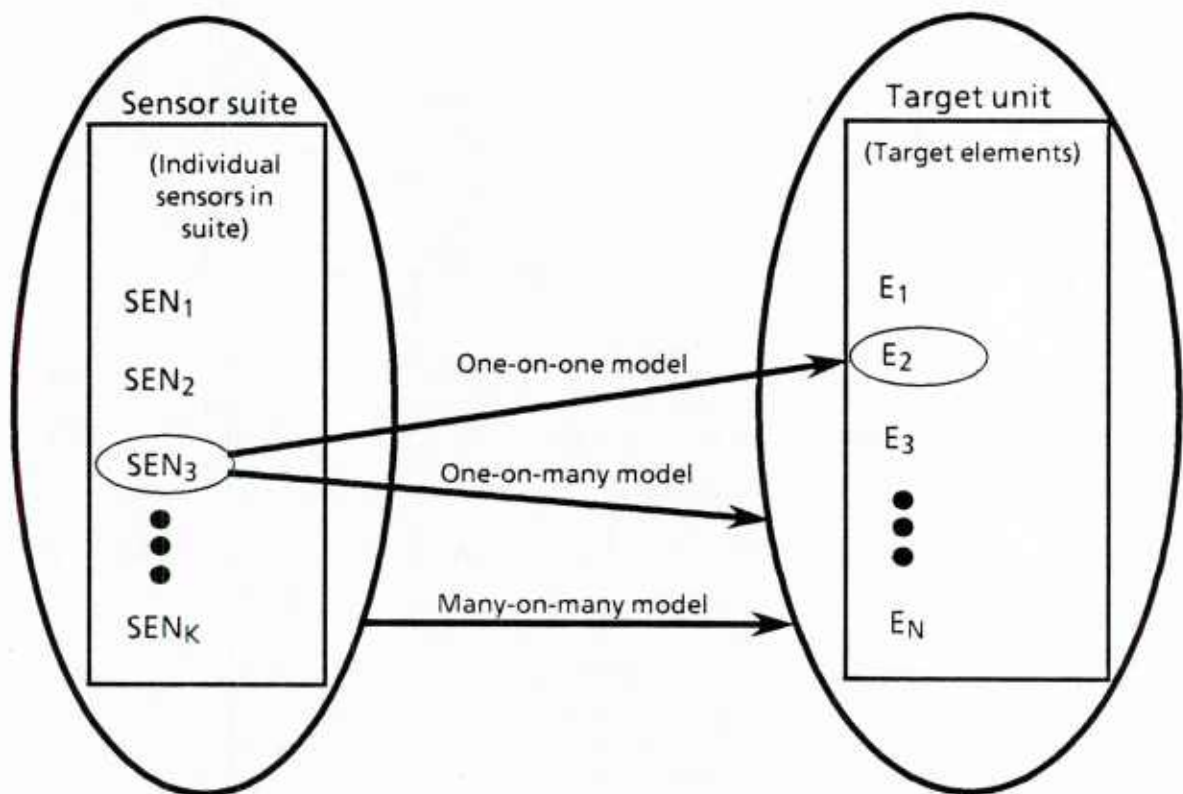


Figure 2-2. Diagrammatic Representation of Sensor Model Resolution Categories

d. Nesting of Models. The definitions of the model resolution categories suggest the nesting of models shown in Figure 2-3. While one-on-one models could be used as subroutines in many-on-many models, the level of detail for scenarios with significant force sizes would often be difficult to implement on a computer. It is more efficient to use the one-on-one models to create a catalog of empirical functions or factors enabling the many-on-many model to access precomputed results (perhaps through a lookup table) for sensor-target interaction under a specified set of conditions. Ideally, the precomputed results would be in the form of empirically derived functions keyed to only a few of the many variables considered by the one-to-one model. To produce these functions, a large number of carefully defined (by the analysts using the many-on-many model) executions of many one-on-one models (the province of engineers) must subsequently be fitted to algorithms (the province of statisticians) to be used in the many-on-many model (by operations researchers) who report to management (the province of nonscientists). The overall task is complicated by the needs for communication and cooperation among diverse technical specialties. Instead of functions, a many-on-many expected value model, like TADER, often resorts to lookup tables, usually giving single sensor-single element detection probability as a function of range for a variety of conditions. Both the origin as well as the applicability of the one-on-one results reflected in such lookup tables are often ill-defined (if defined at all).

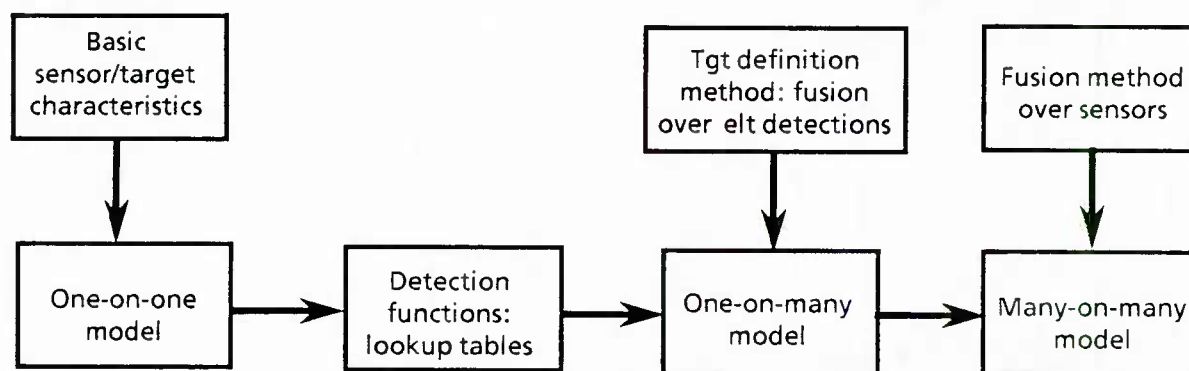


Figure 2-3. Hierarchical Nesting of Target Acquisition Model Processing

2-4. FACTORS IN TARGET ACQUISITION MODELING. Figure 2-4 shows the interaction of the major generic elements in assessment of combat target acquisition performance. Qualities of the sensors, the targets, and the environment all interact with the tactical scenario to form the components of target acquisition assessment. Models of target acquisition in large (e.g., corps-level) echelons are many-on-many models which treat sensor performance factors in broad terms. These sensor performance factors used in models are often the result of a nesting, via aggregation, of higher resolution performance factors. Thus, detailed system factors which affect sensor performance are combined and aggregated into a smaller set of generic factors for use in low-resolution modeling.

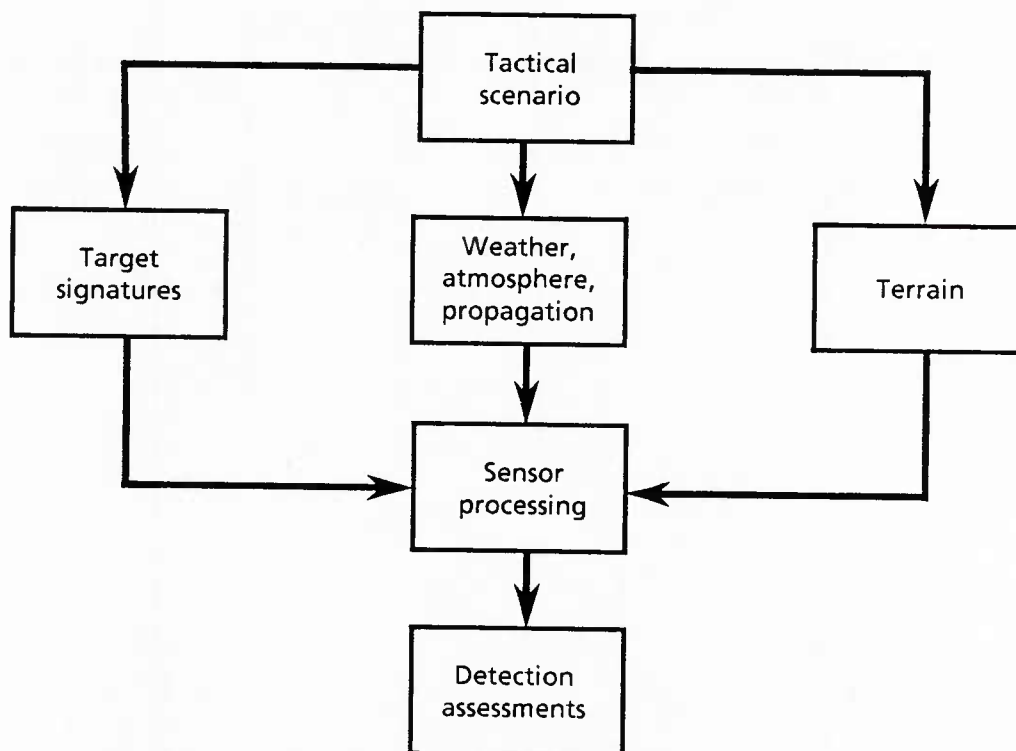


Figure 2-4. Major Elements in Target Acquisition Performance

a. **System Factors.** Table 2-2 summarizes the system factors that can affect sensor performance. Different factors often apply to different sensor types, e.g., thermal contrast applies only to thermal sensors. The number of factors in Table 2-2 is too large to be processed for the large number of sensor-target interactions in a surveillance model of a large combat force. In addition, little is known about the effects of human factors, such as operator fatigue and stress, on detection performance. Most system tests are engineering and machine oriented. The test environment is set to a standard "baseline" environment. Theoretical or subjective adjustments are often made to baseline measurements to account for degradation. "Real-world" testing is both costly and difficult to control; the range of available data is therefore limited.

b. **Generic Model Factors.** Low-resolution models will use generic sensor performance factors, each of which may represent the combined effect of a group of detailed system performance factors. Acquisition algorithms were examined in three many-on-many expected value models: TADER, the COMWTH (Combat Worth) Model by BDM, and the SAI (Science Applications Inc). Target Acquisition Model. A summary of common generic sensor performance factors in expected value surveillance models was constructed. Table 2-3 shows these generic factors. The detailed sensor performance factors comprising each generic model factor are listed in the rightmost column of the table. Not all models treat all these factors.

Table 2-2. Factors Affecting Sensor Performance

Sensor	Target	Environment	Other
Search area	Size, shape	Weather	Range to target
Duration of search	Visual contrast	Lighting	EW countermeasure
Deployment position	Thermal contrast	Terrain masking	Radio interference
Availability	Noise	Foliage	Decoy/false alarm
Reliability	Deploy pattern	Propagation	Operator fatigue
Survivability	Motion/activity Cues	Dust/smoke Clutter	Operator stress Eye function

c. **Resolution.** The importance of representation resolution of performance factors in a many-on-many expected value model of target acquisition is often neglected. Such a model is frequently used to assess the probability of acquisition of a notional type target in a notional (e.g., average or random) location over a notional timeframe. The output measure is a probability of acquisition characterizing a target class, but not necessarily a uniquely located target unit. TADER, for example, computes probability of acquisition for a target unit randomly located in a target zone defined in terms of distance intervals from the forward line of own troops (FLOT). All sensor-target interactions have to be modeled and merged, but the level of detail that is modeled in the sensor performance factors may be low because:

(1) **Computer Memory and Processing Time Requirement are Constrained.** If sensor-target interactions are assessed for each target over many sensor/target locations and points in time, then the dimensionality of the assessment problem can become so large that solution processing is unwieldy, even on a computer. (Processing time requirements for even a very small computer program can rapidly increase as additional DO-loops are nested). If all sensor-target interactions can be treated as independently occurring at an "average" location over a common time period, then the combined effects might be simply, and efficiently, represented in terms of product and exponent operations on notional acquisition assessments.

(2) **High Input Resolution can be Inappropriate for Assessing Notional Targets.** If the end product of the many-on-many target acquisition model is an acquisition probability characterizing a class of targets, rather than a unique target, then "approximate" inputs may be commensurate with notional outputs. Little may be gained by splitting hairs on process details, whose results will be heavily aggregated into a single "average" value assessment.

Table 2-3. Generic Factors for Model Aggregate Representations of Sensor Performance

Generic model factor	Description	Applicable sensor performance factors
Pcov	Probability the target is within coverage range of the sensor	Sensor deployment position Duration of search Cues Sensor search pattern Target deployment pattern
Plos	Probability of unmasked line of sight from sensor to target	Terrain masking Foliage Sensor deployment position Target deployment position
Pwx	Residual detection capability from degradation due to weather	Weather Lighting Thermal contrast
Pobs	Residual detection capability from dust/smoke or interference	Dust/smoke Clutter EW countermeasure/interference visual/thermal contrast
Pfa	Residual detection capability due to decoys/false alarms	Decoy/false alarm
Pav	Fraction of time sensor is available	Sensor availability Sensor reliability Sensor survivability
Pcrew	Residual detection capability due to operator performance	Operator stress Operator fatigue Eye function
Pd	Inherent detection probability for sensor observing target under baseline test conditions and under various target cover/activity conditions	Range to target Sensor/target deployment Duration of search Target size, shape, contrast Target noise Target motion/activity (baseline) light, propagation
Prec	Probability target is recognized, given it is detected	Same as for Pd

(3) **Detailed Sensor Input Data is Often Extremely Uncertain.** As noted earlier, there appears to be no comprehensive data base on sensor performance that is available for many-on-many assessments. Theoretically, a user could insert one-on-one sensor performance models as subroutines into his/her many-on-many expected value model (since engineering-based models do exist). However, this is impractical because the required level of detail would easily overwhelm computer resources needed to process it. Since test data on sensor performance is based on limited test environments, even engineering models are constrained by data unavailability. In the absence of consistent comprehensive sensor performance data, much data must be subjectively adjusted or constructed using results from other models and studies which were not designed to support the user's problem. No precision may be gained by representing an uncertain quantity in terms of several uncertain component quantities. In the extreme case, the attitude may be: why use a dozen guesses when one will suffice? The use of notional input characteristics may be justified if there are insufficient data measurements to usefully characterize the data uncertainty through a probability distribution. (There is the alternative of working the problems of target acquisition methodology development and input data construction in tandem. This is the approach taken by the TAME Study with its linkage to the TAS IV data generation effort).

d. **Illustrative Example of Comparative Resolution.** Table 2-4 illustrates two levels of model resolution for each of the generic sensor performance factors shown in Table 2-3. Except for coverage probability, all of the low-resolution representations shown are in terms of lookup tables. Higher resolution consists of integration over mathematical functions. In the case of coverage probability, the low-resolution option is based on the ratio of system coverage area to the area of the combat arena. By assuming uniformity of lateral coverage by sensors, these ratios can estimate "average" coverage without having to process the geographic pattern of specific sensor deployments. Processing can then be greatly simplified relative to the higher resolution option which requires testing each specifically located target point for coverage by each specifically located sensor. In Table 2-4, target zone refers to an area within which the same notional factors are deemed to apply. Expressing Pd as a function of duration of search refers to the expressing of probability of target acquisition for a sensor-target pair as a function of elapsing sensor search time (among other things).

**Table 2-4. Alternative Modeling Representations for
Generic Model Factors**

Generic model factor	Alternative 1 low resolution representation	Alternative 2 higher resolution representation
Pcov	Compute ratio of area covered by sensor(s) to area containing target	Test whether each point in target area is covered by each sensor. Compute fraction area covered by n sensors, n=1, 2, ...
Plos	Input lookup table giving Plos as function of sensor range to target and/or height of sensor and/or zone containing target	Given each sensor/target and position and terrain grid, compute if terrain cuts LOS at each point in target area. Average the effects
Pwx	Input lookup table giving Pwx as function of sensor type and/or season	Integrate (weight) Pwx over lookup table values computed for each set of scenario conditions
Pobs	Input lookup table giving Pobs as function of generic battle state and sensor type	Integrate (weight) Pobs over lookup table values computed for each set of scenario conditions
Pfa	Input lookup table giving Pfa as function of generic battle state and sensor type	From input data on false targets, compute Pfa as function of the ratio (true targets/all targets) in the search area
Pcrew	Input lookup table giving Pcrew as function of generic battle state and sensor type	Same as Alternative 1
Pav	Input lookup table giving Pav as function of generic battle state and sensor type	Same as Alternative 1
Pd	Input lookup table gives Pd for sensor-target-environment combination under the fixed scenario search interval	Detection probability for each sensor-target-environment combination with a specified search interval is computed by integrating a detection function over duration of search
Prec	Evaluated in same way as Pd	Evaluated in same way as Pd

2-5. MEASURES OF EFFECTIVENESS (MOE). There are several measures of effectiveness for assessing the acquisition potential of a suite of sensors arrayed against a target unit in a many-on-many model. Since sensor performance varies with operational time and sensor-target distance, a target acquisition MOE must treat a target acquisition probability in terms of time and space. The following MOEs can be used to characterize the susceptibility to acquisition of a target unit by a suite of sensors:

a. Fixed Interval Snapshot of Acquisition Probability. One approach is to compute an acquisition probability (for a target unit) that is averaged over a potential target location area and reflects sensor performance cumulated over a prespecified duration of search with assessment implicitly occurring at the end of the search period. In a sense, the MOE is an "interval snapshot," in time, of sensor performance. For example, the POTA MOE, as used in TAS, TAS II, and TAS III is defined as follows in CAA-TP-79-4 (Ref 5):

"POTA is the probability of detecting, recognizing, and locating various types of potential targets at prescribed distances from the FLOT during a random but limited period of time in a day of intense combat."

The "limited period of time" used in the TAS III effort was 2 hours. Such an interval snapshot MOE may be useful for specific scenarios, but scenario-restrictive input is often required to produce it. Lookup tables used by a many-on-many model to generate an acquisition MOE for a 2-hour search must consist of results from one-on-one models restricted to a 2-hour search. Flexibility and generalizability are lacking.

b. Steady State Probability of Acquisition. In Figure 2-1, target acquisition is represented as an event in a scenario. The acquisition event is followed by a "retention state," during which the acquisition is retained or presumed to be retained (e.g., if the target is stationary). Therefore, an average, or steady state, acquisition MOE for the scenario timeframe may be defined as the probability that, at a random time in the scenario, a target unit is in an acquisition retention state relative to the opposing sensor suite. Use of this measure removes the time-restrictiveness implied in "interval snapshot" MOEs. However, time-dependent sensor performance functions are required to generate steady state probabilities of target acquisition.

c. Mean Time to Acquisition. Another "steady state" acquisition MOE is the mean time to target acquisition (by the opposing sensor suite). This measure also removes the time-restrictiveness of the "snapshot" MOE and must be based on time-dependent sensor performance functions. A performance function represents a probability distribution which has the mean time to acquisition as a defining parameter. The associated probability distribution can be integrated over time to produce an "interval snapshot" probability of acquisition for any arbitrarily specified duration of search. Though a mean time to acquisition is not a probability, it is associated with an underlying probability distribution. Since lookup tables are easier to use (and define) than time-based functions, many-on-many expected value models generally are restricted to "interval snapshot" acquisition MOEs.

