Optimizing the Allocation of Sensor Assets for the Unit of Action

Author: Stephanie J. Tutton
Center for Army Analysis
6001 Goethals Road
Fort Belvoir, Virginia 22060
(703) 805 – 5631
Stephanie.Tutton@caa.army.mil

STUDENT PAPER

Advisor: W. Matthew Carlyle
Naval Postgraduate School
Department of Operations Research
Monterey, California

Advisor: Donovan Phillips
Training and Doctrine (TRADOC) Analysis Center
Monterey, California

Abstract

The U.S. Army's Objective (Future) Force is being developed as a faster, lighter, more rapidly deployable alternative to the current force structure. The development of a strategy for the allocation of the Unit of Action's organic sensing assets is necessary to achieve the maximum situational awareness and information dominance required for successful combat operations on the future battlefield. This thesis presents a methodology for finding an appropriate mix and allocation strategy for organic Unit of Action sensors in a given scenario.

Three aggregate levels are identified: sensors, platforms, and packages and performance measures are developed at each aggregate level. Two optimization models were developed, (1) a Sensor Mix Model that, given a fixed mix or inventory, allocates assets to target areas on the battlefield, and (2) a Sensor Mix Model that suggests an organic mix of sensors for consideration in developing the Objective Force structure. These models have the potential use as an operational decision support tool for the unit commander.

The notional data set used for model development included ten each platform types, target clusters, target categories, and four enemy orders of battle, and four outcomes, however these inputs are easily modified based on requirements of the user or analyst.

OVERVIEW.

The United States Army is in the process of transforming itself into a faster, lighter, more rapidly deployable force capable of facing any threat in any environment. "The Objective (Future) Force is our future full spectrum force: organized, manned, equipped and trained to be more strategically responsive, deployable, agile, versatile, lethal, survivable and sustainable across the entire spectrum of military operations from Major Theater Wars through counter terrorism to Homeland Security" (U.S. Army White Paper, 2002).

Organic sensing assets at the Unit of Action (UA) level play a critical role in developing the superior situational understanding required by UA commanders to shape the battlefield and maneuver to positions of advantage. "The key to the success of UA operations is the ability to build and maintain a credible knowledge base in order to know more about what is going on and dominate the battlespace" (UA O&O 2002). Currently there is little information detailing, or published literature outlining, effective employment strategies of UA organic sensing assets.

The United States Army is in the process of developing superior sensing technology but, without a methodology or procedure to assist in determining an effective employment strategy of sensor assets, units will not realize their full sensing capability nor achieve the highest level of situational awareness and understanding.

PURPOSE.

The objective of this paper is to provide a methodology that suggests different allocations and employment strategies for unmanned sensor assets organic to the Unit of Action. Objective (Future) Force units will be distinguished from Legacy Force units by their ability to maintain what the Army terms the "Quality of Firsts." Objective (Future) Force units at all levels, engaged in any type of operation, will "See First, Understand First, Act First, and Finish Decisively" (White Paper, 2002).

This paper focuses on "See First," where Objective (Future) Force units detect, identify and track enemy units utilizing intelligence made available from higher echelons and assets organic to the unit. These assets include organic sensors, Special Operations Forces, joint air and ground reconnaissance operations, etc.

The following two questions are explored in this research:

(1) Given an initial inventory of C4ISR assets, how should they be employed?

(2) What C4ISR assets should be organic to the UA?

Two models were developed to assist with providing answers to the above questions. The Sensor Mix Model (SMM) extends the Sensor Allocation Model (SAM) by treating the initial inventory of assets as the key decision variable, and provides a tool to analyze the mix and allocation of organic sensors by maximizing expected target detections within the UA's Area of Operations. The SMM does not determine actual detected targets on the battlefield. An expected number of target detections is calculated based on the allocation of sensors suggested by the model prior to the actual employment of assets. This model also does not suggest specific search methods or patterns. Rather, it uses results from search theory to estimate the performance of various allocations of sensors.

BACKGROUND

Objective (Future) Force Structure

The Divisional Unit of Employment has operational command and control of the UA and continues the intelligence gathering process begun at higher echelons and in coordination with joint assets. The Divisional UE is responsible for creating the Common Relevant Operational Picture (CROP) and providing an accurate assessment of conditions in the theater. The Unit of Action, however, must be prepared to fight immediately upon entering the theater of operations and uses the CROP for initial planning during the Entry Operations and Actions Before Forces are Joined stages. These stages are briefly explained in a following paragraph.

The Unit of Action is responsible for integrating organic and supporting Intelligence, Surveillance, and Reconnaissance (ISR) assets, fires, and Command and Control (C2) immediately upon entrance into the theater of operations. Once the UA is committed, the Divisional UE immediately begins refocusing its intelligence assets and shaping the battlefield for the follow-on fight (UA O&O, 2002).

An extremely vulnerable phase of any military operation is the transitional period when a unit assumes command and control from another unit. The Sensor Allocation Model provides a method for the UA commander to utilize the UE's Intelligence Preparation of the Battlefield (IPB) and the CROP while enroute to the theater of operations. The ability to immediately deploy sensing assets and begin shaping operations within the UA Area of Interest allows continued development of the tactical infosphere and is critical to reducing operational risk to soldiers during the UA's acceptance of Battle Command from the UE.

Stages of Contact

The Objective (Future) Force concept describes five main stages of contact with enemy forces: Entry Operations, Actions Before Forces are Joined, Actions during Combat, Tactical Assault and Transitions. Each stage requires a specific level of situational understanding and intelligence integration sufficient for accomplishment of the mission and to achieve success on the battlefield

The goal is to maximize the expected number of targets detected in the designated search areas. The Sensor Allocation Model is a tool designed to upgrade the intelligence integration effort from "sufficient for accomplishment of the mission" to "superior situational dominance," based on the optimization of sensor-to-target pairings with available UA organic assets, thereby reducing casualties and decreases in operational momentum.

Entry Operations

Entry Operations are characterized by speed, precision, and knowledge. During operational planning, the UA commander must develop a plan to immediately and effectively begin gathering intelligence within the UA's Area of Operations and begin providing updates to the CROP. "The access that the UA has to joint intelligence capabilities enables the UA's ability to prepare the battlespace even while still enroute to the point of entry" (UA O&O, 2002).

Actions Before Forces are Joined

Actions Before Forces are Joined stage closely follows the Entry Operations stage. This stage completes the transition of Battle Command from the UE commander to the UA commander. The UA commander must quickly deploy unit organic sensing assets in a near optimal configuration to identify targets, target clusters and locations, maneuver routes, and gain the situational awareness and situational understanding needed in order to conduct tactical operations during the follow-on stages of contact. Figure 2 below depicts the UA's reliance on non-organic and organic ISR capabilities at different stages in an operation.

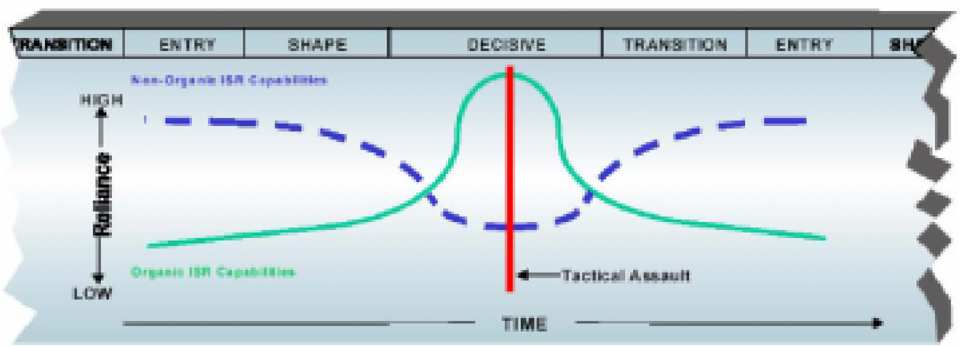

Figure 2. Non-Organic/Organic ISR Relationship (From Ref. UA O&O, 2002)

The focus of the model is at the decisive stage when the UA begins to reduce reliance on non-organic ISR assets and begin deployment of organic ISR assets. The Sensor Allocation Model is designed to assist unit commanders with the allocation of organic assets to target areas on the battlefield in an effective manner.

METHODOLOGY

Overview

This research developed a mathematical programming model to analyze the mix and allocation of organic UA sensor assets using an optimization-based approach. The model requires the following inputs: an inventory of sensors and platforms, a list of asset configurations known as packages, and an intelligence-based clustering of targets. The model then creates operationally feasible assignments of packages to target clusters, maximizing the weighted number of targets detected.

The following Operations Research techniques were used, stochastic optimization and mixed integer linear programming, to accomplish this goal. Using this approach, the allocation or assignment of sensors suggested by the model is robust to uncertainties in sensor performance and available threat information (i.e. location, type and quantity of targets). Other factors taken into consideration include sensor characteristics such as cost, latency, logistical footprint, and survivability.