2-6. COMPARISON OF MANY-ON-MANY MODELS. After a literature search, documentation was found on two many-on-many expected value models of target acquisition. These are the COMWTH Model created by BDM Corporation and the SAI Target Acquisition Model, denoted herein as the SAI model. COMWTH, the SAI model, and the TADER model, were analyzed for comparative approaches to the modeling of the generic sensor performance factors of Table 2-3. Summary results of this comparison are shown in Table 2-5. A brief description of each of these models is given below. More detail on TADER, COMWTH, and the SAI model is presented in Appendixes D, E, and F, respectively.

a. TADER. For a sensor suite observing a target unit randomly located within a target zone, TADER computes the POTA as the probability of acquisition by (at least one sensor of) the sensor suite for the target unit over a 2-hour sensor search period. Inputs include:

- (1) Battlefield sector searched (target zones).
- (2) Sensor types, numbers, deployments, characteristics, coverage patterns, degradation factors for various operating conditions (weather, dust, etc.), availability, survivability.
- (3) Lookup tables for single sensor versus single target element. (These are results of one-on-one assessments).
- (4) Target units, target elements in units, target activity (firing, moving/static) frequency, target concealment state frequency.
- (5) Thresholds of target unit lucrativeness, i.e., the minimum number of target elements that must be detected to classify a group of target element detections as a worthwhile target.

The output for a target unit in a target zone is the average probability that the unit in (a random location in) that target zone is detected at a lucrative level. TADER computes a POTA, for the target unit scanned by the sensor suite, at a large number of points in the target zone and averages them to obtain a zone POTA for the unit. Sensor-target coverage is also evaluated for each specific sensor/target location based on patterns radiating from sensors. Basic one-on-one input data are lookup tables giving single sensor probability of acquisition for each sensor type-target element combination in each target zone for each activity state and concealment state. All data and resulting POTAs are configured for a fixed search period. One-on-one results are fused into a many-on-many POTA by assuming and applying statistical independence of detections.

Table 2-5. Performance Factor Representation in the TADER, COMWTH, and SAI Models

Generic model factor	Acquisition model		
	TADER	COMWTH	SAI Model
Pcov	Each possible target location is tested for coverage by each deployed sensor	Coverage determined by ratio of sensor coverage areas and target areas relative to size of sector and no targets in sector	Coverage determined by ratio of sensor coverage areas to sector size
Plos	Lookup table by sensor type and range band	Lookup table for each sensor type-signature-range band combination	Lookup table by sensor type and range band
Pwx	Input value for each sensor type	Input value for each sensor type	Visibility/attenuation factor by sensor and target unit type
Pobs	Input value for each sensor type	Not explicitly treated	Not explicitly treated (included in Pwx)
Pfa	Not treated	Based on ratio of (input) no. of tgt elts in tgt to (input) no. of non-tgt elts of same type in area searched	Not treated
Pcrew	Input value for each sensor type	Not explicitly treated	Not explicitly treated
Pav	Input value for each sensor type. Separate survivability factor is input by sensor type	Input value for each sensor type	Input value for each sensor type. For air missions, a separate mission survival factor is input
Pd	Lookup table gives single sensor Pd for each sensor-tgt elt combination by range band for each activity/concealment state of a tgt elt	Lookup table gives single sensor Pd by sensor-signature combination in each range band	Lookup table gives single glimpse Pd by sensor-tgt unit combination in each range band for each tgt concealment state
Prec	Not explicitly treated (must be combined with Pd)	Input value for each sensor-equipment type pair	Lookup table configured in same way as that for Pd

b. COMWTH. A BDM report on Tactical Target Acquisition (Ref. 6) describes COMWTH as a discrete event, deterministic simulation of a many-on-many assessment of target acquisition effectiveness. For each sensor system, observing a target unit, COMWTH computes the probability of target acquisition by (at least one sensor of) the sensor system over the system mission cycle. COMWTH inputs include:

- (1) Battlefield size.
- (2) Sensor types, target signature types detected by each sensor type, number of sensors, sensor swaths, minimum and maximum ranges, activity frequencies, information processing time, mission cycle parameters, weather and visibility degradation factors, and availability.
- (3) Lookup tables giving single sensor-single element/signature probability of acquisition as a function of range.
- (4) Target unit types, target elements/signatures in units, depth behind forward edge of the battle area (FEBA), size, and activity (detectability) frequency.
- (5) Number of "false" target elements of each target type in the battlefield area (used to generate probability of false alarm).

COMWTH output for a sensor system suite observing a unit is the probability of acquisition for the mission cycle. The assumption of statistical independence is used to fuse one-on-one (lookup table) results and sensor system acquisition probabilities into a many-on-many result. Simulating these mission cycles and information processing times in an overall scenario timeframe enables the time-phasing of "interval snapshot" system acquisition probabilities into an approximation of overall acquisition probability as a function of time. Neither sensors nor targets are deployed in specific two-dimensional locations in COMWTH. Coverage is based on input sensor coverage areas and target areas. A lucrativeness threshold of one element detection (minimum required for unit acquisition) is implied.

c. SAI Target Acquisition Model. An SAI report (Ref. 7) on combat system survivability and an Army report (Ref. 8) on target acquisition model comparison state that the SAI target acquisition model was initially developed as a subelement of a larger model, the SAI combat survivability model. However, it was subsequently modified for use as a standalone model. The SAI model generates an overall "interval snapshot" probability of acquisition for a target unit at a specified distance from the FEBA observed by a suite of sensors over a specified scenario search period. Inputs include:

- (1) Battlefield size.
- (2) Sensor types, number of sensors, sensor coverage areas, degradation factors for line of sight and atmospheric attenuation, and sensor availability factors.
- (3) Lookup tables (of one-on-many results) giving single sensor-target unit probability of acquisition for a single sensor glimpse as a function of range and target concealment state.

(4) Target unit types, target activity (movement) frequency, and target location.

(5) Search period duration.

The output is essentially an "interval snapshot" overall probability of acquisition by (at least one sensor of) the suite over the specified search period. Summed sensor coverage areas are used to determine overall coverage. No particular two-dimensional sensor deployment is specified. Basic building blocks are lookup tables of one-on-many results (for single sensor versus a target unit) which are fused over sensors, using statistical independence, to produce an overall assessment.

CHAPTER 3

DEVELOPMENT OF A STEADY STATE ACQUISITION METHODOLOGY

3-1. BACKGROUND. As noted in Chapter 2, the target acquisition problem must treat both time and space. A stochastic process that changes state over time may be treated as a steady state process represented by the probability distribution of states at a random moment in time. Such a steady state probability distribution can be used to stochastically generate a state value for a representative (pseudorandom) point in time. "Interval snapshot" acquisition probabilities specified for a fixed search interval are steady state results only if a steady state probability distribution of search effectiveness over time is used to compute them. As noted in Chapter 2, target acquisition is an event in a scenario followed by a "retention state," during which the acquisition is retained. For steady state purposes, the duration of this "retention state" and of the acquisition search state characterize acquisition. This chapter will develop some approaches for deriving a steady state acquisition probability assessment.

3-2. TARGET ACQUISITION IN TACTICAL NUCLEAR SCENARIOS. In a tactical nuclear scenario, acquisition information is vital for targeting at the time (nuclear) fire authorization (the "nuclear trigger") is released. Acquisition and contingency targeting must be done prior to the nuclear trigger, but no (nuclear) action is taken until then. The timing of the nuclear trigger in a scenario is not adjusted based on the timing of the acquisition of targets. Therefore, it may be plausible to model the preplanned nuclear trigger time as a random point relative to the scenario. Prior to the nuclear trigger, target units are continually being acquired, retained, lost, and reacquired. Until the nuclear trigger time, a target unit is subject to the following states and events.

a. Search State. In the search state, the target is being sought by sensors. (It is not acquired, nor is it being tracked).

b. Acquisition Event. At the time of an acquisition event, the target is acquired (or reacquired after a previous acquisition had been lost).

c. Retention State. In the retention state, the target, having been acquired, is placed on a target list as an active target acquisition. The duration and presence of the retention state is assessed in light of knowledge from tracking sensors and/or prior knowledge of inherent target characteristics (e.g., some target types are known to be stationary over the long term).

d. Loss Event. At the time of a loss event, the target retention state is terminated when the original acquisition is assessed to be no longer valid or active (due to aging information, loss of tracking, or target disappearance).

These states and events are schematically illustrated in Figure 3-1.

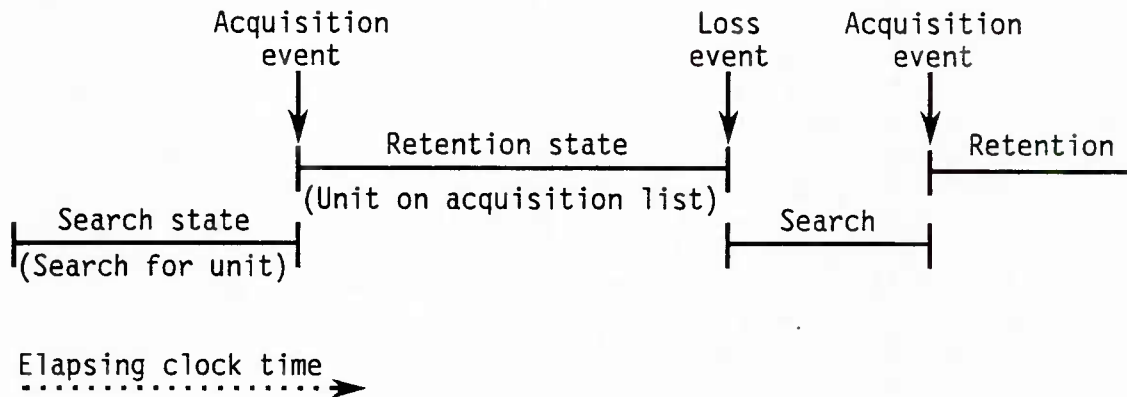


Figure 3-1. Target Acquisition Events and States

3-3. **STEADY STATE PROBABILITY OF ACQUISITION (SPOTA).** The steady state probability of acquisition (SPOTA) as described in paragraph 2-5 is an appropriate measure of target acquisition performance in a tactical nuclear scenario with acquisition events and states as depicted in Figure 3-1. For a target in such a scenario, the duration of search and of acquisition retention are represented as probability functions dependent on elapsing time from start of search and of retention respectively. At any time, a target is represented as either being sought or else, having been acquired, it is being retained as an active acquisition on a target list. Thus, a target's state is represented in a time continuum. The SPOTA is just the probability that, at a random point in the continuum, a target unit is in an acquisition retention state relative to the opposing sensor suite. Selection of a time for target assessment for fire planning in a tactical nuclear scenario is dependent on factors other than target acquisition processes, and can therefore be treated as random in the continuum. In quantitative terms, referring to Figure 3-1, we have, for a specific target unit u :

$$SPOTA_u = \frac{MRT_u}{MTA_u + MRT_u}$$

where MTA_u = mean time to acquire target unit u
 = mean search state duration for unit u

MRT_u = mean retention state duration for acquired target u

The above formulation was proposed in CAA research papers (Refs. 9, 10) as an appropriate acquisition measure for use within NUFAM at CAA. The values for MRT_u and MTA_u can be stochastically estimated using acquisition functions and retention time functions. These are described in subsequent paragraphs.

3-4. ACQUISITION FUNCTIONS. An acquisition function for a target, relative to a sensor suite, describes the probability of the sensor suite acquiring the target as a function of elapsing search time. The target is assumed fixed at a specified location relative to the sensor under specified environmental conditions. In order to compute a SPOTA, the mean time to acquisition must be evaluated (or estimated) from the associated acquisition function. Different types of acquisition functions include the one-on-one acquisition function expressed in terms of acquisition of a single target element (e.g., a single tank) by a single sensor, the one-on-many acquisition function expressed in terms of acquisition of a target unit (a collection of target elements of several types) by a single sensor, and the many-on-many acquisition function expressed in terms of acquisition of a target unit by a suite of sensors.

3-5. TARGET RETENTION FUNCTIONS. Given that a target unit has been acquired, the target retention function defines the probability distribution of the duration of the associated retention state. During this retention time period, the acquisition is retained on the list of active acquisitions. The retention time may depend on tracking capabilities of sensors or on knowledge of a target's tendency to remain in place. Thus, retention time is a measure of acquisition perishability, either as realized or perceived. The target retention function defines a conditional probability distribution. This distribution is conditioned on the occurrence of a preceding acquisition event because retention time is defined in terms of time since (last) acquisition of the target. In order to compute a SPOTA, the mean of the target retention function must be evaluated (or estimated).

3-6. SPOTA FROM ONE-ON-ONE ACQUISITION FUNCTIONS. We must calculate a mean time to acquisition, MTA_U , for a target unit, u , observed by a sensor suite. In addition to the definition of the acquisition functions, we also require a means of fusing single element acquisitions into a unit acquisition as well as a means of fusing single sensor acquisition probabilities into a sensor suite acquisition probability. We can also apply a lucrativeness criterion by requiring at least a specified minimum number of target elements (of one or more specified types) of the unit to be acquired before the unit is considered acquired. Using these concepts, with the one-on-one acquisition functions for each type of target element expressed as a cumulative probability function, the value of MTA_U can be stochastically estimated from averages over a large number of sampling simulation replications in the following procedure. This procedure is only one of several ways for estimating the value of MTA_U . In each simulation replication:

a. The time to acquisition of each element (e.g., each truck) in the target by each sensor in the suite is stochastically sampled by inverting the associated acquisition function.

b. For each sensor, the times to acquisition are rank ordered for each element type in the target unit. If M_j is the lucrativeness criterion (minimum element acquisitions required) for element type j , then the M_j -th-largest of the ranked times to acquisition for that element type is the sample time to target unit acquisition for the j -th element type for the given sensor in this replication. The smallest of the j element type acquisition times is the single sensor acquisition time for this unit.

c. The smallest of the single sensor sample times to acquisition, as computed in paragraph 3-6b above, is the sensor suite sample time to acquisition for this simulation replication.

d. The sample times to acquisition are averaged, over all replications, to yield an estimate of MTA_U .

The above process is explained in detail in Appendix G.

3-7. LIMITATIONS OF ONE-ON-ONE FUNCTIONS

a. **Unavailability of Component Acquisition Functions.** Application of the above algorithm requires that all one-on-one acquisition functions be well defined. There is no catalog of such functions. It is not likely that one-on-one acquisition functions are well behaved--they would probably be empirical. For sensors that interact with each other during assessment, the use of one-on-one functions may even be inappropriate.

b. **Restrictions on Fusion Methods.** Application of the assumption of statistical independence is frequently used to define a "standard" fusion method. There is no comprehensive fusion methodology for interdependent observations that is suitable for a many-on-many expected value model. Use of autocorrelation and other fusion concepts applied in the Joint Tactical Fusion Program would require extensive input data and high simulation resolution. Required resources are prohibitively large for use of these techniques as subroutines in low resolution models.

3-8. **A MANY-ON-MANY METHODOLOGY USING TAS IV PRODUCTS.** The TAME interface with the TAS IV effort has suggested a steady state methodology for determining an SPOTA from TAS IV products.

a. **TAS IV Production.** The projected allotment of analytic responsibilities in the TAS IV effort is:

(1) AMSAA will simulate surveillance results for suites of sensor systems in a wide spectrum of scenario conditions against designated target unit types. Models exercised are projected to include:

(a) The Tactical Simulator (TACSIM) model to simulate performance of electronic intelligence (ELINT) sensors and communications intelligence (COMINT) sensors.

(b) Sensor system performance models from the US Army Training and Doctrine Command Analysis Center at White Sands Missile Range (TRAC-WSMR).

(c) The Sensor Interaction Model (SIM) at AMSAA. AMSAA will fuse results from one-on-one system models with a methodology based on that used by the All Source Analysis System (ASAS) office.

(2) The TAS IV contractor will fit the AMSAA-generated results to algorithmic functions showing two measures of sensor suite performance for each specified combination of scenario conditions as a function of elapsing time and possibly other parameters. Performance measures for an arbitrary interval, T , of elapsed time will be:

time and possibly other parameters. Performance measures for an arbitrary interval, T , of elapsed time will be:

(a) The probability that a specific type of target unit sought in a specified target zone/area is acquired (detected and identified) by a specified suite of deployed sensors within elapsed time T (from start of search). Parameters (e.g., systems) critical to overall performance will also be identified where possible. This function is denoted as the contractor acquisition function (for the specified target unit and the specified combination of scenario conditions).

(b) The probability that a previously acquired target unit of specified type has been continuously retained as an active acquisition for time interval T (since acquisition). This function is denoted as the contractor target retention function (for the specified target unit and the specified combination of scenario conditions).

b. Application of Contractor Algorithms. A methodology for application of the TAS IV contractor algorithms to requirements for assessing target acquisition in NUFAM at CAA is described in detail in Chapter 4. This method is denoted as the candidate TAME methodology. This paragraph summarizes the methodology. For an arbitrarily placed assessment time, T , in the NUFAM scenario timeframe (corresponding to a nuclear fire window), NUFAM requires, for each specified target unit type:

(1) The probability, considering the scenario, that the specified target unit has been acquired, and is still being retained on the acquisition list (at assessment time T), by the suite of sensors deployed in the scenario. This probability is denoted as the SPOTA for the specified target unit in the scenario.

(2) The probability distribution for the duration of time remaining in the retention state after assessment time T (for a target unit acquired at or prior to T). This is denoted as the residual target retention time distribution.

These would appear to be very similar to the products of the contractor algorithms defined in paragraph 3-8a(2) above. However, a typical contractor algorithm gives a performance measure, over elapsing time, only for a constant environment corresponding to a specific fixed combination of scenario conditions. The TAME scenario, to support NUFAM applications, will be dynamic, with conditions changing as time passes. A performance algorithm for elapsing time over the dynamic scenario is required. As shown in Chapter 4, this may be constructed, for each of the performance measures, by building a composite performance function by connecting "pieces" of the contractor functions corresponding to interval "slices" during which conditions in the NUFAM scenario are treated as constant. Also, since the SPOTA defined above is a probability of acquisition and retention at random time in the scenario, and since the residual target retention time is dependent on when (within the scenario) acquisition occurs, a simulation solution is required to treat the time and event dependencies.

3-9. ADVANTAGES OF THE CANDIDATE TAME METHODOLOGY. Presuming that the product algorithms of TAS IV are delivered, the candidate TAME methodology has the following distinct advantages over methods based on one-on-one subroutines:

- a. The component acquisition functions will be available (from TAS IV).
- b. The fusion of one-on-one results will be implicit in the component acquisition functions.
- c. The use of many-on-many acquisition functions precludes having to process data at compartmented security level since the sources of component sensor results are masked by merging.
- d. As noted in the next chapter, the methodology can be implemented as a computerized process for a sufficient and well-defined set of component acquisition functions.

CHAPTER 4

IMPLEMENTATION OF CANDIDATE TAME ACQUISITION METHODOLOGY

4-1. PURPOSE. This chapter details the specific algorithms of the candidate TAME acquisition methodology described in summary fashion in Chapter 3. The adaptability of the method to computerization is illustrated via the step-by-step algorithmic presentation.