Assumptions

Several basic assumptions are required for the development of the optimization models. A major assumption is that a certain level of intelligence is available to the UA from other than organic assets (i.e. higher echelons, joint, national, etc); however, this intelligence is assumed static. Additionally for simplicity, it is assumed all sensor platforms are launched from a single location and centrally controlled. However, the model is easily modified to account for multiple launch locations. Also within the UA's Area of Interest, potential search areas are identified and targets within these areas are assumed independent and randomly and uniformly distributed. Target speed is assumed negligible in relation to searcher speed in the case of moving platforms. A final basic assumption deals with consolidated packages and assumes a positive or enhanced capability when platforms are teamed to form the consolidated packages.

Package Consolidation

The following are the defined model levels of sensor aggregation: sensors, platforms, and packages. Sensors are identified as specific technologies or capabilities, such as infrared (IR), acoustic, and radar, and their performance can be measured by a probability of detection at a given range against a specific target type. Platforms have the capability to carry one or more sensors based on size, weight, and payload capacity. UA platforms are further identified as ground or aerial and moving or stationary and consist of such entities as the Unmanned Aerial Vehicle (UAV), Armed Robotic Vehicle (ARV), and Unattended Ground Sensor (UGS).

Finally, packages are defined as combinations of platforms based on the ability of the individual platform to enhance the collective sensing capability or performance of the package. A package consisting of two or more platforms is assumed to perform at least as well as two or more independent platforms. This (potentially) increased performance is the result of a platform's ability to cue another platform assigned to a package configuration and provide a complementary target signature (i.e. sensors working together in a dependent relationship). Figure 5 summarizes the sensor aggregation levels through an example using four sensor types, three platforms, and two packages.

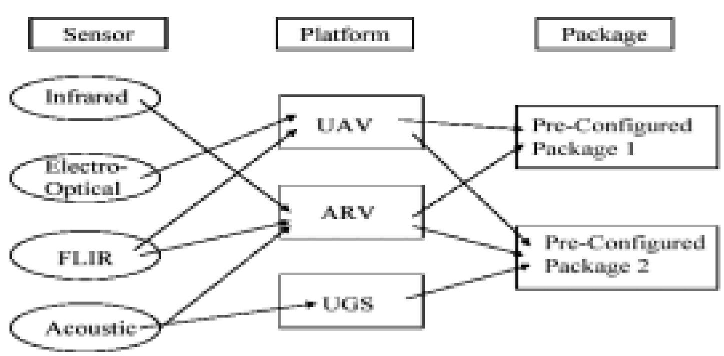

Figure 5. Sensor Aggregation Levels

The Unit of Action has a designated inventory of platforms organic to the unit. Each platform has one or more mounted sensors, and an average performance level based on the underlying platform performance (i.e. velocity, operational time) and sensor performance (i.e. probability of detection against a specific target at a specific range).

Platforms are combined to form pre-configured packages prior to assignment or allocation. Packages consist of a single platform or multiple platforms. Single-platform packages and pre-configured packages containing multiple platforms are referred to as basic packages. Consolidated packages are combinations of basic packages, and are generated automatically.

In a single platform package, the performance of the package is the same as the performance of the platform. When multiple platforms are teamed together and designated as a pre-configured package, a combined platform performance is calculated to determine an overall package performance level. Table 1 illustrates the set of example basic package configurations. Our model explicitly forms consolidated packages based on combinations of the user provided basic packages.

Table 1. Basic Package Configurations

Platform / Package ID	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV	UGS
P1	1					
P2		1				
P3			1			
P4				1		
P5					1	
P6						1
P7	1	1				
P8			1	1		
P9			1		1	
P10				1		1

All packages, basic or consolidated, are considered single entities for employment or allocation purposes. For each package, overall performance is pre-processed for use by the model using, in this case an Excel worksheet. The Sensor Mix Model uses the performance of each package to determine an effective assignment of packages to target clusters.

Target Clustering

The basic assumption that a certain level of information is available to the UA commander through the UE IPB and the CROP, represents the commander's initial intelligence estimate of the situation. Uncertainty still exists in relation to the 'true' or actual locations, type, and estimated number of targets on the battlefield.