4-2. SCOPE OF PROBLEM. We consider a scenario timeframe consisting of a strip of elapsing time, beginning at time $t = 0$. A scenario will apply to a specific designated type of target unit, u . At any point in the scenario timeframe, the scenario state may be described as a specific combination of states of subconditions ($C_1, C_2, \dots, C_n$). Example subconditions may include the number and types of sensors seeking the target, the weather state, and the target activity level. Example subcondition states for, say, the target activity subcondition might be target moving and target static. We assume that subconditions change state at discrete points over elapsing time according to defined probability distributions for the subscenario conditions. Thus, elapsing time is partitioned into consecutive intervals such that subcondition states are constant within an interval. Let $t_0, t_1, \dots, t_n, \dots$ denote the serially ordered (in time) end points of these intervals (so that (t_{m-1}, t_m) is the m -th consecutive interval). Also let S_m denote the combination of subcondition states applying in (t_{m-1}, t_m) . S_m may be thought of as the subscenario applying in the m -th interval. The structure of the scenario timeframe is portrayed in Figure 4-1.

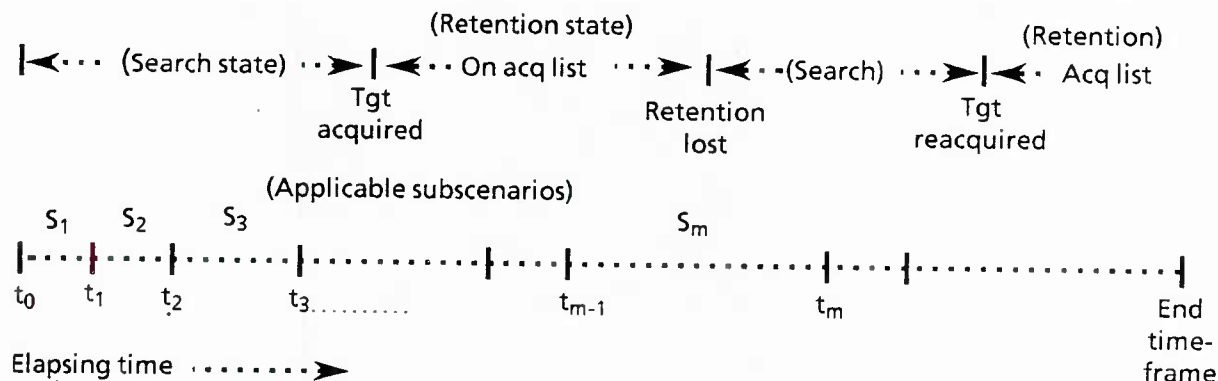


Figure 4-1. Schematic of the Scenario Timeframe

4-3. TARGET STATES. A target unit is treated as subject to the following states and events during the scenario timeframe:

Search state - the target is being sought by sensors. (It is not acquired, nor is it on a target retention list).

Acquisition event - the target is acquired (or reacquired, having previously been dropped from a target retention list).

Retention state - the target, having been acquired, is being actively listed as a valid target acquisition.

Retention loss event - the target retention state is cancelled by the target being dropped from the acquisition list.

These states and events are also illustrated in Figure 4-1.

4-4. PROBLEM. For a randomly placed instant, $t = T$, in the scenario timeframe, evaluate, for specified unit type, u :

a. The steady state probability of acquisition for target unit u , denoted by $SPOTA_u$ = probability of target unit u acquisition being in a retention state at time T .

b. Given that target unit u is in a retention state at time T , the associated residual retention time distribution function, denoted by $RTDF_u$, is the probability distribution of the duration, after time T , that the acquisition is retained. (If T is randomly placed in the scenario timeframe, then this distribution is equivalent statistically to the probability distribution of the residual life of the target retention time duration distribution).

Other problems can be treated, but the above embraces requirements for the Nuclear Fire Planning and Assessment Model (NUFAM) at CAA.

4-5. SOLUTION TOOLS. The TAS IV contractor will provide algorithms for representing the following functions over the (to be defined) spectrum of subscenario states, $S_1, S_2, \dots, S_k$, which can apply to a target unit type.

(1) For each target unit type, u , and for each applicable subscenario S_j , define, for all $z > 0$, the subscenario acquisition function:

$PA_u(z, S_j)$ = probability the target unit u is acquired within elapsed time z under subscenario S_j conditions.

Also define the subscenario target retention time function:

$PT_u(z, S_j)$ = probability the target unit u acquisition is retained, after acquisition, for at least time duration z under subscenario S_j , given that it was acquired.

4-6. SOLUTION APPROACH. Given subscenario state transition times $t_1, t_2, \dots$, we first construct a composite acquisition function, $PAC_u(z)$, defined as:

$PAC_u(z)$ = probability that the target unit u is acquired within elapsed time z after the last retention loss event for this target in our scenario timeframe (Figure 4-1).

In the formulas of the following methodological exposition, z denotes elapsed time relative to a state (search/retention) transition while t denotes absolute (clock) time in the scenario timeframe (Figure 4-1). The scenario timeframe consists of a series of successive changes of subscenario states. Therefore, given a retention loss event time, t_1 in the scenario timeframe, the acquisition function, $PAC_U(z)$, associated with elapsing time in timeframe intervals following t_1 , can be treated as a composite function constructed by piecewise connection of segments from the acquisition functions (the $PA_U(z, S_k)$) for the subscenarios associated with the timeframe intervals immediately following t_1 . Construction of the composite acquisition function associated with timeframe intervals immediately following t_0 (start of timeframe) is as follows:

In the scenario intervals of the timeframe in Figure 4-1, process the intervals in order of increasing time, beginning with (t_0, t_1) and initially treating t_0 as the time of last previous retention loss.

For time interval (t_0, t_1) in the scenario timeframe and $PAC_U(z)$ defined for elapsed time $z = 0$ to $z = (t_1 - t_0)$, $PAC_U(0)$ denotes the acquisition probability at scenario start and $PAC_U(t - t_0)$ denotes the acquisition probability at time t . Then, $PAC_U(0) = 0$ and $PAC_U(t_1 - t_0) = PA_U(t_1 - t_0, S_1)$.

For (t_1, t_2) , first locate the elapsed time value, z_1 , for which $PA_U(z_1, S_2) = PAC_U(t_1 - t_0)$. Define $PAC_U(z)$ for $z = (t_1 - t_0)$ to $z = (t_2 - t_0)$ as equivalent to the segment of subscenario function $PA_U(z, S_2)$ between $z = z_1$ and $z = z_1 + (t_2 - t_1)$. Thus, $PAC_U(t_1 - t_0) = PA_U(z_1, S_2) = PA_U(t_1 - t_0, S_1)$ and $PAC_U(t_2 - t_0) = PA_U(z_1 + (t_2 - t_1), S_2)$. Continue construction in the above manner, i.e.: for $m > 1$ and for (t_m, t_{m+1}) and $PAC_U(z)$ to be defined for $z = (t_m - t_0)$ to $z = (t_{m+1} - t_0)$, first locate the elapsed time value, z_m , for which $PA_U(z_m, S_{m+1}) = PAC_U(t_m - t_0)$. Define $PAC_U(z)$ for $z = (t_m - t_0)$ to $z = (t_{m+1} - t_0)$ as equivalent to the segment of subscenario function $PA_U(z, S_{m+1})$ between $z = z_m$ and $z = z_m + (t_{m+1} - t_m)$. Thus, $PAC_U(t_m - t_0) = PA_U(z_m, S_{m+1})$ and $PAC_U(t_{m+1} - t_0) = PA_U(z_m + (t_{m+1} - t_m), S_{m+1})$.

4-7. DETERMINATION OF SIMULATED EVENTS AND STATES. The problem will be solved by simulating the target events and states over the subscenarios $S_0, S_1, \dots, S_m$. These are the target acquisition events, the retention loss events, the search states, and the target retention states. Only a single specified target unit will be processed during the simulation. The target may be lost and reacquired. The frequency of states and events over a large number of simulation states and replications will yield a solution to our problem. The problem, restated, is:

Given a randomly chosen timepoint, T , in the scenario timeframe, determine, for a specified target unit type, u :

- $SPOTA_U$ = the frequency (probability) of target unit u being in a retention state at time T
- $RTDF_U(z)$ = the probability distribution of the (residual) retention time remaining (until retention state is lost), given that the acquisition of target unit u was being retained at time T

= probability that retention time remaining after time T is less than z , given that the target unit u is being retained at time T

Each replication proceeds as follows to simulate the sequence of events and states:

a. The timepoint, T , is randomly chosen within the scenario timeframe. A time-phased simulation starting with all state attributes initialized to zero is characterized as using a "cold start." In this case, the simulation may initially generate statistically biased state values because dependence, over time, of successive states can be affected by the zero initial state. To avoid a bias from a "cold start," it may be desirable that the first part of the scenario timeframe is a "warmup period" and that T is sampled only from times after the "warmup period".

b. Draw a random number R_1 in $[0,1]$. This number will be used to locate the time of the first acquisition event. We treat t_0 as the time of last retention loss.

c. For each successive interval following t_0 , (t_{N-1}, t_N) , construct, by piecewise connection as in paragraph 4-5 above, the portion, for z between $(t_{N-1} - t_0)$ and $(t_N - t_0)$, of the composite acquisition function $PAC_u(z)$. (Since there are no prior acquisitions yet, this function is the probability of acquisition in elapsed time, z , from starting point t_0). Process intervals only until, for some K , $PAC_u(t_{K-1} - t_0) < R_1 < PAC_u(t_K - t_0)$. Then, interpolate to locate a time, t_A , with $t_{K-1} < t_A < t_K$ for which $PAC_u(t_A - t_0) = R_1$. Further construction of the composite acquisition function is unnecessary and inappropriate. Since we started at time t_0 , t_0 is treated as the time of the last retention loss event. The interval between $t = t_0$ and $t = t_A$ is a simulated search state for target u in this replication. A simulated acquisition event occurs at time $t = t_A$.

d. Draw another random number R_2 in $[0,1]$. This number will be used to locate the time of the first simulated retention loss event.

e. Over each successive interval after t_A , construct a composite target retention time function for elapsing retention time, z , beginning at t_A . This construction is done by piecewise connection of retention time functions $(PT_u(z, S_K))$ in a manner exactly analogous to construction of the composite acquisition function, except that construction is done for timeframe intervals after t_A . The composite retention time function, given a previous target acquisition at time t_A , is defined as:

$PTC_u(z)$ = probability the target unit u acquired at time t_A is retained for at least time duration z (after time t_A).

Note that $PTC_u(0) = 0$ for acquisition at time t_A .

Construct this composite retention time function only for intervals up to the first interval (t_{K-1}, t_K) such that $R_2 < PTC_u(t_K - t_A)$. Then interpolate to find a time, t_L , in that interval for which $PTC(t_L - t_A) = R_2$. Then $(t_L - t_A)$ is the (simulated) duration of the acquisition retention

time begun at t_A , i.e., a (simulated) retention loss event (for the target acquired at t_A) occurs at time t_L .

f. Draw a random number, R_3 in $[0,1]$. This number is used to locate the time of reacquisition of the target.

g. For successive timeframe intervals after time t_L in the scenario timeframe, construct a new composite acquisition function for the scenario intervals beginning at t_L . This construction is similar to the algorithm in paragraph 4-5, except that t_L (instead of t_0) is treated as the time of last retention loss.

As before, this is done by piecewise incrementation of subscenario acquisition functions ($PA_u(z, S_k)$) associated with the time intervals after t_L . Locate a time t_B for which $PAC_u(t_B - t_L) = R_3$ (in an analogous manner to the way t_A was located).

h. Successive search-retention states are simulated by continuing the above steps until the first event (either acquisition or retention loss) after time T is simulated. The replication processing ends at that point.

i. The following replication results are noted and stored:

- Whether the target was in a retention state at time T .
- The duration after T that the target was retained, if it was in a retention state at time T .

4-8. SOLUTION. After a large number of replications are done, we estimate, for the scenario timeframe:

$SPOTA_u$ = steady state probability of acquisition for target unit u
 = probability of unit u being in a retention state at random time
 = fraction of replications with target unit u in a retention state at time T

and $RTDF_u(z)$ = residual retention time distribution function for target unit u
 = probability distribution of residual retention time remaining after a random timepoint
 = the empirical frequency distribution, over all replications in which unit u was in a retention state at time T , of the duration, z , of retention time remaining after time T

4-9. SCENARIO INITIALIZATION. As noted above, if the start point of processing is not initialized to a random steady state value, calculations can be biased by a "cold start." One way to reduce this bias is to sample assessment time only after a preceding "warmup period" in the scenario. In

the warmup period, subscenario state transitions, acquisition, and retention are simulated, but there is no assessment of status. If the subscenario state transitions can be expressed in terms of steady state probability distributions of component conditions, then a more efficient initialization alternative is possible. In that case, the residual distribution of each component condition probability distribution can be sampled to create an initial random entry point into a subscenario state. No warmup period would then be required.

4-10. STEADY STATE INITIALIZATION. If the subscenario state transitions can be expressed in terms of steady state probability distributions of component conditions, then simulations which sample of a single acquisition event and a single target loss event (instead of a series of such events) can be used to determine $SPOTA_u$ and $RTDF_u(z)$. In this case, we can define:

$$SPOTA_u = \frac{MRT_u}{MTA_u + MRT_u}$$

where MTA_u = mean time to acquire target u in the scenario timeframe

MRT_u = mean retention time duration for an acquired target u

The above is equivalent to the previous algorithmic process which simulates an explicit randomly chosen timepoint, T , in the scenario timeframe at which the assessments of $SPOTA_u$ and $RTDF_u$ are made. A series of simulation replications can be done, with each replication starting in an initialized random subscenario state. In each replication, the time of first acquisition would be simulated, as would the duration of target retention after acquisition. Target acquisition and loss would be simulated exactly as in the algorithm described previously. The estimated value of mean retention time duration, MRT_u , is the mean of the empirical frequency distribution of retention time duration, over all replications. The empirical retention time distribution can be used as the basis for statistical estimation of the distribution, $RTDF_u(z)$, of residual retention time. The mean time to acquisition, MTA_u , is found by averaging over replications. $SPOTA_u$ can be directly calculated from MTA_u and MRT_u .

4-11. DEFINITION OF SUBSCENARIO STATES. The above methodology assumes that the scenario timeframe is defined in terms of subscenario states under which the TAS IV algorithms are generated. Ideally, a combat simulation using the TAME acquisition measures would define the time-sequenced subscenarios of the methodology. However, many detection subconditions are not explicitly gamed in NUFAM, as well as in other combat models. Therefore, a scenario generator is needed to provide the candidate TAME methodology with a time sequence of subscenario states which is compatible with a specified NUFAM scenario. In the simplest case, this generator can be a set of defined data. However, a stochastic scenario generator may be needed to generate appropriate time-sequenced states for the scenario being processed by the methodology. Such a processor would have to treat the variability of the subconditions (e.g., weather) which are the components of each subscenario state. Dependence over

time and correlation between subconditions must also be considered. Specific sensor and target activities over time may be simulated to determine subcondition states dependent on them. The definition and construction of a scenario generator can be complex. The TAS IV products need only define the menu of subscenario states. The probability distribution of state occurrences over time must subsequently be defined in the scenario generator. The generator can then determine a state timeframe compatible with any specified application.

CHAPTER 5

TARGET ACQUISITION FOR NUFAM

5-1. **INITIAL NUFAM III OVERVIEW.** Available documentation (Ref. 11) describes the Nuclear Fire Planning and Assessment Model III (NUFAM III) as a two-sided, event-driven, stochastic simulation of tactical nuclear/chemical warfare. With no munition constraints, the model can be used for determining munition requirements. With munition constraints, it can be used to assess force capability. NUFAM III is written in SIMSCRIPT II.5 language for the UNISYS 1100/84 computer. Target acquisition is simulated in discrete 2-hour cycles. A fire planning cycle occurs only at times generated according to user specifications. A fire planning cycle generates fire planning orders against acquired targets. Fire units and munitions are allocated and scheduled against selected targets. The fire planning cycle is succeeded by a fire execution cycle. During a fire execution cycle, delivery of weapons, if feasible, is simulated along with damage assessment. Since NUFAM III does not simulate conventional fire, no fire action is simulated except the nuclear fires at the times designated in the fire plans. These events, over time, are represented in Figure 5-1. In the figure, target acquisition is represented as a continuous succession of cycles. Each cycle updates target unit status and a target list for fire planning. However, a number of cycles may well pass with no fire planning. At the designated fire plan time, a fire planning cycle and a fire execution cycle are activated. These use the current cycle target list. Any altered status of targets (e.g., making a target ineffective) resulting from the fire cycles is input to succeeding acquisition cycles.

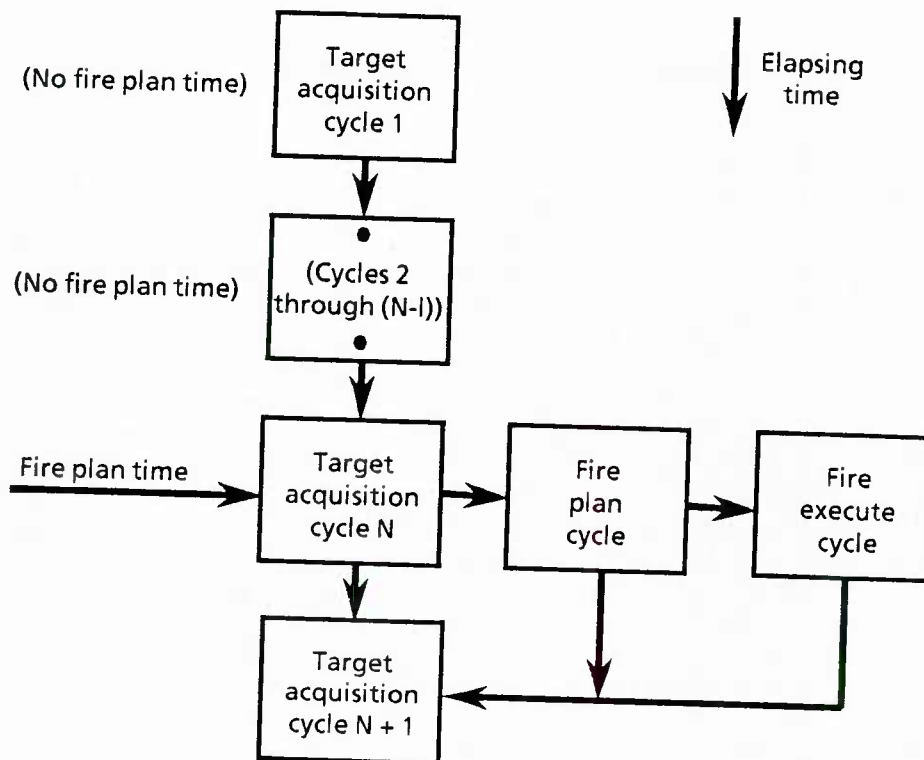


Figure 5-1. Time Sequencing of Event Cycles in NUFAM III

5-2. **TARGET ACQUISITION IN NUFAM III.** Target units are subject to the states and events described in paragraph 3-3, Chapter 3, and Figure 3-1, viz.:

- a. Search state - the target is being sought by sensors.
- b. Acquisition event - the target is acquired.
- c. Retention state - the target unit, having been acquired, is registered on an acquisition list as a current valid target.
- d. Drop event - the target unit is dropped from the acquisition list of valid targets.

The duration of the retention state for an acquired target unit is denoted as the target retention time for that acquisition. A dropped target is subject to reacquisition. (The drop event is denoted as a retention loss event in Chapter 3, but is renamed here for consistency with terminology in NUFAM III documentation). The concept behind the NUFAM III target acquisition module is based on the question: is an enemy unit acquired? If it is, it is placed on an acquisition list for consideration as a possible target. Whether a unit is acquired or not is a function of two inputs: the target zone in which the unit is located and the unit's POTA. Since the TAS III POTA is defined in terms of probability of detection over a 2-hour cycle, each unit's POTA is checked against a random draw at the beginning of each (2-hour duration) target acquisition cycle to determine whether the unit is acquired

in that cycle. If it is acquired, the exact time of the acquisition event within the cycle is simulated, and a drop event is scheduled after a period of time equal to the expected duration of the retention state. Beginning with the next acquisition cycle after the drop event, the target unit becomes subject to reacquisition. The target acquisition cycles are continuous except during simulated nuclear fires. The analytic purpose of the acquisition process in NUFAM III is to have a current target list, with acquisition status, at the (preset) time that fire planning occurs. A schematic of the interaction of acquisition and fire planning/execution is shown in Figure 5-2. The changing acquisition status of a target is portrayed. In the figure, the presence of a target on an acquisition list is indicated by the line between the acquisition and succeeding drop events. At fire plan time, a candidate target is removed from the current prioritized list of target acquisitions and checked to see if it meets standards for receiving fire (e.g., weapons being available and engagement meeting preclusion requirements). Fire execution follows fire planning if constraints (available fire units, ammo) allow. The target unit will not receive fire if the munition time on target (TOT) is later than the acquisition drop time.

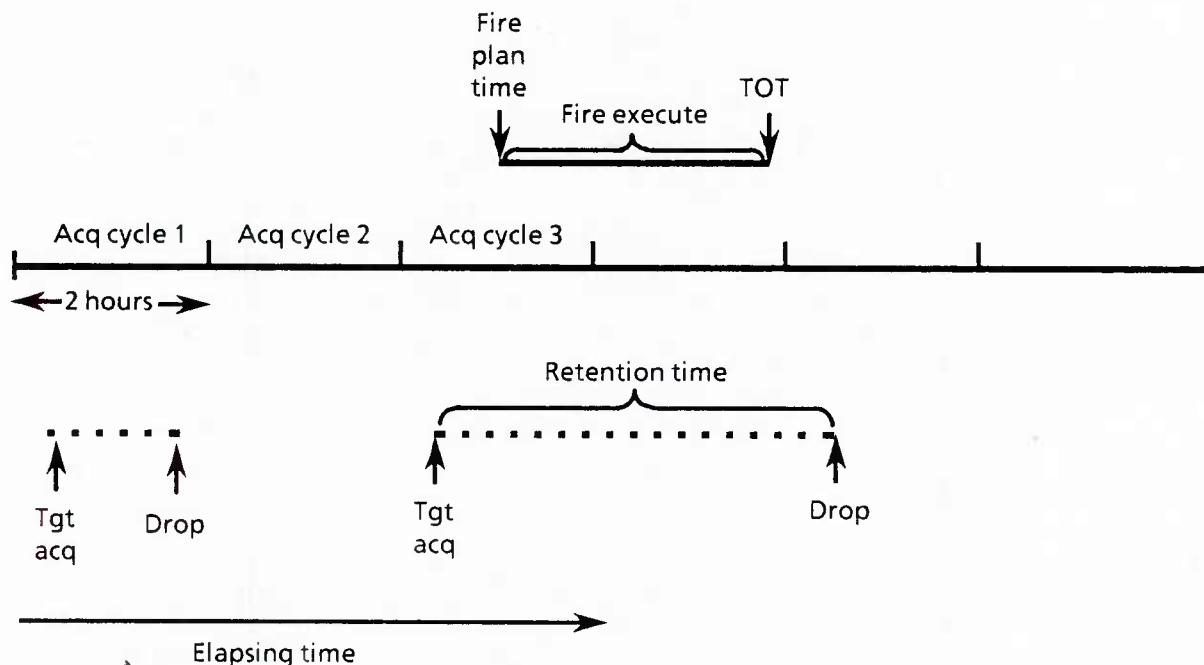


Figure 5-2. Acquisition and Fire Planning Events in NUFAM III

5-3. DEFICIENCIES OF POTA IN NUFAM. The TAME study team assessed the following deficiencies in the applicability and use of the TAS III POTAs in NUFAM III. Some of these are related to the TADER deficiencies noted in Chapter 1.

a. Uncertain Data Genesis. The TAS III Study, which generated POTAs for NUFAM III, used as input a modified version of an existing sensor data base created for the TAS III Study. In the absence of comprehensive quantified performance data, selected subjective adjustments were made to perform system data updates. There was no visible audit trail for most of the system descriptors in the baseline TAS II data base. The uncertainty in TAS III input data credibility carries over to detract from NUFAM credibility.

b. Inadequate Treatment of Reacquisition. In NUFAM III, a target dropped from the target list in an acquisition cycle cannot be reacquired until the next acquisition cycle. Since the cycles are of 2-hours' duration, the cyclic simulation of acquisitions may incorrectly ignore significant multiple acquisitions within a cycle. Greater resolution in time is needed for completeness. However, the TAS III input data base is restricted to a sensor data base for a fixed 2-hour search period. The resolution of the TAS III POTAs, produced by TADER for use in NUFAM III, is likewise restricted to a 2-hour search cycle.

c. No Treatment of SIGINT. The TAS III POTAs were based on data for only non-SIGINT sensor systems because no adequate SIGINT input data base for TADER was available. Inclusion of SIGINT effects is required for completeness and accuracy.

d. Inadequate Treatment of Elapsing Time. Time is not explicitly treated in the TAS III POTAs, which are based on a specific 2-hour search period. The POTA reflects an "interval snapshot" assessment of the probability of a unit being acquired at least once during an "average" 2-hour period. The only analytic basis for such a measure is an integration of search effectiveness over elapsing time. No explicit integration over time is evident in either the TADER methodology or the inputs to it. The single sensor-single target element input to TADER is defined as the acquisition probability over a 2-hour search period. The use of such a discrete search period is not meaningful without consideration for, and treatment of, search events prior to the beginning of the search period. The timing of an event is dependent on previous events. The current POTAs treat the beginning of each acquisition cycle in NUFAM III as a "cold start" because there is no dependence on preceding events. A corrected acquisition measure and methodology are needed to properly treat elapsing time.

5-4 IMPROVEMENT POTENTIAL OF SPOTA. A steady state probability of acquisition (SPOTA) similar to that defined in paragraph 3-3 can adequately account for elapsing time. The SPOTA is the average probability of target acquisition at a random point in time. In order to be useful in NUFAM, analogous steady state measures of target retention should be computed. The value of steady state measures in NUFAM is twofold:

a. Correct treatment of elapsing time is introduced.

b. NUFAM can be made more efficient because the acquisition status at fire planning time can be directly determined probabilistically without the tedious simulation of successive acquisition cycles to generate a continual series of target lists which are acted on (for fire planning) only rarely.

5-5. INTERIM TARGET ACQUISITION MODIFICATIONS IN INITIAL NUFAM III. A CAA analyst working with NUFAM III, MAJ Mark Youngren, noted in a technical paper (Ref. 12) that the target acquisition simulation in NUFAM could be represented in terms of steady state probabilities since the POTAs were unchanging and cyclically applied. The TAS III POTA, as applied in NUFAM III, is equivalent to treating a POTA as the defining parameter of a geometric probability distribution. From this distribution for a given target unit, u , the mean time to acquisition (MTA_u) can be computed. The mean retention time (MRT_u) can be computed from the retention time distribution. The probability of acquisition of unit u at random time, $PACQ_u$, is then:

$$PACQ_u = \frac{MRT_u}{MTA_u + MRT_u}$$

Since the (preset) fire plan time is independent of the acquisition status, this is also an estimate of the probability of acquisition at the time of fire planning. $PACQ_u$ is equivalent to the SPOTA defined in paragraph 3-3. Using the $PACQ_u$ probabilities, acquisitions need only be simulated by random draw (against the $PACQ$ values) at the fire planning time. This eliminates the tedious, time-consuming simulation of states and events in acquisition cycles in which there is no fire planning. NUFAM efficiency is thereby increased. However, no increase in resolution or accuracy is gained by this improvement because these qualities are lacking in the basic TAS III POTAs, whose values are unchanged in the above procedure. A better basic acquisition measure is required. For increased efficiency of operation, the version of NUFAM III current at the start of the TAME effort will be modified in the above manner to include a steady state representation with the TAS III POTAs. Because they do not constitute a quality improvement, these changes represent only interim target acquisition modifications to NUFAM.

5-6. APPLICABILITY OF CANDIDATE TAME METHODOLOGY. The candidate TAME acquisition methodology described in Chapters 3 and 4 will serve to enable generation of valid and improved SPOTAs for use by NUFAM III. The basic technique for determining an SPOTA was applied in the interim NUFAM SPOTA modification described above. However, the use of a geometric acquisition function based on 2-hour glimpses and of an arbitrary retention time function is inadequate. This will be remedied in the candidate TAME methodology through use of the appropriate contractor-generated acquisition functions and retention functions from TAS IV. The methodology is defined in terms of integration over time and is directly derived from results of high-resolution sensor performance models. The NUFAM scenarios must be defined in terms of time-sequenced condition sets which correspond to those in the family of acquisition functions from TAS IV. Development of an improved NUFAM to process the new SPOTAs from the TAME methodology should parallel the development of that methodology.

CHAPTER 6

MODELING OF ENVIRONMENTAL DEGRADATION

6-1. INTRODUCTION. Table 2-2 of Chapter 2 noted the major factors affecting sensor performance. These factors were partitioned into system factors, environmental factors, target factors, and "other." Since limited field/test data is available for detection capability of systems in varied environments, most models must operate with input data for systems under a "baseline" environment. Capabilities under nonbaseline conditions are then generated by adjustment of values for baseline acquisition capability. Variation of conditions may be over both time and space. Representation of acquisition capability under degraded conditions must consider the interdependence of factors as well as their correlation over individually deployed sensors and target elements. In addition, a minimum degree of resolution in representing environmental (or other) variation is needed.

6-2. DEPENDENCE

a. Interdependence Among Performance Factors. Degradation factors have often been represented as residual fractions of baseline capability remaining after the degraded performance factor is applied. Degradation factors may be computed separately for different performance factors. For example, separate degradation factors for weather, foliage, smoke, and crew performance might be given. In such a case, the separate factors must at some point be fused into an overall degradation factor. In a simulation, this may be implicit in the successive generation of events. In an analytic model, the easiest method of fusion is to multiply the separate factors together to estimate the average combined degradation effect of all factors. Such multiplication assumes statistical independence of the underlying performance factors. If the component factors are not properly defined, independence can be inapplicable, even as an approximation. For example, weather and foliage may be highly correlated in some scenarios. Weather conditions associated with high detectability may generally occur with foliage conditions associated with high detectability. In such a case, the product of the weather and the foliage degradation factor will overstate the combined degradation effect because a common (to both weather and foliage) degradation influence was "double counted." Probability rules do exist for combining effects of correlated factors if quantified measures of correlation are given. Unfortunately, the associated computations can become complex and intractable as the number of factors increases. The only alternative to separate factor effects is to construct an overall average. This can only be done by integrating over a joint probability density function. The joint density function would give the probability of acquisition for each combination of environmental conditions. Construction of such a function can be done from empirical results of high-resolution system performance models.

b. Dependence Among Sensors and Targets. Consider the effect of a single degradation factor. If it is applied to a single sensor observing a single target element, then a means must be found for combining this one-on-one modifier over sensors and target elements to yield a many-on-many modifier. Any method for such fusion must consider whether the associated performance factor is correlated over sensors and target elements. For example,

identical weather conditions apply to all target elements of a compact unit and to all nearby sensors simultaneously observing them. In such a case, a weather degradation factor is properly applied only after a many-on-many assessment under baseline conditions has been made. As a simple example, suppose that there are two weather states, good and bad. Also suppose that single sensor-single residual detection fraction is 1.0 for good weather and 0.0 for bad weather. Suppose also that good weather and bad weather each occur 50 percent of the time. Suppose that the baseline condition is perfect detectability. Consider the weather degradation effect for a single sensor observing a cluster of 10 target elements. Consider first the case with perfect weather correlation over target elements, i.e., all elements have the same weather state. In this case, the entire target (all 10 elements) is detectable half the time, and nothing is detected the other half of the time. Thus, the probability of detection for the unit in this case is .50. Now consider the case in which no correlation over elements is assumed. Then each element (of the 10) has a .50 probability of detection. Assuming statistical independence in this case, the probability that at least 1 element (of the 10) in the unit is detected is $1. - (.5)^{10} = 1.00$. Under this assumption, the unit is essentially always detectable. This example illustrates the importance of defining and applying dependence of effects among elements and sensors. The modeler must understand the types of variation of an environmental effect in the "real world" and model it appropriately. He (or she) must consider whether effects are constant over separate target elements of a target unit. If all target elements of a unit are nearly collocated, then an area environmental effect, such as lighting, may well be constant for all elements of the target unit. Treating such effects as varying will distort acquisition assessment of the unit. Specific correlation assessments might be needed to measure interdependence.

6-3. RESOLUTION. The importance of sufficient resolution in the representation of environmental degradation effects has been noted in guidance provided to TAME by the NUFAM development team at CAA. The usual treatment in analytic many-on-many models is to multiply a baseline acquisition probability by a single average degradation factor for each environmental condition. This implies that a determination has been made of the average level of degradation present over time and the sensor response to this average level of degradation. It is important that this determination be done in an analytically correct way. The associated method should use conditional and marginal probabilities which will give the desired result, i.e., the average acquisition probability of the sensor, adjusted for the environmental degradation. The following examples, based on an unpublished memorandum (see reference 13 of Appendix C), will help to clarify this.

a. Example 1. Suppose that we are examining the effect of the cloud cover over the target area on optical systems (visual or photographic observation). There is some inherent probability of detecting a target unit under conditions of no degradation--i.e., 0 percent cloud cover. As cloud cover increases, the probability of detection decreases. The cloud cover reported by the Air Force Weather Service (AFWS) represents an average area covered by clouds. Thus, a 30 percent cloud cover means that 30 percent of the target area is covered by clouds and 70 percent is not. In this case, the probability of detecting a target element, given a 30 percent cloud cover, is 70 percent of the unobscured (baseline) value. Generalizing, if p

is the baseline inherent detection probability and C is the percent cloud cover, then the conditional probability of detection, given C , is:

$$P(\text{detect} | C) = p (1. - C)$$

To generate a single average unconditional value for detection probability in this case, we should integrate, over all cloud conditions, the product of the above conditional detection probability and the probability of occurrence of the associated cloud condition. This accords with the statistical definition of an average value. If, for example, the probability density function for C is a Beta function of the form $\text{Beta}(3, 1.5)$, then the average unconditional detection probability is:

$$P(\text{detect}) = \int_{c=0}^{\infty} P(\text{detect} | C) P(C = c) dc = p/3$$

from the properties of a Beta distribution.

Also from the properties of the Beta distribution, we have:

$$\text{average cloud cover} = E[C] = .67$$

Therefore, in this case, average $P(\text{detect}) = p (1. - E[C])$

$$= p \times \text{average residual cloud cover}$$

However, the adjustment may not always be so straightforward. Suppose that the conditional detection probability in the above example was changed to degrade with the square of the cloud cover parameter, i.e.,

$$P(\text{detect} | C) = p (1. - C^2)$$

In that case, the adjustment factor would be $1. - \text{Var}[C] - E[C]^2$, where $\text{Var}[C]$ denotes the variance of the distribution of C .

b. Example 2. Consider now an adjustment for wind speed which (hypothetically) degrades the ability of an airborne sensor system. Suppose that the aircraft carrying the sensor is allowed to fly only whenever the wind speed is less than some average threshold level, T . Suppose that the average wind speed is 15 mph, while the takeoff threshold, T , is 10 mph. Use of only the average wind speed in this case means that the aircraft never takes off and a zero acquisition probability results. This is clearly wrong, because it is likely that sometimes the wind speed is below 10 mph and the aircraft can take off. Suppose, from the probability distribution of W , that we know that probability $(W < 10) = .25$. Then this value is an appropriate adjustment factor. Thus, the correct adjustment factor for wind speed is the cumulative distribution function for W evaluated at T . To evaluate this, we need to know the distribution of the environmental effect (wind speed) and the probability of detection conditioned on values of the environment.

c. Summary Assessment. Although we were able, in the above examples, to express the average unconditional adjustment factor as the product of an "average" factor and a baseline detection probability, this is not the same approach as multiplying the probability by some sort of average of the environmental effect distribution. Application of the correct method requires integration of the probability distribution of (occurrence of) an environmental condition with the conditional probability of detection, given each specific condition state. This does beg the question of where to obtain the required distributions. Distributions might be fitted to available empirical data. Models can then be run using environment state values that reflect "real-world" variation over time.

6-4. REPRESENTATION IN EXISTING MODELS. Chapter 2 summarized the representation of effects degradation in existing models. As was shown in Table 2-5, the TADER, COMWTH, and SAI many-on-many expected value models all apply input values that are simple multipliers for the residual effect of "average" environmental states. No method for calculating or estimating these adjustment factors was given. In addition, statistical independence of effects was assumed. A linkage to one-on-one model results was not apparent.

6-5. DATA REQUIREMENTS. Proper treatment of dependence and resolution in degradation modeling requires the use of probability distributions for environmental states as well as the detectability of each sensor in each state. Empirical data, where available, must be generated or extrapolated. Detectability functions then need to be fitted to this empirical data. Thus, a data generation or algorithm generation effort should precede or parallel any many-on-many acquisition assessment effort.

6-6. REPRESENTATION IN CANDIDATE TAME METHODOLOGY. As noted earlier, fusion and dependence of environmental factors at any fixed time is implicit in the TAS IV detection algorithms in the models used to generate the data underlying them. Variation in environment conditions over time is explicitly integrated, via stochastic simulation/estimation, in the implementation described in Chapter 4. The parallelism of the development of the steady state methodology and the data/algorithm effort of TAS IV should ensure feasible and appropriate treatment of environment. Credibility and completeness of the TAS IV products will require careful coordination between CAA, AMSAA, and the contractor.

6-7. ASSESSMENT OF OPTIONS. The candidate TAME methodology offers the best chance to construct a many-on-many acquisition assessment methodology based on high-resolution effects modeling. Environmental variation in static assessments is processed by high-resolution models used by AMSAA to generate results which can be combined over elapsing time. The documented analytic many-on-many models, such as TADER, COMWTH, and the SAI model, lack time resolution during detection assessment. No audit trail for environmental effects, even for "interval snapshot" effects, is found in these models. If TAS IV were to generate a data base for them, that data would not be usable for steady state assessment over a scenario with probabilistic variation in search time. Only the candidate TAME methodology is designed to support a valid steady state acquisition assessment and appears to be the preferred methodology.