Using the intelligence estimate provided to the UA, targets are clustered, or grouped together utilizing the simple Euclidean distance formula. Other more sophisticated techniques can be substituted. Of special note is, the term "target cluster" does not indicate targets are tactically related. Figure 6 provides an example of target clustering on the battlefield.

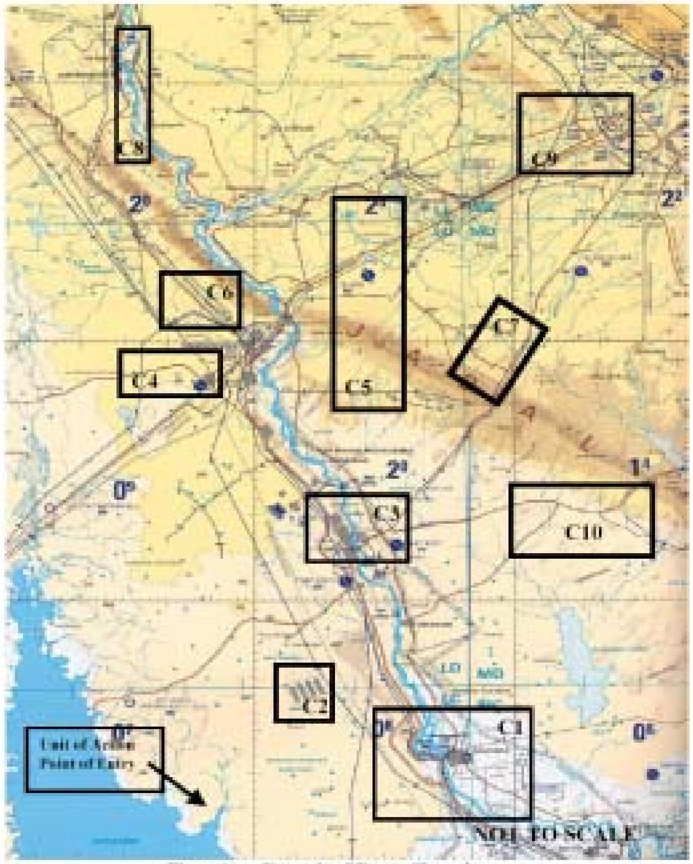

Figure 6. Example of Target Clustering

The number of target clusters in the model was limited to ten for expository purposes. The number of clusters can vary based on user specification, outcome requirements, experimental design, etc. The model utilizes total cluster area, thereby allowing target clusters to vary in size or dimension as defined by the user. Target clusters are then identified by dimension and approximate center grid location within the model. The intelligence represented by Figure 6, is used to complete Table 2, which enumerates the target cluster dimension and location data, and represents a data input into our model.

Table 2. Target Cluster Dimension and Location Data

	Dimensions		Center Grid Coordinate	
Cluster Identifier	Length (km)	Width (km)	X	Y
C1	20	16	4360	3455
C2	20	15	4390	3430
C3	20	10	4375	3457
C4	10	5	4350	3485
C5	5	20	4392	3525
C6	15	10	4353	3505
C7	10	10	4397	3488
C8	5	15	4335	3540
C9	20	10	3520	3530
C10	17	14	3556	3574

METRIC DEVELOPMENT

A set of metrics is needed to represent individual sensor and platform capabilities and performance levels. For ease in calculation and understanding, we partitioned metric development into the same three levels that define the UA aggregate sensor levels: sensor, platform, and package. This framework allows the user to provide inputs and receive outputs at each level and assists in determining overall effectiveness of the desired system or platform allocation strategy.

Aerial and ground platforms have the ability to carry or maintain more than one type of sensor. Current information on UA sensor capabilities and platform configurations is under continual update. Table 3 summarizes the current sensor/platform pairings as identified in the Future Combat Systems Book, Version 1.6. Entries in bold face are the basis for combinations used in this research and the Sensor Mix Model.

Table 3. Possible Sensor/Platform Configurations

Sensor \ Platform	UAV Class I	UAV Class II 1,2	UAV Class III	UAV Class IVa 1,2,3	ARV-RSTA	UGS
Infrared	**640x480**	**640x480**		**yes**		yes
Electro-Optical	**small**	**small**	**medium**	yes	**Mast**	yes
Acoustic		yes	**yes**		**Yes**	**yes**
LWIR			yes	**yes**		
FLIR					**yes**	
LADAR			yes			
Seismic						**yes**
Magnetic						

Additional Capabilities: 1. Ground Moving Target Indicator
2. Synthetic Aperture Radar
3. See Through Foliage

Random Search Theory

The actions and capabilities of the different sensor aggregation levels (sensor, platform, package) are described and modeled by techniques from random search theory. The use of these techniques requires the following assumptions: (1) uniform and random target distribution throughout the search area, (2) the platform track is random but uniformly distributed, and (3) no search effort falls outside the search area (Stone, 1975).

The first assumption is reasonable for the level of detail associated with this model. For example, an enemy armor company defensive posture would deliberately emplace individual tanks in a tactical manner and would not disperse them uniformly over a hundred kilometer square area. However, it is not clear whether non-uniform grouping would increase or decrease the expected number of targets detected. Target clusters and EOBs are aggregate inputs, and this assumption is kept in perspective with the understanding that target location, type, and quantity are not known with certainty.

The second assumption is reasonable if targets are expected to move unpredictably, and the third assumption is reasonable when total search area is significantly larger than the sensor's effective detection range. The decision to use random search theory was based on mathematical simplicity, type and amount of data available, and its ability to provide a lower bound on the effectiveness of a systematic search of a particular area (Stone, 1975). Utilizing random search theory attempts to prevent significant overestimation of the detection capability of UA sensing assets.

Sensor Level Metric

The performance of a sensor is summarized by a function called the lateral range curve (Wagner, 1999). Each sensor detects targets with a certain probability at a certain range resulting in a lateral range curve for each specific sensor/target pair. Figure 7 illustrates a typical lateral range curve. However sensors are not guaranteed to move directly toward a target but pass the target at some lateral range within the sensor's detection zone. Figure 8 illustrates a sensor detection zone.

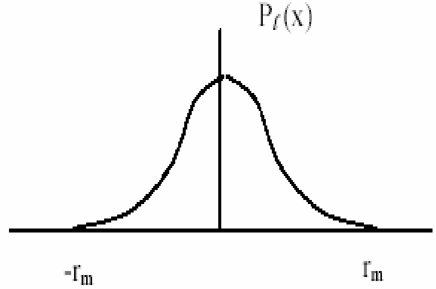

Figure 7. Lateral Range Curve (From Ref. Wagner, 1999)

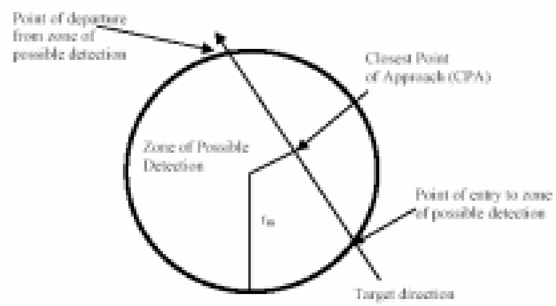

Figure 8. Sensor Zone of Detection (From Ref. Wagner, 1999)

Closely related to the lateral range curve is **sweep width (W)**, a scalar measure of the search effectiveness of a sensor (Washburn, 1996). By definition, sweep width is equal to the area under the lateral range curve and represents the effective width of the sensor detection zone:

$$W = \int_{-r_m}^{r_m} P_l(x)\,dx \qquad (1)$$

Each sensor's performance can be represented as a probability of detection at a certain range against a specific target type. Using equation (1), a sweep width (W) is calculated for each sensor type against each possible target type. These values are used to generate cumulative detection probabilities for other levels of aggregation (see Platform Level Metric section below).

A degree of uncertainty exists in relation to actual sensor performance. Performance level is affected by many different factors such as terrain, weather, battlefield clutter, enemy deception tactics, etc. In order to account for potential variation in sensor performance, four possible outcomes were modeled. Each outcome represented a different level of sensor performance based on several of the factors previously mentioned.

Each outcome also had the possibility of each different EOB occurring. The ability to model this uncertainty assisted in providing a more robust allocation of assets to target clusters. Again, the number of outcomes developed, based on identified uncertainty factors, is not limited to four but determined by the user.

Platform Level Metric

The platform metric is developed in terms of **Cumulative Detection Probability (CDP),** where CDP is the probability that a platform searching for a target over a specific time interval detects that target at least once (Wagner, 1999). Each platform CDP, or performance level, is determined by transit speed, sensing velocity, adjusted sweep width (defined in the next paragraph), and operational time.

Adjusted Sweep Width

When two or more sensors are mounted on a single platform, an adjusted sweep width must be calculated to account for the cumulative sensor capability on the platform. The assumption is made that a platform operates at the optimal altitude for all mounted sensors with the understanding that an appropriate combination of sensors has already been considered for a single platform.