CHAPTER 7

MODELING OF SIGINT

7-1. INTRODUCTION. SIGINT (signals intelligence) sensors detect electronic emission signatures rather than target elements. A signature is present only if the associated equipment is "on," i.e., transmitting/emitting in the electronic spectrum. This paper considers only SIGINT detection modeling. Jamming and deception are not treated. SIGINT sensor types may be further subdivided into ELINT and COMINT sensor types. ELINT sensors detect electronic emissions other than radios. COMINT sensors intercept and analyze radio communications. The object of SIGINT search is to identify and/or locate the type of emitter. In the case of COMINT, the identification of a type of radio net is often the goal. SIGINT information is usually passed to an intelligence processing center, such as an All Source Analysis System (ASAS), for analysis. Rather than being used as a primary source for targeting, SIGINT information is more often used to prepare an order of battle, to cue another sensor to a target area, or to add confirmatory information on the identity of a previously sensed target.

7-2. OPERATIONAL ASPECTS. SIGINT sensors may be ground-based or airborne. Ground-based sensors are generally deployed as a netted cluster of two to four sensors and a net control station (which may also act as a sensor). The net arrangement is needed to generate effective lines of bearing (LOBs) for triangulation and direction finding. While only two sensors are theoretically needed to triangulate, ghost effects can be produced. These effects are significantly reduced with three LOBs. Airborne SIGINT sensors can generate LOBs during the mission path, but this may create processing delays. The series of states that must precede a successful SIGINT detection is schematically summarized in Figure 7-1. In brief: the target signature must be present, the sensor must be set to recognize it, the target must be in the field of view (FOV) of the sensor, and the signal/noise ratio (S/N) at the sensor must be large enough to discriminate the target emission. The major factors affecting SIGINT detection are listed in Table 7-1. A SIGINT sensor is usually set to search only a selected spectrum of frequencies, dictated by the search priorities of the seeking force. An emission will be invisible to a sensor unless it is programmed to recognize it. An emitter is also undetectable if its signal is masked by interference from other equipment on the same channel. The frequency of transmission of an emitter, known as its duty cycle, is likely to be correlated with its distance from the FLOT during combat. Forward units and combat units tend to have high duty cycles. Near the FLOT, the duty cycle will also tend to depend on combat posture, but this effect levels off toward the rear of the force. In the case of COMINT, a clear line of sight (LOS) is not always necessary to detect, but significant propagation loss can result from masking. The time-dependence of the duty cycle, and the time- and space-dependence of the interference effects make SIGINT especially difficult to model.

Table 7-1. Major Factors in SIGINT Detection

Sensors	Emitters	Other
Location, altitude	Location	Background interference
Frequencies searched	Duty cycle	Propagation effects
FOV searched	Frequencies emitted	Terrain masking
Receiver sensitivity	Power	

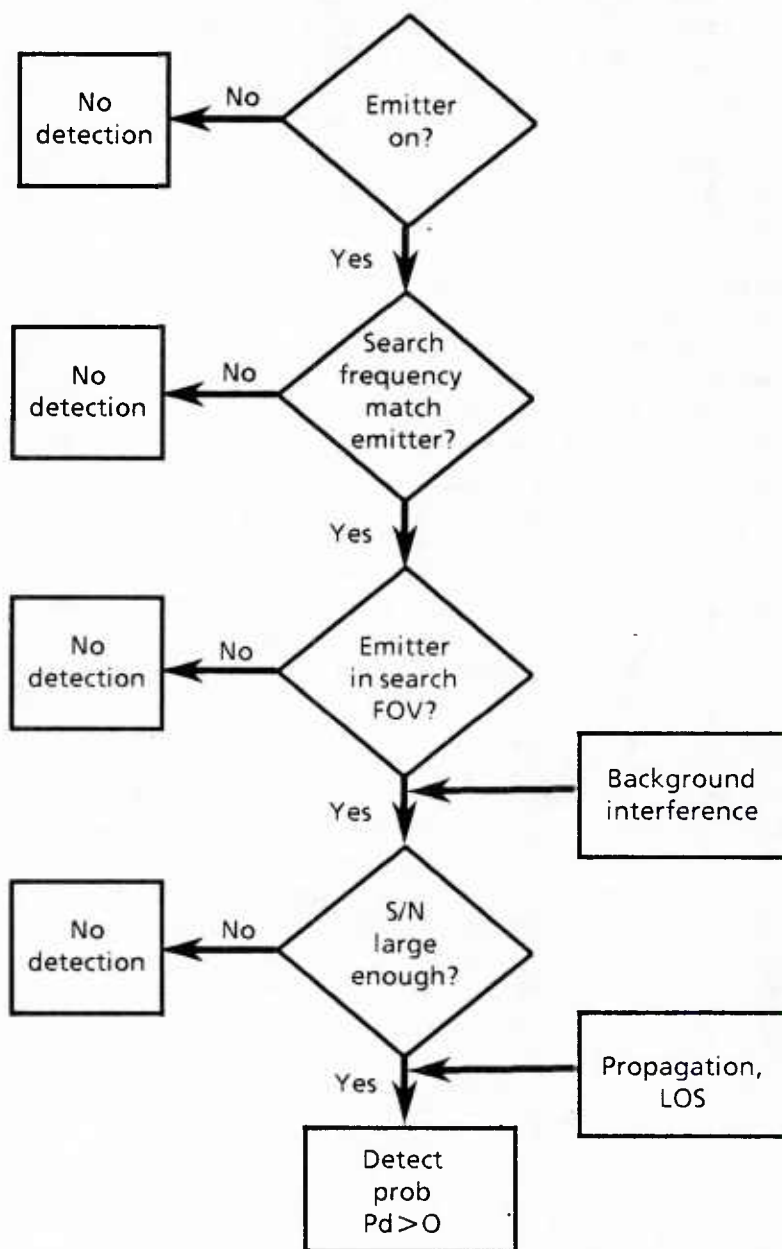


Figure 7-1. State Sequence for SIGINT Detection

7-3. SYSTEM TYPES. Table 7-2 shows descriptive names for typical SIGINT sensors. Unless otherwise noted, only US systems are represented. The table shows only airborne and ground-based systems. Theoretically, satellite systems may also be capable of ELINT and COMINT sensing, but information on capabilities of such national systems would generally be at compartmented security (SCI) levels. TERC denotes the Tactical Electronic Reconnaissance System, while PLSS is the Precision Location and Strike System.

Table 7-2. Typical SIGINT Systems

COMINT		ELINT	
Ground-based	Airborne	Ground-based	Airborne
AN/TRQ-32 TRAILBLAZER VAMPIRE (UK)	SENIOR SPEAR RIVET JOINT GUARDRAIL QUICK FIX	TEAMPACK BEADY EYE (UK)	TEREC QUICK LOOK SENIOR RUBY RIVET JOINT PLSS

7-4. HIERARCHY OF ANALYTIC REPRESENTATION. The hierarchical tree of one-on-one models, one-on-many models, and many-on-many models described in Chapter 2 also applies to SIGINT. The principal factors to be modeled are those summarized in Table 7-1. The SIGINT modeling problem is considerably more complex than that for non-SIGINT. The time-dependence of the equipment duty cycle, the time- and space-dependence of interference effects, and the netting of SIGINT sensors are especially difficult to represent analytically. Interactions over time and space require a stochastic simulation to model effectively. Since a SIGINT sensor is often specialized to detect only one type of signature, the concept of a one-on-many model is often redundant for SIGINT.

7-5. DATA CONSTRAINTS. As noted earlier, capabilities of SIGINT systems, especially national systems embracing high technology, are often disseminated only at SCI security levels. Computer modeling of these capabilities also requires authorization for computer operation with SCI data. These constraints severely restrict the modeling of SIGINT using one-on-one input data. The merged results of one-on-one models, however, can likely be disseminated at the SECRET level if the component system results of any SCI systems are not referenced.

7-6. CURRENT MODEL REPRESENTATION. In spite of the above difficulties in modeling SIGINT with a many-on-many expected value model, several approaches have been tried. Usually, these require exercising another model offline to generate results for SIGINT sensors. The offline results are then input to the main model, where they are combined with non-SIGINT sensor results. Of

the many-on-many expected value models described in Chapter 2, TADER does not treat SIGINT at all, but COMWTH and the SAI model do treat SIGINT, albeit offline. The first TAS methodology at CAA (a precursor of TADER) also included SIGINT. SIGINT methodology in these models is described below. Since many-on-many modeling depends on the results of one-on-one models, a discussion of the latter is appropriate before discussing the former.

a. One-on-one Methodology. The methods of one-on-one models depend on equations from physics. The following aspects of one-on-one SIGINT modeling are described in a SIGINT analysis study performed by R&D Associates for the Defense Nuclear Agency (DNA) (Ref. 14).

(1) **ELINT.** The intensity of a stationary emitting radar signal, as measured by an ELINT sensor searching the radar frequency, is a function of the radar power, the directional antenna gain of the radar, the radar wavelength, and the range to the sensor. A nonzero probability of detection results if the target radar antenna gain in the direction of the sensor is greater than the minimum gain for which detection (by the sensor) is possible at that range. A single look probability of detection is calculated, based on a specified minimum observation duration. If the emitter is moving, the assessment is complicated by the requirement to integrate detectability over dynamically varying sensor-target conditions.

(2) **COMINT.** A COMINT sensor detects an emitting transmitter if the computed signal-noise (S/N) ratio exceeds a minimum threshold required for detection/discrimination. The S/N ratio is a function of transmitter power, band width, sensor receiver gain, system noise, and propagation loss. An important COMINT degradation effect results from cochannel interference caused by simultaneous transmissions from radios on the same frequency. The interference problem may not affect ground radio nets, but can be significant for an airborne COMINT sensor searching a large field of view.

(3) **Fusion.** In ground-based SIGINT nets, fusion of netted SIGINT sensor results may be done under the assumption of statistical independence. For example, if at least two sensors from a net of three are needed to fix a detection, then, if p denotes the single look probability of detection for a single sensor, then the net probability of detection, P_N , might be computed as $P_N = p^3 + 3(1-p)p^2$. One-on-one models usually generate single look results that are conditioned on the emitter continuously emitting and a sensor being set to the correct matching search frequency.

An adjustment for intermittent operation and uncertain search requires the melding of such one-on-one results into a specialized SIGINT simulation. Such simulations are often complex and not well documented. In addition, a simulation that can incorporate SCI systems is likely to have documentation restricted for security reasons. Examples of comprehensive SIGINT simulations include the TACSIM Model, used by the US Army Intelligence Center and School (USAICS) and the Intelligence and Electronic Warfare Simulation Systems used by the US Army TRADOC Systems Analysis Activity at White Sands Missile Range.

b. TAS Methodology. The 1976 TAS methodology at CAA used an offline many-on-many SIGINT analysis performed by the US Army Security Agency (USASA). Prior to the SIGINT analysis, the CAA study team determined the

radio and emitter population for each target unit type in the observed forces. Using these emitter deployments, USASA provided a probability of operational detection (POTA) for a force's total SIGINT assets versus each opposing target unit type located in each of four target zones. The USASA analysis was conditioned on the targets emitting and the sensors being available. The study team applied the following three operational degradation factors:

- (1) The fraction of time that the target radios/radars were emitting.
- (2) The fraction of time that SIGINT sensors were available.
- (3) The probability of no degradation by SIGINT system crew performance.

Only one value of each factor was specified for a force. The force SIGINT POTA computed by USASA was multiplied by the product of the above degradation factors to yield an adjusted operational SIGINT POTA. The adjusted SIGINT POTA was combined, via mathematical independence, with the independently computed POTA for non-SIGINT systems. The study documentation provided no specific information on the type models used by USASA to obtain its results. It would appear more appropriate for the degradation factors to be applied in a dynamic, high-resolution simulation.

c. SAI Model. The SAI model is a many-on-many analytic model which does assess the acquisition potential of SIGINT sensor systems. A target is individually specified as either being an ELINT target, a COMINT target, or neither. No consideration is made for cover and concealment. Also, all SIGINT targets are treated with range-independent, single look probabilities. ELINT sensors are treated very similarly to non-SIGINT sensors in the methodology. The target's ELINT signature is simply treated as a target element. Target activity factors for a SIGINT target are represented in terms of the frequency of emissions. The COMINT methodology computes the probability that the net control station of "important" communications nets will be detected and located during the search period. The COMINT model is an offline stochastic simulation of the time-dependent events which must occur for SIGINT acquisition. It is not an engineering model of signal propagation, probability of intercept, or location errors of COMINT hardware. The COMINT simulation model does treat:

- (1) Number of sensor assets available for intercept and direction finding (DF).
- (2) Number of radio nets (important and unimportant).
- (3) Transmissions per hour from each net type.
- (4) The number of nets each target equipment belongs to.
- (5) The number of detected transmissions required (by a processing center) to qualify a target detection as important.
- (6) Intelligence processing time delays of various types.

Using the above inputs, the SIGINT simulator then computes a value, PA, for the average acquisition probability for a net from SIGINT in the following steps in each simulation replication.

- (1) Determine the probability of intercepting a single radio transmission from an important net.
- (2) Generate (by stochastic simulation) a time sequence.
- (3) Simulate the number of net control stations located.
- (4) Compute average acquisition probability of a net, PA, as the ratio of the number of net control stations that were located to the number of nets.

After all replications are done, PA is averaged over all replications to yield an average value, PAV. Since each control station may participate in more than one net, the overall COMINT acquisition probability for the scenario is $PESM = 1. - (1. - PAV)NRPT$, where NRPT denotes the number of nets to which the target belongs. Using mathematical independence, the overall acquisition probabilities from COMINT (PESM), ELINT (PELINT), and non-SIGINT systems, PNSIG, are combined into an overall POTA, PACQ, by:

$$PACQ = 1. - (1. - PESM)(1. - PELINT)(1. - PNSIG)$$

d. **COMWTH Model.** COMWTH assesses a SIGINT signature in exactly the same way as any non-SIGINT target element. "Interval snapshot" single sensor probabilities of detection are input, via lookup tables. These are adjusted for the fraction of time the emitter (associated with the signature) is "on." No simulation of time and equipment interaction or engineering determination of one-on-one capability is done. Any one-on-one modeling has to be implicit in the single-element, single-signature lookup table input used by COMWTH.

7-7. REPRESENTATION IN CANDIDATE TAME METHODOLOGY. The candidate steady state acquisition methodology described in Chapters 3 and 4 applies the inputs from many-on-many models. SIGINT system assessment is therefore implicit rather than explicit. The input component acquisition functions (detection as a function of time) from TAS IV are built from the combined "net assessment" results of higher resolution models operated by AMSAA. The SIGINT systems' effectiveness will be modeled through operation of high-resolution models, such as TACSIM and SIM. Where necessary, input sensor effectiveness values for these models will be generated using sensor performance models from TRAC-WSMR. During the course of the TAS IV effort, AMSAA and the TAS IV study team at CAA will jointly define the scope of the results to be generated for use by the TAS IV contractor in building acquisition functions. Detailed sensor and target deployments will be developed for input to the TACSIM and SIM sensor performance models run by AMSAA. This will ensure the quality and quantity of data sufficient to construct the component function "building blocks" for TAME to apply over a variety of scenarios, using the methodology described in Chapter 4. This approach is consistent with the hierarchical application of nested models suggested in Chapter 2.

7-8. EXAMPLE SIGINT REPRESENTATION IN CANDIDATE TAME METHODOLOGY. A subscenario environment for a TAS IV sensor acquisition function is defined in terms of a combination of scenario/environment condition states. Table 7-3 gives a stylized example of a set of condition state values for defining SIGINT subscenario environments for an acquisition function. Each subscenario environment is defined in terms of a combination of states for each of the five conditions. A total of $(2)(4)(2) = 16$ subscenario environments can be mathematically constructed from Table 7-3. A composite acquisition function would be computed by the TAME candidate methodology (from Chapter 4) for a time-sequenced succession of subscenario environments from the table. This function implicitly includes the conditions in the table. A generalization of this stylized example would be used in the practical application of the candidate TAS IV methodology.

Table 7-3. Example Condition States Defining SIGINT Subscenario Environments

Condition	State values
Target movement	Stationary, moving
Emitter activity	Silent, low power, medium power, high power
Time of day	Day, night

7-9. ADVANTAGES OF CANDIDATE TAME METHODOLOGY. The candidate TAME methodology has the following advantages relative to the approaches used in the TAS, COMWTH, and SAI models:

a. Visible Audit Trail. The linkage of the method's development to the TAS IV product construction should enable a derivable audit trail to the conditions modeled during the preparation of inputs (the acquisition functions and target retention functions). No audit trail was evident in the available documentation for many-on-many models of target acquisition.

b. Use of Inputs Generated from Existing Credible Models. The TAS IV products, which are input to the proposed method, are derived from higher resolution models with a history of operational credibility in US Army analytic centers.

c. No Severe Security Restrictions on Applications. As noted above, the implicit, rather than explicit, modeling and representation of any systems with compartmented security characteristics should allow combined, net, acquisition assessment results to be generated and disseminated at SECRET level. The increased knowledge transference permitted by this can only be beneficial to the US Army.

CHAPTER 8

FINDINGS AND OBSERVATIONS

8-1. PURPOSE. The purpose of this chapter is to address the elements of analysis for the TAME Study as stated in Chapter 1 and to present key findings and observations resulting from the study.

8-2. ELEMENTS OF ANALYSIS. The study directive identified five elements of analysis, which are restated below with a summary of the responses based on the results of the study.

a. Should the methodology be modified to take into account, separately and directly, the steady state acquisition capability of each type sensor?

(1) The TAME acquisition methodology should treat acquisition probability as a function of both time and space. In a tactical scenario, a target essentially alternates between two states relative to opposing sensors. It is either being sought (not yet acquired), or it is acquired and on an acquisition list. It is subject to reacquisition (from renewed search) after being dropped from the acquisition list. Descriptors characterizing these states can be meaningfully and feasibly determined only from steady state algorithms which express probabilities of target acquirability and retainability (on an acquisition list) as a function of elapsing time.

(2) A new acquisition measure, the steady state probability of target acquisition (SPOTA) was developed for TAME. The SPOTA for a target unit opposed by a force of sensors in a scenario timeframe is defined as:

$$SPOTA = \frac{MRT}{MTA + MRT}$$

where MTA = mean time (for sensor force) to acquire the target unit in the scenario timeframe

MRT = mean target retention time duration (on acquisition list) for the target unit, given that it is acquired

The SPOTA, as defined above, appears to be the most meaningful and feasible way to represent steady state acquisition status in a scenario.

(3) Use of nested models and data is advisable to avoid the difficulties in modeling and processing a multidimensional problem with high resolution. Under appropriate assumptions, a many(sensors)-on-many(target elements) model can be theoretically structured in terms of one-on-many models and one-on-one models. Existing many-on-many expected value models (TADER, COMWTH, SAI model) which were studied have no documented audit trail to high-resolution results. The TAME methodology should be clearly based on performance model results.

(4) The linkage of TAME to the TAS IV Study has produced a proposed TAME acquisition methodology, denoted herein as the candidate TAME methodology. That methodology will use a comprehensive catalog of fixed-scenario acquisition algorithms, to be generated in TAS IV through the US Army Materiel Systems Analysis Activity (USAMSAA). The function catalog will be based on empirically generated, time-dependent results of sensor performance models. The methodology will use the catalog to build composite algorithms for assessing steady state measures of target acquirability and retainability in a dynamic scenario. These can be used to compute an estimate of the SPOTA for a scenario.

(5) The candidate TAME methodology is preferred over existing approaches studied because it is clearly linked (via TAS IV) to accepted sensor performance model results, appears implementable, treats sensor fusion implicitly, and minimizes security restrictions in processing.

b. Can the methodology effectively support the NUFAM version current as of 15 December (1988) at CAA?

(1) The definition of SPOTA, as used in and generated by the candidate TAME methodology, is compatible with the acquisition event states of NUFAM III. The computed SPOTAs from the method can be directly used by NUFAM. The greater credibility of the SPOTA values, relative to the TAS III POTAs, will enhance the credibility of NUFAM.

(2) NUFAM use of SPOTAs from the candidate TAME methodology requires that TAME scenarios for use with NUFAM be defined in terms of time-sequenced condition sets which are included in the catalog of acquisition functions from TAS IV. This requires effective interface between NUFAM development/improvement efforts and TAME to ensure that a useful and practical mechanism is applied to construct the time-sequenced condition sets associated with NUFAM applications using the TAME products.

c. How can modeling of environmental degradation factors be improved by using conditional probabilities to transform basic environmental data into modifiers for specific scenarios?

(1) An "average" detectability adjustment for an environmental condition should be computed by integration of the probability distribution of (occurrence of) states of that condition with the conditional probability of detection, given each specific condition state.

(2) In the candidate TAME methodology, fusion and dependence of environmental factors at any fixed time is implicit in the acquisition functions in the TAS IV catalog. Variation in environmental conditions over time is explicitly integrated, via stochastic simulation.

d. To what degree can derived methodologies be automated? The algorithmic process description of the candidate TAME methodology directly corresponds to the processes of a stochastic, event-based simulation program. The structure of the underlying simulation events requires definition by TAS IV. The program will be an interface between the TAS IV data catalog and an input scenario. The feasibility of the process automation is apparent, given availability of specific TAS IV products. The application of the methodology

to a combat scenario depends on the availability of a mechanism for representing a scenario timeframe as a time-sequenced succession of (TAME methodology) scenario states.

e. What are the implications to the target acquisition methodology of including SIGINT contributions directly rather than through intelligence preparation of the battlefield, as in TAS III?

(1) The SIGINT modeling problem is specialized. Transient emissions, rather than objects, are sensed. The seeker characteristics (frequencies searched) of sensors can change dynamically over time. The multidimensional (time and space) complexity of the SIGINT scenario imposes a burdensome data and processing requirement. Past acquisition models of large scope have either omitted SIGINT or have input aggregated SIGINT performance factors evaluated offline. However, a documented credible audit trail of the origin of SIGINT factors is usually lacking. Dissemination of performance data for some SIGINT systems may be limited by classification as compartmented information. Modeling of such systems is similarly restricted. Few computer sites are authorized operation with compartmented data.

(2) The recommended candidate TAME methodology has a visible audit trail, the TAS IV algorithm catalog, which will be derived from inputs generated by established sensor performance models. In addition, the use of combined performance assessments, rather than single system performance assessments, in the TAS IV product should allow processing at no higher than SECRET level.

8-3. THE CANDIDATE TAS IV METHODOLOGY

a. Input Algorithms. AMSAA will exercise computerized sensor performance models to simulate surveillance results for suites of sensors in a wide spectrum of constant scenario environments against various target unit types. The TAS IV contractor will fit the AMSAA-generated results to algorithmic acquisition and retention functions showing probability of target acquisition and probability of target retention as a function of time under each constant scenario environment.

b. Input Scenario. The scenario to be assessed should be representable as a series, over elapsing time, of environmental states. Each state must correspond to one of the environment states used in the derivation of the TAS IV algorithm catalog.

c. Simulation. The method stochastically simulates the target acquisition status and retention status at a random assessment point in the scenario timeframe. This is done, in each replication, by dynamic construction of composite (relative to the set of environments) target acquisition and retention functions. Each composite function is constructed by piecewise connection of "slices" of functions from the TAS IV data catalog.

d. SPOTA. After a sufficient number of replications is completed, the SPOTA is estimated as the empirical average frequency, over all replications, of the acquisition state being present at the random assessment time. The SPOTA can be used to assess whether an average unit, of a specified type in a

scenario, is on an acquisition list at the assessment time. The assessment is integral to NUFAM scenarios at CAA.

e. Residual Retention Time. The duration of retention time remaining for an acquisition starting at the random assessment time is denoted as the residual retention time. An estimate of the distribution of residual retention time duration can also be produced with the method. The estimated residual retention time distribution can then be used to estimate the probability that an acquisition remains a valid target until the completion of the fire execution cycle. This probability can be used to determine fire events in NUFAM scenarios at CAA.

8-4. RECOMMENDATIONS. In consideration of the reported findings, it is recommended that:

a. The candidate TAME methodology be adopted as the TAME acquisition methodology.

b. The TAME project team should work with the TAS IV project and the NUFAM development project to:

(1) Define the environmental states and state values for which the TAS IV/TAME acquisition algorithms must be computed.

(2) Define the mechanism for representing TAME scenarios as a time-sequenced succession of environment states from TAS IV.

(3) Define the interface between TAME and NUFAM scenarios to ensure compatibility and credibility for specific NUFAM applications.

c. Upon definition of the TAS IV product algorithms, the TAME project team should construct operational programs to:

(1) Compute the TAS IV algorithms needed in the TAME methodology.

(2) Express a TAME scenario as a time-sequenced succession of TAS IV environment states.

(3) Apply the TAME methodology documented herein to compute the steady state probability of acquisition (SPOTA) and the residual retention time distribution for TAME scenarios.

APPENDIX A
STUDY CONTRIBUTORS

1. STUDY TEAM

a. Study Director

Mr. Walter J. Bauman, Force Systems Directorate

b. Other Contributors

MAJ Mark A. Youngren

2. PRODUCT REVIEW BOARD

Mr. David A. Hurd, Chairman

MAJ Mark A. Youngren

Mr. Greg Andreozzi

Mr. Michael K. Herberle

3. EXTERNAL CONTRIBUTORS

Mr. William Clay, USAMSAA

APPENDIX B

STUDY DIRECTIVE



DEPARTMENT OF THE ARMY

US ARMY CONCEPTS ANALYSIS AGENCY
8120 WOODMONT AVENUE
BETHESDA, MARYLAND 20814-2797

REPLY TO
ATTENTION OF:

CSCA-FSC

07 NOV 1988

MEMORANDUM FOR ASSISTANT DIRECTOR, FORCE SYSTEMS DIRECTORATE

SUBJECT: Target Acquisition Methodology Enhancement (TAME) Study

1. **PURPOSE OF STUDY DIRECTIVE.** This directive provides study guidance for the enhancement of the Army's Target Acquisition methodology through the Target Acquisition Methodology Enhancement (TAME) Study.

2. **BACKGROUND.** POTA values reflect many complex technical and operational considerations and have been widely used in Army, Joint, and SACEUR studies. Most recently, the Target Acquisition Study III (TAS III) at the U.S. Army Concepts Analysis Agency (CAA) developed and operated a new model, "Target Detection Routine (TADER)," to generate POTA values for U.S., non-U.S. NATO, and Warsaw Pact (WP) forces in various postures (i.e., defense, attack, on the move, and assembly). Experience with this model and analysis of its results have shown the need for further enhancement of this methodology, in particular, treatment of detection perishability, treatment of SIGINT, and improved interface with the CAA Nuclear Fire Assessment Model (NUFAM).

3. **STUDY SPONSOR.** Director, U.S. Army Concepts Analysis Agency (CAA).

4. **STUDY AGENCY.** Force Systems Directorate, U.S. Army Concepts Analysis Agency.

5. TERMS OF REFERENCE

a. **Scope.** The general scope of the TAME Study includes the evaluation and implementation, where feasible, of methodology improvements for enhancing the use and applicability of the NUFAM Model as well as for broader applications. These can only be realized in two phases. The TAME Study effort described herein consists only of a methodology analysis/feasibility assessment phase. Work will be guided by ongoing upgrades of NUFAM and objectives of the TAS IV Study at CAA. When products from NUFAM improvement and TAS IV become available, this first phase should be succeeded and completed by a second implementation and issue analysis phase.

b. **Objectives.** Assess approaches for and feasibility of the following methodological improvements in target acquisition:

(1) Development and use of a single glimpse detection capability and variable sensor search time to represent steady state acquisition probability.

(2) Improved integration with the NUFAM Model at CAA.

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SUBJECT: Target Acquisition Methodology Enhancement (TAME) Study

(3) Use of conditional probability distributions to better represent environmental degradation for a scenario.

(4) The automating of computations for methodologies developed.

(5) A SIGINT methodology.

c. Assumptions and Limitations

(1) The order of battle is well known prior to determination of the acquisition probabilities.

(2) The capability of a suite of sensors to acquire (recognize and locate) target units in an operational environment can be measured by the probability of detecting user-specified combinations of single elements of those units.

(3) The sensors modeled can differentiate between wheeled and tracked vehicles. There will be no significant confusion due to civilian traffic and personnel, and the probabilities of detection of different elements in a target unit are statistically independent of one another.

(4) Much of the input data is widely averaged over area, time, and sensor/target conditions.

(5) The sensor data catalog product of the TAS IV Study will be sufficiently developed to provide information on sensor characteristics and capabilities for methods developed. Data products from the TAS IV Study suitable for implementation in specific applications may not be available to this study.

(6) The validity of an acquisition methodology depends on the validity of the input sensor data.

d. Elements of Analysis

(1) Should the methodology be modified to take into account, separately and directly, the steady state acquisition capability of each type sensor?

(2) Can the methodology effectively support the NUFAM version current as of 15 September 1988 at CAA?

(3) How can modeling of environmental degradation factors be improved by using conditional probabilities to transform basic environmental data into modifiers for specific scenarios?

(4) To what degree can derived methodologies be automated?

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SUBJECT: Target Acquisition Methodology Enhancement (TAME) Study

(5) What are the implications to the target acquisition methodology of including SIGINT contributions directly rather than through intelligence preparation of the battlefields, as in TAS III?

6. LITERATURE SEARCH. DTIC search has been conducted. Selected references ordered are being received and will be consulted as documentary and informational need dictate.

7. REFERENCES

a. CAA Technical Paper, CAA-TP-76-2, Target Acquisition Study (TAS), May 1976 (SECRET).

b. CAA Technical Paper, CAA-TP-79-4, Target Acquisition Study II (TAS II), August 1979 (SECRET).

c. CAA Study Report, CAA-SR-87-23, Target Acquisition Study III (TAS III), September 1987 (SECRET).

d. Unpublished research paper, Youngren, Mark A., Modeling Target Acquisition, May 1987 (UNCLASSIFIED).

8. ADMINISTRATION

a. Support. Funds for travel and per diem will be provided by CAA. CAA Requirements Directorate will provide analytic support defining the interface between this study and the NUFAM Model.

b. Milestone Schedule:

Study directive approval	15 Oct 88
Phase I:	
Assessment of single glimpse methodology	30 Oct 88
Assessment of improved NUFAM integration	30 Nov 88
In Process Review ARB	1 Dec 88
Assessment of environmental degradation enhancement	31 Dec 88
Assessment of method automation	31 Dec 88
Assessment of SIGINT approaches	15 Jan 89
Technical Paper ARB	06 Feb 89
Technical Paper published	01 Mar 89



E.B. VANDIVER III
Director

APPENDIX C

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10. Youngren, Mark A., Simulating Alternating States, unpublished research paper, US Army Concepts Analysis Agency, 1988 (UNCLASSIFIED)
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12. Youngren, Mark A., Analytic Representation of the Target Acquisition Process in NUFAM III, CAA-TP-89-2, US Army Concepts Analysis Agency, (to be published) (UNCLASSIFIED)
13. Youngren, Mark A., Suggestions for Improvement of Target Acquisition Methodology, unpublished memorandum, US Army Concepts Analysis Agency, January, 1988 (UNCLASSIFIED)

14. Tactical Acquisition Considerations for engagement of Mobile Targets by Tactical Nuclear weapons, Volume 2, Technical Data, RDA-TR-115902-003, R&D Associates, November 1981 (SECRET)

15. Law, Averill M. and Kelton, W. D., Simulation Modeling and Analysis, McGraw Hill Co., 1982 (UNCLASSIFIED)

APPENDIX D

TARGET DETECTION ROUTINE (TADER) METHODOLOGY

D-1. SYNOPSIS OF METHODOLOGY. The principal purpose of TADER is to determine the probability of detection of combat units of various types at different distances from the FLOT. The values developed are called "POTA" (probability of operational target acquisition) or "unit POTA" values. The target units typically are of company, battalion, command post, and battery sizes. The POTA values are averages over zones of prespecified depth, currently 0-3, 3-12, 12-25, 25-100, and 100-300 km. The POTA values for a zone are developed by first determining the POTA values for uniform (1 km) squares in the zone, and then averaging these over the whole zone.

a. Input Summary. The following input data are required by TADER:

(1) Types, composition, and locations of deployed sensor suites. A sensor suite containing only sensors of a common type is denoted herein as a sensor system, i.e., each sensor of the system has exactly the same characteristics except for emplacement location.

(2) The inherent single sensor-single element detection probability value for each sensor type against targets located in each sensor-target distance zone.

(3) Degradation factors which are multipliers of inherent detection probability to adjust for the following conditions:

(a) Relative effectiveness due to weather.

(b) Relative effectiveness due to wind.

(c) Relative effectiveness due to dust and smoke.

(d) Relative effectiveness due to crew performance.

(e) Relative effectiveness due to line of sight restrictions.

(f) Relative effectiveness due to visibility restrictions.

(g) Fraction of time the sensor is available (excluding attrition effects).

(h) Probability sensor survives.

(4) Activity/environment factors, which multiplicatively degrade inherent detection probability to account for the effects of: moving in the open, moving in woods or towns, stationary in the open, and stationary in woods or towns.

(5) Coverage patterns for each sensor.

(6) Unit structure in terms of the number and types of target elements in the unit in a target zone. Element types include: personnel, wheeled vehicles, tracked vehicles, artillery/rocket tubes or launchers, mortar tubes, and artillery/rocket/mortar volleys fired in the search period.

(7) Fraction of units which are firing during a search period.

(8) Frequency of time spent by each target unit in each activity/environment state: moving in the open, moving in woods or towns, stationary in the open, and stationary in woods or towns.

(9) The "OR" lucrativeness level for each element type in a unit, i.e., a fraction of elements required to be detected such that detections in a unit are "OR" lucrative if at least the "OR" level is detected for at least one element type in the unit. TADER assesses only lucrative detections in a unit.

(10) The "AND" lucrativeness level for each element type in a unit, i.e., a fraction of elements required to be detected such that detections in a unit are "AND" lucrative if at least the "AND" level is detected for each (and every) element type.

b. Summary. The zone unit POTA computed by TADER is for a target unit randomly located in a target zone and searched for by all scenario systems. The sequence of computations is summarized below. More detail is provided in paragraph 2-5, Chapter 2.

(1) The target zone is partitioned into grid squares of uniform (input-specified) size.

(2) For each deployed sensor of each system, a single-sensor unit POTA for each grid square is computed, based on the target unit being in that grid square and scanned by that sensor. This is the probability that the sensor detects the target unit as lucrative.

(3) For each system, a single-system POTA for each grid square is computed by combining single-sensor POTAs. This is the probability that the system detects the target as lucrative.

(4) Over all noncounterfire systems, the noncounterfire unit POTA for each grid square is computed by combining single-system POTAs versus the unit. This is the probability that at least one noncounterfire system detects the unit as lucrative.

(5) Over all counterfire systems, the counterfire unit POTA for each grid square for each unit capable of firing artillery/rockets or mortars in the grid square is computed by combining single-system POTAs versus the unit. This is the probability that at least one counterfire system detects the unit as lucrative.

(6) The combined unit POTA for each grid square is computed by combining the noncounterfire and counterfire unit POTAs in each square. This is the probability that at least one system detects the target unit as lucrative.

(7) The unit POTA for the target zone is computed by averaging the grid square unit POTAs over all grid squares in the target zone. Averaging randomizes the effects of target location over the target zone.

D-2. POTA CALCULATION OVERVIEW (TOP DOWN). The end product of TADER is the unit POTA for a target unit randomly located in a target zone and searched for by all scenario systems. This zone unit POTA is determined in the following manner.

a. The unit POTA for a target zone is computed as the arithmetic average of the unit POTAs computed for each grid square g of the target zone.

POTA = unit POTA in target zone z

$$= \left(\sum_{g=1}^{nz} POTA_g \right) / nz$$

where

nz = number of grid squares in target zone z

and

$POTA_g$ = the combined unit POTA in any grid square

b. The combined unit POTA for a grid square g is computed by combining the noncounterfire and counterfire POTAs for the unit.

$POTA_g$ = probability at least one system detects the target unit in g as lucrative

$$= 1 - (1 - POT1_g)(1 - POT2_g)$$

where

$POT1_g$ = probability at least one noncounterfire system detects the unit in g as lucrative

$POT2_g$ = probability at least one counterfire system detects the unit in g as lucrative

c. A noncounterfire POTA for all nn noncounterfire system s versus the unit in grid square g is computed as:

$POT1_g$ = probability at least one noncounterfire systems of nn systems detects the unit in g as lucrative

$$= 1 - \prod_{s=1}^{nn} (1 - POT_{sg})$$

where

POT_{sg} = probability system s detects the unit in g as lucrative

d. A counterfire POTA for all nc counterfire systems versus the unit in g is computed as:

POT_{2g} = probability at least one counterfire system s of nc systems detects the unit in g as lucrative

$$= \left[1. - \prod_{s=1}^{nc} (1. - POV_{sg}) \right] (PFIR)$$

where

POV_{sg} = probability counterfire system s detects the unit as lucrative, given that the unit is firing

PFIR = probability the target unit is firing

e. For a noncounterfire system s versus a target unit in grid square g,

POT_{sg} = probability system s detects the unit in g as lucrative

$$= 1. - \prod_{i=1}^M (1. - PU_{isg})$$

where

M = number of sensors in system s

PU_{isg} = probability the single sensor, i, detects the target unit as lucrative

f. For a counterfire system s versus a firing unit in grid square g,

POV_{sg} = probability system s detects the unit as lucrative

$$= 1. - \prod_{i=1}^M (1. - PO_{isg})$$

where

M = number of sensors in system s

PO_{isg} = probability the sensor i (of system s) detects enough volleys (of the unit in g) to be "OR" lucrative

= the probability of at least TO_v detections in a binomial distribution of volleys with single detection probability = P_{isvg}

where

$T0_v$ = "OR" lucrativeness threshold for volleys

P_{isvg} = the weighted operational probability, given coverage, that a single sensor (of the specified system s) detects a single volley of the target unit in g .

g. For each emplaced sensor i of a noncounterfire system s scanning a grid square g :

$P_{U_{sig}}$ = probability the single sensor, i , detects the target unit as lucrative

$$= \left(P A_s \right) \left(1 - \prod_{j=1}^5 (1 - P O_{isjg}) + A \right)$$

$P O_{isjg}$ = probability the sensor i (of system s) detects enough element j (of the unit in g) to be "OR" lucrative
 = the probability of at least $T0_j$ detections in a binomial distribution of N_j elements with single detection probability = P_{isjg} , where $T0_j$ is the "OR" lucrativeness threshold for element type j and N_j is the number of element type j in the unit.