A second assumption is made that sensors are considered cookie-cutter, which means a target is detected the moment it enters the zone of detection and is not detected beyond that range (Washburn, 1996). This does not realistically model sensor performance where detection is certain within a certain radius and impossible outside of that radius. However, the cookie-cutter approximation is a convenient and reasonable device to allow fast, accurate calculation of time-dependent CDP values for various sensor-target pairings.

Multiple sensors mounted on the same platform perform at least at the level of the best sensor and no better than the cumulative sum of all sensors. Summing the individual sweep widths over-estimates the performance of the entire platform and assumes complete independence between multiple sensors on the platform. This is an upper bound. However, considering only the largest sweep width of all sensors underestimates the platform capability, assumes complete dependence, and provides a lower bound on the platform performance. This also indicates no added benefit of more than one sensor on a single platform.

Therefore, an **adjusted sweep width** is calculated by selecting the maximum sweep width (lower bound on sensor performance for the platform) and applying a dependence factor to the remaining cumulative sum of the sweep widths. The resulting equation is:

$$W_{adj} = \underset{s}{MAX}(w_s) + \alpha * \{\sum_s (w_s) - \underset{s}{MAX}(w_s)\} \qquad (2)$$

where w_s represents individual sensor sweep widths, and α is a positive dependence factor indicating added benefit of multiple sensors mounted on a single platform.

The Sensor Mix Model methodology assumes a positive benefit of multiple sensors working in concert. This benefit is due, in part, to the ability of sensors to cue other sensors to specific target locations on the battlefield, and multiple sensors detecting the same target provides a greater level of fidelity in that single detection.

Time on Station

Platform speed and operational time are directly related to platform size, fuel capacity, payload carrying capacity, etc. **Transit speed** is the speed at which the platform can travel to, and return from the search area. During transit, the platform is assumed to have its sensors in a passive mode, where no information is actively transmitted to the CROP. Platform **sensing velocity** is generally less than the platform transit speed and is the velocity at which a sensor is able to provide accurate detection capability at the level of resolution or fidelity required for the CROP. **Operational time** is the amount of time a platform can remain operational, including transit time and search time.

Using the Euclidean distance formula to calculate the distance from the platform launch site to the search area, and taking into account the platform transit speed, and total operational time, an associated **time on station** (time available over the search area) is determined by:

$$\text{Time On Station} = T_{op} - (2 * \frac{D}{V_t}) \tag{3}$$

where T_{op} is total operational time, D is the distance to the search area, and V_t is transit speed.

Coverage Factor

Another important factor in the platform metric calculation is total search area covered. Fixing the total area of a target cluster, platform sensing velocity, time on station, and the adjusted sweep width, a **coverage factor** is determined. This factor is the ratio of cluster area swept by the given platform (Wagner, 1999).

The coverage factor for a particular platform is calculated as follows,

$$\text{Coverage Factor} = \frac{v_s W_{adj} t}{A} \tag{4}$$

where v_s is the platform sensing velocity, W_{adj} is the adjusted sweep width of the platform, t is the time on station, and A is total area of the cluster.

Platform CDP

It has been shown (Wagner, 1999) that the probability of detection of a target by a platform can be expressed as

$$F_d(t) = 1 - e^{-\frac{vW_{adj}t}{A}} \tag{5}$$

Given, that sensing velocity, adjusted sweep width, and the time on station are fixed for a particular platform, expression (5) yields a constant probability of detection. We can model the coverage of a cluster by multiple platforms of the same type by assuming that each individual platform “covers’ an equal proportion of the cluster. It follows, then, that

$$F_d(p) = 1 - e^{-\frac{vW_{adj}t}{A\frac{1}{p}}} \tag{6}$$

yields the probability of detection for *p* platforms searching within the target cluster. This expression is known as the Cumulative Probability of Detection (CDP). Figure 12 shows a graphical example of a CDP.

Package Level Metric

Basic packages are single platforms or combinations of platforms teamed together for various reasons. Teaming platforms has the potential to reduce the number of intervals where targets may be blocked from view and/or multiple signatures of the same target in the search area increase the probability and fidelity of a target detection (Klein, 1993). Consolidated packages are combinations of basic packages. Each package then has an associated overall CDP that is a combination of the individual platform CDPs.

Similar to multiple sensors on a single platform, a package has an overall CDP at least as good as the best individual platform. However, teamed platforms configured into basic and consolidated packages are assumed to have an improved performance level over independently employed platforms.

Summing the individual platform CDPs suggests complete independence and no overlap of search effort, which does not realistically represent multiple platforms over a search area. The high potential in overlap of search effort between platforms implies some type of dependence. However, substituting only the best individual platform performance as the overall package CDP implies the opposite, or a complete dependence between platforms and no added benefit is gained from teaming platforms.

A positive benefit is assumed with package configurations to account for cueing between platforms, enhanced performance, thoroughness of search area coverage, and the improved fidelity of information being processed and transmitted to the CROP.

A CDP is calculated for each individual platform (for each target type) using the platform's sensing velocity, adjusted sweep width, time on station, and area of the target cluster. Figure 9 shows an example of individual performance levels (CDP) for two platforms, if each independently searched target cluster 1.

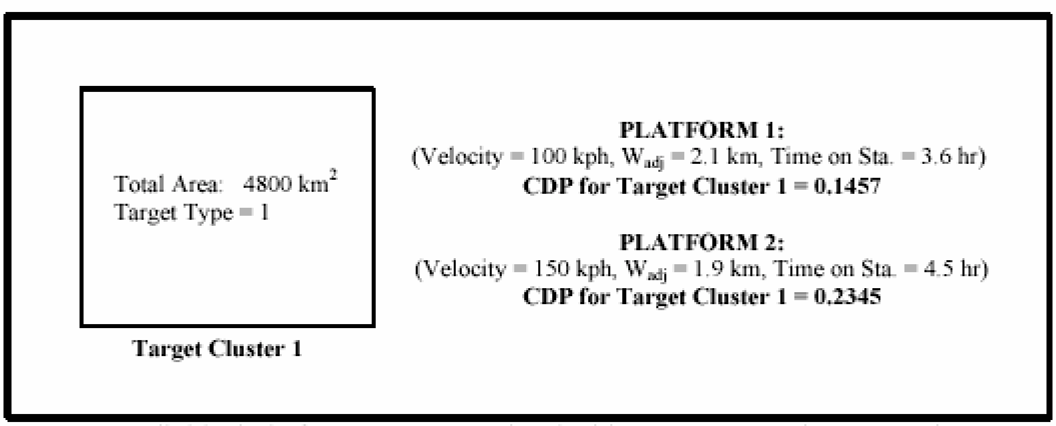

Figure 9. Individual Platform CDPs Associated with Target Type 1 in Target Cluster 1

The goal at the package level is to maximize the minimum CDP of all platforms in the same package and this occurs when all platforms have the same CDP. The proportion of the search area that each platform covers represents an effective distribution of the cluster area for the operating platforms.

Using platform 1 and platform 2 from Figure 9, and designating a package configuration, each platform searches a portion of the total area of the target cluster. Figure 10 shows a possible scenario where each platform is modeled as being responsible for fifty percent of the total area.

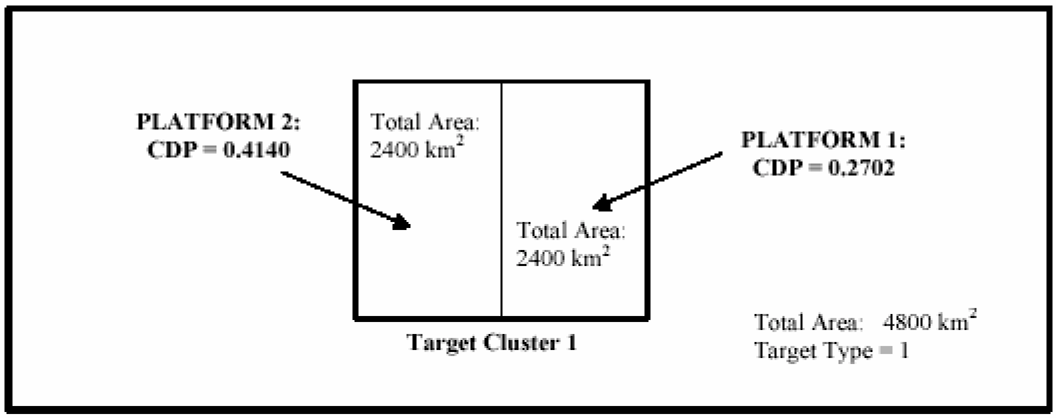

Figure 10. Visualization of Two Platforms Searching a Target Cluster (50% of the Area)

Since we have assumed uniform target distribution, the overall "effectiveness" of this package, then, is the simple average of the two CDPs (0.3421), which represents the expected proportion of all targets detected within the cluster. This is not the most efficient distribution of detection effort of the two platforms, however; the most efficient distribution of detection effort occurs when the minimum CDP is maximized (i.e., the two are equal).