$P A_s$ = availability/survivability factor for system s

and

A = a term accounting for effects of "AND" lucrativeness

P_{isjg} = weighted operational probability, given coverage that a single sensor (of system s) detects a single target element (of specified type j) of the target unit in g

h. The P_{isjg} definition depends on whether system s is a noncounterfire or a counterfire system. For each sensor of each system, P_{isjg} is a single sensor/single element operational detection probability whose computation is based on the target unit being in that grid square and scanned by that sensor. The various sensor degradation factors, the sensor capability activity/environment factors, and the inherent detection probability are combined to form an operational probability of detection, given coverage, of a single target element by a single available sensor for each activity/environment condition. This is then weighted by the activity/environment frequencies for element types in the target unit to yield P_{isjg} .

(1) **Noncounterfire System.** For each emplaced sensor i of a noncounterfire system s scanning a single target element of type j in a specific grid square, g :

$$p_{isjg} = \left(\sum_{e=1}^4 FACT_{ej} \right) \left(PDET_{isjg} \right) \left(DEG_{sje} \right)$$

where

- e = 1, 2, 3, or 4 is, respectively, (a), (b), (c), or (d) of paragraph 2-3b(3)
- $FACT_{ej}$ = frequency of element type j in activity/environment e
- $PDET_{isjg}$ = input inherent detection probability for the single sensor, i , of system s against a single element of type j located in grid square g
- DEG_{sje} = product of the sensor degradation factors (excluding availability/survivability) for element type j in activity/environment e .

(2) **Counterfire System.** For each emplaced sensor i of counterfire system s scanning a grid square g ,

$$p_{isjg} = \left(PA_s \right) \left(PVOL_{isjg} \right)$$

where

- PA_s = availability/survivability for system s
- $PVOL_{isjg}$ = operational probability that at least one round of an in-range volley fired by element type j in a grid square g is detected by the single sensor, i , of system s . This includes weighting for sensor degradation factors, but excludes activity/environment degradation factors.

APPENDIX E

THE COMBAT WORTH (COMWTH) MODEL

E-1. MODEL PURPOSE. The COMWTH Model, developed by BDM Corporation is a computerized simulation of the major battlefield factors that affect the target detection and evaluation process. COMWTH is designed to run on an IBM-PC (personal computer) AT. Given a target unit with a mix of target signatures being observed by a suite of sensors, COMWTH will determine the associated probability of acquisition.

E-2. MODEL INPUTS. Each sensor is described by the target signature it will detect. A target unit consists of numbers of equipment types. Each equipment type has up to six signatures which are detectable by sensors. The basic element detected is an equipment signature. The COMWTH input data base is as follows:

a. Sensor Data

- (1) Type sensor.
- (2) Number sensors deployed for each sensor type.
- (3) Minimum and maximum scan ranges behind the front, for each sensor type.
- (4) Swath width of sensor coverage pattern for each sensor type.
- (5) Number of swaths scanning an area, for each sensor type.
- (6) Probability of single sensor-single signature detection as a function of range, for each sensor type.
- (7) Probability of single equipment identification given a detection, for each equipment type detected by each sensor type.
- (8) Probability of line of sight as a function of range, for each sensor type.
- (9) Relative effectiveness of sensor type due to weather conditions.
- (10) Fraction of time that sensor is active.
- (11) Time required by sensor type to complete one mission cycle.
- (12) Downtime needed by each sensor type to prepare for next mission.
- (13) Response time needed to evaluate data obtained during a mission, for each sensor type.
- (14) Target location error for each sensor type.
- (15) Resolution of each sensor type.

b. Target Data

- (1) Distance (depth) of target unit from front.
- (2) Size (area) of target unit.
- (4) Number of target units present in the battlefield.
- (3) Number of each equipment type in the target.
- (4) Fraction of time each equipment type of each signature is detectable.
- (5) Number of elements in each equipment class which are present in the battlefield but which are not associated with the target unit. This data is used to estimate the possibility of a false alarm due to the acquisition of a non-target element.

E-3. COMWTH COMPUTATIONS. The computations performed by COMWTH can be divided into the following stages:

a. Determination of Coverage in Space by a Sensor. COMWTH computes the probability of coverage in space by taking into account the battlefield size, target size, sensor swath width, number of sensors deployed, number of swaths scanned in a mission, and the number of targets located on the battlefield. The probability of coverage is determined by a ratio of the areas covered by the sensors and the targets. The depth of the target behind the front is compared with the sensor range to determine if the probability of coverage should be zeroed out due to insufficient sensor range. If the sensor is tagged as cued, then the probability of coverage is increased due to the fact that the sensor is now scanning a smaller area of the battlefield which is known to contain the target.

b. Determination of Coverage in Time by a Sensor. A COMWTH acquisition probability is computed for a specified duration of search period. COMWTH checks whether the sum of the (input) mission cycle time and response time for a sensor are less than the search period duration. If so, the probability of coverage in time is 1.0. Else, it is zero. This calculation is used to make acquisition probability a function of elapsing time.

c. Determination of Equipment Class Contribution to Acquisition. Each type of equipment in a unit is evaluated to determine its overall contribution to overall target unit acquisition. This contribution is a function of the number of elements of that equipment type contained in the target unit, the number of elements not contained in the target but present in the battlefield, the fraction of time that the equipment type is detectable by the sensor, and the probability of equipment type identification given detection.

For example, assume that a given equipment type has only one signature type and is being observed by only one sensor type over a search period, T. Let:

NE = number of equipments of the equipment type in the target.

F = fraction of equipments that are detectable

Prec = probability of equipment identification given detection by the sensor type

Pd = probability of detection of a single equipment signature by the sensor type

Pnfa = probability of no false alarm detection of the equipment type by the sensor type

Then the equipment type contribution to acquisition, given coverage, is the probability of target unit acquisition by the sensor type, computed as:

$$1. - [1. - (Pd)(Prec)(Pnfa)]^F \times NE$$

c. Probability of Target Recognition if Covered. The overall probability of target unit recognition given detection by a sensor can be determined once the individual equipment contributions have been obtained. The probability of overall target recognition if covered, P_{ac} , is just:

$$P_{ac} = 1. - \prod_{K=1}^E (1. - P_{aK})$$

where P_{aK} denotes the acquisition contribution of equipment signature type K and E denotes the number of equipment signature types.

d. Probability of Target Unit Acquisition. The probability of target acquisition, over a search period, T, for a sensor system is a function of the probability of coverage in space (P_{cov}), the probability of coverage in time for search period T (P_{tm}), the probability of line of sight (P_{los}), the probability of target recognition if covered (P_{ac}), and the relative sensor effectiveness due to weather conditions (P_{wx}). The overall probability of target unit acquisition by the sensor system is then:

$$P_{acq} = (P_{ac})(P_{cov})(P_{tm})(P_{los})(P_{wx})$$

A probability of target unit acquisition, P_{tot} , over a search period T, for a combination of several different sensor systems can be determined by combining the P_{acq} values (for each sensor type) using statistical independence, viz.:

$$P_{tot}(T) = 1. - \prod_{i=1}^{NS} [1. - P_{acq}(i,T)]$$

where $P_{acq}(i,T)$ = single system probability of target acquisition for sensor system I over search period T

NS = number of sensor system types

e. Probability of acquisition as a function of time (search period) can be computed and plotted by varying the length of period T . However, this computation assumes a "cold start" at time zero, when no sensors are assumed active.

APPENDIX F

THE SAI TARGET ACQUISITION MODEL

F-1. BACKGROUND. The SAI Target Acquisition Model was developed by Science Applications Inc. from the target acquisition module of the SAI Combat Survivability Model, which primarily assessed nuclear weapon effects. The model computes total target acquisition (defined as detection and classification) probability, using input values for single sensor types detecting targets. Primarily, the model computes the time-adjusted aggregate probability of detecting a given target using many individual single sensor probabilities (all assumed to be operating independent of each other). Time slices must be short enough so that the majority of targets can be considered stationary.

F-2. INPUT

a. Sensor Data. The sensor scenario is defined in terms of available sensor assets as opposed to specific deployments of sensor arrays. A target unit is characterized in the model by its "acquisition type." An acquisition type is essentially a target unit type. The basic sensor detection data are detection probabilities for each sensor type against each acquisition type. The model separately treats fixed sensor systems, sweep-rate systems that penetrate beyond the FEBA, sweep-rate systems that fly along the FEBA, and patrols. Input on SIGINT detection is generated offline by a separate stochastic simulation model. Sensor inputs include:

(1) Single-look acquisition probability for each acquisition type observed by each sensor type, expressed as a function of range and cover/concealment mode (target in open, target in light cover, or target in heavy cover).

(2) Single-look classification probability, given detection, for each acquisition type observed by each sensor type, expressed as a function of range and cover/concealment mode. Classification refers to identifying the type of target detected.

(3) Time to detect and classify (and report to an intelligence collection center) for each acquisition type observed by each sensor type, expressed as a function of range and cover/concealment mode.

(4) Number of sensors of each sensor type.

(5) Swath width of sensor for each sensor type.

(6) Minimum and maximum ranges (only fixed sensors, patrols, and aircraft flying along FEBA) for each sensor type.

(7) Aircraft velocity (for airborne penetrators only) for each sensor type.

(8) Total area to be searched (penetrating sensors only) for each sensor type.

(9) Mission survival probability (airborne sensors only) for each sensor type.

(10) Probability of line of sight (for non-ELINT sensors only) as a function of range (from sensor) and sensor type.

(11) Visibility/attenuation factor for each ELINT sensor type.

(12) An activity factor for each sensor type against each acquisition type. The activity factor is expressed as the fraction of time that the specified acquisition type is detectable by the specified sensor type.

(13) Fraction of time sensor is available for each sensor type.

(14) The maximum range beyond the FEBA for COMINT acquisitions.

(15) The overall acquisition probability due to COMINT against communications type targets.

(16) Area searched per unit time, for patrol sensor types only.

b. Target Data. The targets are target units. Each target unit is characterized by its acquisition type for purposes of assessing detectability. Input data include:

(1) Target name and location.

(2) Acquisition type characterizing each target.

(3) Target permanence, expressed as the expected duration of target stay time (time that the target remains in position, for each target type).

(4) Probability that an acquisition type is in each cover/concealment mode (in open, light cover, or heavy cover).

F-3. METHODOLOGY FOR SINGLE SYSTEMS (EXCEPT COMINT)

a. Fixed and/or Sweep-rate Systems

(1) Calculate the number of looks, NL, that sensors of this type could take in the time period, P, of interest under ideal conditions (i.e., each sensor is continuously available and the target continuously presents the relevant signature). This quantity, for the specified sensor type, is:

(a) $NL = (NSEN)(SW)/WF$ for fixed sensors.

(b) $NL = (NSEN)(VEL)(SW)(T)(PSURV)/A$ for penetrating airborne sensors.

(c) $NL = (NSEN)(VEL)(T)(PSURV)/WF$ for sensors flying along the FEBA.

where NSEN = number of sensors of the specified type

SW = swath width for a sensor of the specified type

WF = width of the battlefield area
 T = length of the acquisition search period P
 VEL = velocity of the penetrating sensor
 PSURV = probability the sensor survives its mission
 A = size of the area to be searched by the penetrating system

(2) Calculate the single system acquisition probability, PA1, for the NSEN sensors of this type against the specified target in a specified cover/concealment mode at a specified range for the specified search period P as:

$$PA1 = 1. - [1. - (PVIS)(PLOS)(PD)(PCLASS)(PE)](NL)(PAV)(PACT)$$

where PVIS = visibility/attenuation factor for this sensor type against this target type

PLOS = probability of line of sight for this sensor and range

PD = inherent single-look detection probability of this target at this range in this cover/concealment mode by this sensor

PCLASS = probability of classification given detection for this combination of sensor, target, range, and cover/concealment mode

NL = ideal number of looks, as calculated in (1), for search period P by this sensor type (assuming sensor availability and target detectability)

PAV = probability the sensor is available

PACT = probability the target signature is detectable by the sensor

PE = probability the target will be available for sufficient time to be reported and classified after detection

$$= \frac{\max [0, \min(T, TSTAY - TDC)]}{\min (T, TSTAY)}$$

where T is the length of the search period

TSTAY = duration of target stay time

TDC = time needed by sensor to detect and classify this target at this range

b. Patrols

(1) Calculate the average coverage per unit area searched by patrols, FC, as:

$$FC = (NPAT)(APAT)(T)/TAP$$

where NPAT = number of patrols

APAT = area searched per unit time by one patrol

T = length of search period

TAP = total area to be searched by patrols (based on input)

(2) Compute the single system acquisition probability, PA1, for all NPAT patrols against a specified target at a specified range and in a specified cover/concealment mode as:

$$PA1 = 1. - (1. - PD)^{FC}$$

where FC is as above and PD denotes the inherent single-look detection probability for a patrol against the specified combination of target, range, and cover/concealment mode

F-4. METHODOLOGY FOR INTEGRATED SYSTEMS (EXCEPT COMINT). Once the values of the single system acquisition probability, PA_{IJT}, have been computed for all non-COMINT sensor types, I, and cover/concealment modes, J, the overall non-COMINT probability of acquisition, PNC, for a specified target of acquisition type, T, is calculated as:

$$PNC_T = 1. - \sum_{J=1}^3 CF_{JT} \left[\prod_{I=1}^{NS} (1. - PA_{IJT}) \right]$$

where CF_{JT} = probability a target of acquisition type T is in cover/concealment mode J

PA_{IJT} = single system acquisition probability for system I against a target of acquisition type T in cover/concealment J

F-5. COMINT METHODOLOGY. The overall acquisition probability from COMINT, PCOM, against all communications type targets, is determined offline by a stochastic model for subsequent input into the target acquisition model. The stochastic COMINT model performs the following sequential steps:

- a. Calculates the probability of intercept for a single radio transmission from a net.
- b. Simulates a time sequence of intercepted transmissions from each net.
- c. Simulates the processing of intercepts and DF results.
- d. Counts the nets located in the search period and computes the fraction located, PN.
- e. Calculates the average value of PN over all replications.

f. Computes overall acquisition probability, PCOM, against all communications type targets as C:

$$PCOM = (1. - PN)^{NNET}$$

where NNET denotes the number of nets which the target is in.

F-6. TOTAL ACQUISITION PROBABILITY. With PNC_T and PCOM computed as above, the total acquisition capability for a target, T, is then:

$$PTOT_T = 1. - (1. - PNC_T)(1. - PCOM)$$

APPENDIX G

A METHOD FOR DETERMINING MEAN TIME TO TARGET ACQUISITION FROM
SINGLE SENSOR DETECTION FUNCTIONS

G-1. BASIC CONCEPTS AND DEFINITIONS

a. **Target Characteristics.** A target unit is assumed to consist of target elements of specified types. Example types are wheeled vehicles, tracked vehicles, and personnel. All elements of a single type (e.g., all tracked vehicles) in a target unit are treated as identical in characteristics and form an element "cluster" for that element type within that target unit.

b. **Sensor Systems.** A sensor system consists of a group of deployed/emplaced sensors with identical characteristics. Depending on the type of system, a single sensor can be an emplaced equipment in static operation or, in the case of a penetrating aircraft, it can be a reconnaissance mission overflying a path through the combat area over a fixed time interval. In the case of a standoff aircraft (e.g., side-looking airborne radar (SLAR)) it can be an aircraft traversing a linear path at a standoff from the FLOT. All scenario sensors can be grouped into systems.

c. **Scenario Search Interval.** The scenario search interval is a period of clock time, in a scenario, over which the desired target acquisition measure is averaged.

d. **Lucrativeness.** For each element type in a target unit, we specify an "OR" lucrativeness threshold and (optionally) also an "AND" lucrativeness threshold. The "OR" lucrativeness threshold is the minimum number of elements (of that type) that must be detected by at least one sensor to qualify the target unit as detected with respect to that element type under the "OR" criterion. For a combination of element types, the set of "AND" lucrativeness thresholds for these types is a set of thresholds (number of elements) which, if detections of those types are jointly at or above all of them, qualify the target unit as detected with respect to the "AND" criteria. The "AND" lucrativeness threshold must be less than or equal to the corresponding "OR" threshold.

e. **Target Unit Acquisition.** A target unit is acquired if either of the following occurs:

(1) The unit is detected, under the "OR" criterion, with respect to at least one element type by at least one sensor of at least one system.

(2) The unit is detected, under the "AND" criterion, by at least one sensor of at least one system.

f. **Single Sensor Detection Functions.** A single sensor detection function describes the single sensor (of a specified type) probability of detecting a target (of a specified type) as a function of consecutive search time. The target is assumed fixed at a specified location relative to the sensor under specified environmental conditions. However, depending on type sensor, the function may be a "one-on-one" detection function in terms of detection of a

single target element (e.g., a single tank) or a "one-on-many" detection function in terms of detection of a target unit (a collection of target elements of several types). Also, consecutive search time can be expressed in terms of continuous elapsing clock time or in terms of successive clock intervals of equal length, called glimpses or glimpse cycles. We classify each sensor type in one of two categories. An "element accumulating sensor" establishes a target unit detection by accumulating and fusing detection information from one-on-one detection functions separately and independently applied to each element in the unit. A "target unit accumulating sensor" accumulates detection information from a one-on-many detection function. These types are described below.

(1) **Example Detection Function for an Element Accumulating Sensor.** For an element accumulating sensor, the single sensor scan of a single element may be treated as a series of consecutive "glimpses" with an implicit cumulating memory causing the probability of detection to tend to increase as the scan continues. The one-on-one detection function then expresses the probability of detection within a specified duration of scan. The CNVEO target acquisition methodology is of this type, with an exponential detection function of the form:

$$F(t) = \text{probability of a single sensor } s \text{ detecting a single target element of type } j \text{ within } t \text{ minutes of scanning}$$

$$= [PLIM_{sj}][1. - \exp(-\{Pl_{sj}\}\{t\}/M)]$$

where

$PLIM_{sj}$ = probability of single sensor s detecting a (single) element in infinite time (infinite glimpses)

M = duration of a single glimpse

Pl_{sj} = single glimpse probability of (single) element detection (by single sensor)

For an element accumulating sensor, the values of Pl_{sj} and $PLIM_{sj}$ in the one-on-one detection function will depend on the distance from the sensor to the target.

A similar glimpse model is the single sensor geometric detection function of the form:

$$F(k) = \text{probability of a single sensor } s \text{ detecting a single target element of type } j \text{ within } k \text{ scan glimpses}$$

$$= [PLIM_{sj}][1. - (1. - Pl_{sj})^k]$$

where $PLIM_{sj}$ and Pl_{sj} are defined as in the previous case.

In the geometric model, we can write:

$f(k)$ = probability of type j element detection by sensor s in exactly k glimpses

$$= [PLIM_{sj}][P_{1sj}(1 - P_{1sj})^{k-1}]$$

(2) Example Detection Function for a Target Unit Accumulating Sensor.

In this case, the system scans and assesses the entire target unit in a single glimpse. The general definition of the associated one-on-many detection function is then:

$F(m)$ = probability of target unit detection by the system in exactly m glimpses ($m = 1, 2, \dots$)

For a target unit accumulating sensor, target unit detection is determined from simultaneously processed (i.e., in the same glimpse cycle) detections resulting from single independent glimpses of each target element in the target unit. In this case, an individual element single glimpse detection is modeled by a Bernoulli probability distribution, and the fusion of individual single glimpse element detections of a single element type is modeled by a binomial probability distribution. This situation may be true, for example, of an air or ground reconnaissance mission, or set of missions, which transit and observe a target unit for only a brief period during a mission cycle. In this case, the specific formula for the one-on-many detection function can be calculated as follows:

For each glimpse s scanning each target element type j in the target unit, let:

p_j = single glimpse probability of single element detection for element type j

N_j = the number of elements of type j in the target

M_j = the minimum number of elements of type j that must be detected in order to establish the target unit detection (i.e., the "OR" lucrativeness threshold for element type j)

M_{1j} = the minimum number of elements of type j that must be detected jointly with at least M_{1k} detections of all other element types (for $k \neq j$) in order to establish the target unit detection (i.e., the "AND" lucrativeness threshold for element type j)

Assuming simultaneous and independent target element processing, we can compute the single glimpse (mission cycle) probability that the entire target unit is detected under both ("OR" + "AND") lucrativeness criteria. This is done by determining and combining single glimpse detection probabilities for the sensor observing all elements of each specified type in the target unit. All elements of a specified type j in the target unit are denoted as the element j cluster in the target unit. The associated computations and combinations are shown below.

(a) Compute, for each element type j:

PSO_j = single glimpse (mission cycle) probability of element j cluster detection under the "OR" lucrativeness threshold

= probability that at least M_j of the N_j elements of type j in the target unit are detected in a single glimpse

$$= \sum_{k=M_j}^{N_j} B(N_j, k) (p_j)^k (1-p_j)^{N-k}$$

where $B(N_j, k)$ = binomial coefficient with N_j and k

and

PSA_j = single glimpse (mission cycle) probability of element type j cluster target detection under the "AND" lucrativeness threshold

= probability that at least M_{1j} of the N_j elements of type j in the target unit are detected in a single glimpse

$$= \sum_{k=M_{1j}}^{N_j} B(N_j, k) (p_j)^k (1-p)^{N-k}$$

where $B(N_j, k)$ and p_j are as in PSO_j above.

If element type j has no M_{1j} specified, then $PSA_j = PSO_j$.

(b) Combine single glimpse element cluster detection probabilities over all element types in the unit to determine the single glimpse target unit detection probability as follows:

PS_s = single glimpse (mission cycle) probability of (entire) target detection under both ("OR" + "AND") lucrativeness criteria

$$= 1. - \prod_{j=1}^{NE} (1. - PSO_j) + \prod_{j=1}^{NE} (PSA_j - PSO_j)$$

where NE denotes the number of element types in the target unit.

(c) Assuming that detections from separate mission cycles are statistically independent, calculate the one-on-many detection function for a single target unit accumulating sensor as:

$F(m)$ = probability that the target unit is detected within m mission cycles

$$= \sum_{k=1}^m (\text{prob target is first acquired during mission cycle } k)$$

$$\begin{aligned}
 &= \sum_{k=1}^m PS_S (1. - PS_S)^{k-1} \\
 &= 1. - (1. - PS_S)^m
 \end{aligned}$$

The target unit detection function for this type sensor is therefore a geometric model with units of time expressed in terms of successive mission cycles.

G-2. METHODOLOGY. The following methodology for calculating a mean time to target unit acquisition from single sensor detection functions was suggested by MAJ Mark Youngren of CAA in an unpublished research paper (reference 9). The method employs stochastic sampling and is therefore not deterministic. Certain simplifying procedures are explained which reduce sampling requirements and increase computational efficiency. The method will first be described in its most basic form, i.e., without any simplifying procedures. The simplifying procedures will subsequently be discussed. Element accumulating and target unit accumulating systems are separately treated. The following definitions of terms and indices are applicable:

Systems $i = 1, 2, \dots, N_Y$
 Available sensors $s = 1, 2, \dots, NS(i)$ (of system i)
 Element types $j = 1, 2, \dots, N_E$
 N_j = Number of elements of type j in the target unit
 M_j = Minimum elements (of type j in target m) to detect ("OR")
 $M1_j$ = Minimum elements (of type j in target m) to detect ("AND")

where

M_j is the "OR" lucrativeness threshold for element type j

$M1_j$ is the "AND" lucrativeness threshold for element type j

a. Algorithm. A number of statistical replications are done. Each replication's final product is a stochastic sample of "time to target acquisition" for all systems observing a specific target unit. After all replications are done, the "time to target acquisition" samples are averaged over all replications to determine a best estimate of this measure. Each replication computes its product according to the following algorithm:

(1) Element Accumulating Systems. Let i denote an element accumulating sensor system consisting of $NS(i)$ sensors.

(a) For each of the $NS(i)$ sensors observing each of the N_j elements in the element j cluster in the target unit, determine a sample value of $T1_{sj}$ = the (sampled) time to detection of a single target element of the cluster by sensor s ($s = 1, 2, \dots, NS$). Assuming invertability of the detection function, this can be done by inverting the element detection function and assigning a very large time value if the element is not detectable. For example, if the geometric detection function of paragraph G-1f(1) applies, and if X is a random draw between 0.0 and 1.0, then:

1. Set $X = F(g)$ = probability of single element detection in g glimpses

$$= PLIM_{sj} [1. - (1. - P1_{sj})^g]$$

2. Solving this for g yields:

$$g = \log(1. - X/PLIM_{sj}) / \log(1. - P1_{sj}) \text{ for } X < PLIM_{sj}$$

so:

if $X < PLIM_{sj}$, then $T1_{sj} = g$ is the drawn (sample) time to sensor s detection of the single target element, expressed as the number of glimpses. This can be converted to clock time through multiplication of glimpse duration.

if $X \geq PLIM_{sj}$, $T1_{sj}$ is set to a very large (unattainable) number to reflect the fact that the element can not be acquired.

(b) For each sensor s of system i versus each element j cluster, determine $T0_{sj}$ = the M_j -th order statistic from the N_j samples of $T1_{sj}$, is the minimum time for the s -th single sensor to detect M_j elements of the cluster for element type j , i.e., under the "OR" lucrativeness threshold.

(c) For each sensor s versus each element cluster j , determine TA_{sj} = the $M1_j$ -th order statistic from the N_j samples of $T1_{sj}$. This is the minimum time for the s -th single sensor to detect $M1_j$ elements of the cluster for element type j , i.e., under the "AND" lucrativeness threshold.

(d) For each single sensor s in system i , compute time until the s -th single sensor acquires the target unit, m , based on both ("OR" + "AND") lucrativeness criteria as:

$$T2_s = \min\{T0_{s1}, T0_{s2}, \dots, T0_{s \text{ NE}}, \max\{TA_{s1}, TA_{s2}, \dots, TA_{s \text{ NE}}\}\}$$

where NE denotes the number of element types in the target.

(e) Compute (earliest) time to target unit acquisition by system i as:

$$TS_i = \min\{T2_1, T2_2, \dots, T2_{NS(i)}\}$$

(2) **Target Unit Accumulating System.** Let i now denote a target unit accumulating sensor system. All $NS(i)$ glimpses, or mission cycles, of the target unit accumulating system are assumed to have identical detection characteristics.

(a) For a single sensor, s , determine a sample value for TU_s = the time to target unit acquisition in a single glimpse. This can be done by inverting the (one-on-many) target unit detection function and assigning a very large time value to TU_s if the element is not detectable. For example, if the geometric detection function of paragraph G-1f(1) applies and if X is a random draw between 0.0 and 1.0, then:

1. Set $X = F(g)$ = probability of target unit detection within g glimpses

$$= 1. - (1. - PS_S)^g$$

where PS_S is the single glimpse detection probability for the target unit as calculated in paragraph G-1f(2)(b) above.

2. Solving this for g yields:

$$g = \log(1. - X) / \log(1. - PS_S)$$

Then $TU_S = g$ is the determined sample value for the time to single sensor acquisition of the target unit, in terms of the number of glimpses. This can be converted to clock time through multiplication by glimpse duration.

- (b) Compute (earliest) time to target acquisition by system i (in this replication) as:

$$TS_i = \min[TU_1, TU_2, \dots, TUN_S(i)]$$

- (3) If necessary, convert all values of TS_i expressed in glimpses to values expressed as search time to acquisition. This may be as simple as multiplication of TS_i by the glimpse duration. In the case of a target unit accumulating system, this may require special processing to account for scheduled inactive periods between missions.

- (4) Calculate earliest time to target acquisition by the entire spectrum of scenario sensor systems observing the target unit (in this replication) as:

$$T = \min[TS_1, TS_2, \dots, TS_{NY}]$$

where all TS_i are in terms of elapsed search time to acquisition.

The values of T are then averaged over all replications to produce a best estimate for the simulation.

b. Processing Time Considerations. While the above method is feasible, the number of random draws required can become large, since, for each target unit in each replication, a draw is required for each sensor/element type combination. If 100 radars are deployed to scan a target with 5 target element types, then at least $100 \times 5 = 500$ random draws are required during the determination of the required order statistics. Since a scenario often employs many systems against a number of target units, the process described above may require significant processing time, even on a computer. Calculation shortcuts that do not degrade precision are therefore highly desirable.

c. Simplifying Procedures. For element accumulating systems, the calculation of order statistics can be simplified, and processing time decreased, by applying the following simplifying procedures.

(1) **First Simplified Order Statistic Sampling Method.** It is well known (Ref. 15) that, given two positive integers n and m , with $n \leq m$, the n -th order statistic from a sample of m uniformly distributed random variables is distributed as a Beta ($n, m - n + 1$) random variable. Therefore, we can quickly obtain a pseudorandom sample of the n -th order statistic of a detection time distribution for a single sensor of an accumulating system observing m target elements as follows:

(a) Let $F(t)$ be the cumulative distribution function of single element detection time by a single sensor of a system that accumulates over time, so that $F(t)$ = probability of single element detection in search time t .

(b) Draw a single pseudorandom sample, S , from the Beta ($n, m - n + 1$) distribution.

(c) Set $F(t_1) = S$ and solve for t_1 .

Then t_1 is a pseudorandom sample from the n -th order statistic of the detection distribution sampled for each of the m target elements. Note that this procedure can be applied only if $F(t)$ is invertible, i.e., if the equation in (c) above is uniquely solvable for t_1 .

The specific use of the above procedure is to simplify the steps (a) through (c) of the basic methodology described in subparagraph G-2a(1) which determines T_{0sj} and T_{Asj} for an element accumulating system. Using the notation of that subparagraph, the replacement steps are:

1. For an element accumulating system s observing an element of type j , e.g., with a geometric detection function of the form:

$$\begin{aligned} F(t) &= \text{probability of element detection within } g \text{ glimpses} \\ &= [PLIM_{sj}][1. - (1. - P1_{sj})]^g \end{aligned}$$

determine the following in each replication for each element type j cluster in the target unit:

a. Draw a pseudorandom sample from the binomial distribution with defining parameters $PLIM_{sj}$ (= probability of detection in infinite time) and N_j (= number of type j elements in target) to determine ND_j = sample number of detectable elements from the N_j in the cluster.

b. For the "OR" lucrativeness criterion with lucrativeness threshold M_j for element type j in the target unit, calculate T_{0sj} = the sampled M_j -th order statistic from a sample of detection times, expressed as numbers of glimpses, for each to the ND_j detectable elements of type j in the target unit as follows:

- If $M_j > ND_j$, then the cluster is not detectable, so set T_{0sj} = a very large value (e.g., 999999)

- If $M_j \leq ND_j$, then set $TO_{sj} = \frac{\ln(1. - S_0)}{\ln(1. - P_{1sj})}$

where P_{1sj} is the single glimpse detection probability and S_0 is a single pseudorandom draw from Beta (M_j , $N_j - M_j + 1$). TO_{sj} should be rounded to the nearest integer.

c. For the "AND" lucrativeness criterion with lucrativeness threshold M_{1j} for element type j in the target unit, calculate TA_{sj} = sample M_{1j} -th order statistic from the sample of detection times for each of the ND_j (same value as in (b) in this replication) detectable type j elements of the target unit as follows:

- If $M_{1j} > ND_j$, then the cluster is not detectable, so set

- TO_{sj} = a very large value (e.g., 999999)

- If $M_{1sj} \leq ND_j$, then set $TA_{sj} = \frac{\ln(1. - S_1)}{\ln(1. - P_{1sj})}$

where P_{1sj} is the single glimpse detection probability and S_1 is a single pseudorandom draw from Beta (M_{1j} , $N_j - M_{1j} + 1$). TA_{sj} should be rounded to the nearest integer value.

2. Steps (d) and (e) are not affected. $T2_s$ and TS_i are computed exactly as described previously.

(2) **Second Simplified Order Statistic Sampling Method.** For a target unit accumulating system, i , consisting of homogeneous missions/glimpses with a geometric detection function, the first order statistic of a sample of times to detection is also geometric. Therefore, if S is a random draw from the uniform distribution, $U[0,1]$, then TS_i = sample time to target unit detection over all missions/glimpses is:

$$TS_i = \log(1. - S) / [NS(i) \log(1. - PS_s)]$$

where PS_s and $NS(i)$ are as in subparagraph G-2a(2).

APPENDIX H

APPROPRIATENESS OF STATISTICAL INDEPENDENCE ASSUMPTIONS

H-1. PROBLEM. Chapter 2 described the assessment of the probability of target unit acquisition by a suite of sensors (a many-on-many model) by combining acquisition assessments for single sensors against single target elements (one-on-one models). This approach assumes that the processes generating the one-on-one results are statistically independent of each other. Independence is the simplest way to fuse separate (in time and/or space) acquisitions of single elements of a target into a multisensor assessment of a cluster of elements defining a target unit. The candidate TAS IV methodology in Chapter 4 assumes independence in at least two areas: between units and between an initial acquisition and a subsequent reacquisition (after the target is dropped from an acquisition list). Thus, the values of mean time to unit acquisition, the mean duration of acquisition retention, and the SPOTA for any specific target unit are not affected by the processes used to generate these measures for any other unit. These assumptions, as is usually the case when independence is assumed, are not true. The applicability analysis contained herein is based on a CAA technical paper (Ref. 12).

H-2. PROLIFERATION. The application of independence assumptions is standard in models of target acquisition that the author is aware of, even those that involve detailed, complex combat simulations. Relative to closed form mathematical models, simulations provide great flexibility in the representation of complex processes in time and space. However, in a combat simulation, statistical independence is inherent in the pseudorandom number draws which generate each stochastic event. This implies independence of the interactions between units.

H-3. IMPACT OF ASSUMPTIONS. The acquisition probabilities for target units are dependent over time, space, hierarchical relationship, and environment. Acquisition of a unit is affected by the knowledge from other acquisitions which are "close" in time or space separation. It is possible to construct examples in which the application of independence assumptions leads to wildly erroneous results. In practice, however, in the nuclear warfare scenarios modeled by NUFAM III, the correlation between variables derived from different units and processes appears to be relatively small. The impact of incorrectly applied independence assumptions can not be quantified unless the correct model, considering dependence, can be defined and evaluated as a "control case" for comparison. These comparison cases have been limited to relatively simple hypothetical examples. Therefore, an analyst is forced to apply judgment as to the degree and extent that the assumption of independence is acceptable.

H-4. LACK OF ALTERNATIVES. Assumptions of statistical independence are used in closed form mathematical models because process formulas treating dependence considerations are either not definable or else are not tractable for analysis. The assumption of independent and/or identically distributed random variables permeates the standard techniques of statistics and probability. Theory does allow the representation of an arbitrary probability density function for a joint distribution of interdependent random

variables. However, a useful family of closed form formulas is not available. A stochastic simulation allows probability distributions to be empirically defined (often via lookup tables). However, the input data requirements geometrically increase with the increasing dimensionality of (and number of state combinations in) an arbitrary joint probability distribution. The increased complexity and magnitude of the input data required to define an arbitrary empirical joint probability distribution function are justified only if the data are sufficiently well-defined. Unfortunately, data for theater-level combat and acquisition models are often scanty and uncertain. The principle of economy and simplicity in the face of uncertainty, expressed philosophically as Ockham's razor, supports the "standard" application of independence in theater model process representations.

H-5. USEFULNESS. In operations research, a model is a simplified abstract approximation of reality. Even if a model does not give accurate absolute quantitative results, the model may be useful for assessing relative comparison of outcomes, both qualitatively and quantitatively. The model can be used to illuminate relationships between inputs and outputs even though the precise values generated can never be regarded as absolute "truth." The fact that some assumptions incorporated into a model do not necessarily hold does not invalidate the model or render it meaningless. It is sometimes possible to extend a model incorporating statistical independence to look at limited and special forms of dependence. Insights, rather than "true" absolute solutions are likely to be gained from such side analyses because of the limited practical size of model representation of interdependent effects.

APPENDIX I
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GLOSSARY

1. ABBREVIATIONS, ACRONYMS, AND SHORT TERMS

AMSAA	US Army Materiel Systems Analysis Activity
AFWS	Air Force Weather Service
ASAS	All Source Analysis System
BDM	Braddock, Dunn, and MacDonald
CAA	US Army Concepts Analysis Agency
CB	counterbattery
CM	countermortar
CNVEO	US Army Center for Night Vision and Electro-optics
COMINT	communications intelligence
COMWTH	Combat Worth (model)
DF	direction finding
div	division
DNA	Defense Nuclear Agency
elt	element
ELINT	electronic intelligence
EO	electro-optic
EW	electronic warfare
FEBA	forward edge of the battlefield area
FLOT	forward line of own troops
FOV	field of view
IDA	Institute for Defense Analysis
IR	infrared
JTFP	Joint Tactical Fusion Program
LOB	line(s) of bearing
MAJ	Major

MOE	measure(s) of effectiveness
MRT	mean retention time
MTA	mean time to acquisition
MTI	moving target indicator
NATO	North Atlantic Treaty Organization
no	number
NUFAM III	Nuclear Fire Planning and Assessment Model III
POTA	probability of operational target acquisition
POTAR	Probability of Operational Target Acquisition Routine
PLSS	Precision Location and Strike System
RTDF	residual retention time distribution function
S/N	signal/noise (ratio)
SAI	Science Applications Inc.
SCI	special compartmented information
SIGINT	signals intelligence
SIM	Sensor Interaction Model
SLAR	side-looking airborne radar
SPOTA	steady state probability of target acquisition
STANO	surveillance, target acquisition, and night observation
TACSIM	Tactical Simulator (model)
TADER	Target Detection Routine
TAME	Target Acquisition Methodology Enhancement (study)
TAS	Target Acquisition Study
TAS II	Target Acquisition Study II
TAS III	Target Acquisition Study III
TAS IV	Target Acquisition Study IV

TEREC	Tactical Electronic Reconnaissance System
tgt	target
TOT	time on target
TRAC-WSMR	US Army TRADOC Systems Analysis Activity - White Sands Missile Range
TRADOC	US Army Training and Doctrine Command
TV	television
UK	United Kingdom
USAMSAA	US Army Materiel Systems Analysis Activity
USAICS	US Army Intelligence Center and School
USASA	US Army Security Agency
WP	Warsaw Pact

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