To maximize the minimum CDP, each platform's search rate is calculated using sensing velocity, adjusted sweep width, and time on station. Equation 7 shows the calculation for a platform search rate:

$$Rate = vW_{adj}t \tag{7}$$

Using the search rate for a single platform (equation 7) and the proportion of the target cluster that the platform effectively covers (equation 8),

$$\text{EffProp} = \frac{Rate \text{ (single platform)}}{\sum Rate \text{ (all platforms in the pkg)}} \tag{8}$$

the package CDP is determined.

By determining the proportion of the target cluster effectively covered, the effect is to move the solid center line in Figure 11 (equivalent to the solid line in Fig. 10) to the right or left until all platforms in the package searching the target cluster have the same CDP.

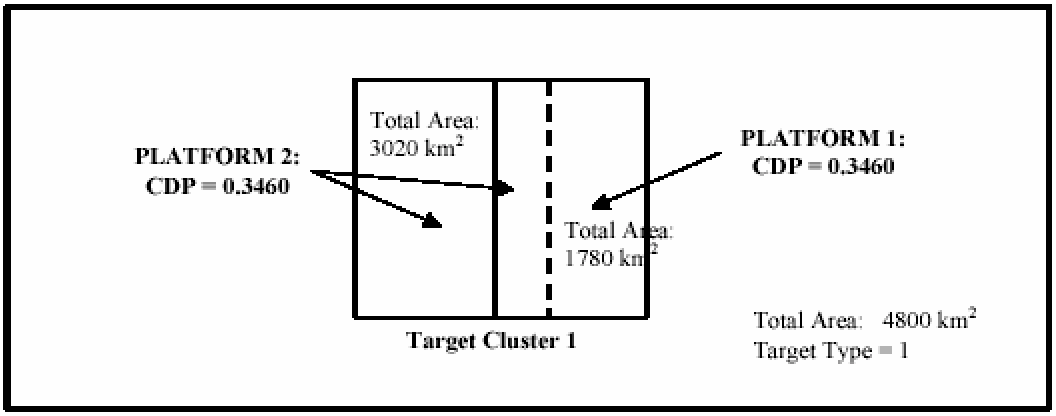

Figure 11. Visualization of Two Platforms Searching a Target Cluster (Effective Proportion of the Area)

Note the overall effectiveness of the package as modeled in Figure 11 exceeds that shown in Figure 10 (0.3460 vs. 0.3421).

The package CDP is determined using the velocity, sweep width, and time on station of *any* platform in the package because each platform has the same CDP once the effective proportion of search area is determined (See Figure 11). The package CDP is calculated using a platform search rate (from equation 6) as follows,

$$CDP_{pkg} = 1 - e^{\left(-\frac{Rate}{A' * \beta_{pkg}}\right)} \tag{9}$$

where *A'* is the total area of the target cluster multiplied by the proportion of the total area effectively covered by the platform (See equation 7) and β_{pkg} is a positive dependence factor associated with a specific configuration of individual platforms designated as a package.

Figure 12 illustrates a CDP curve generated for multiple packages of the same type. As additional packages (of the same type) are allocated to a search area or target cluster the CDP increases asymptotically toward one (probability of detection ≤ 1).

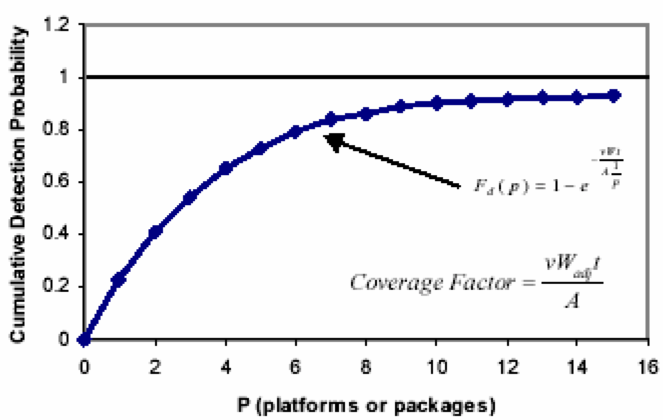

Figure 12. Cumulative Detection Probability Curve

Enemy Order of Battle

Although we assume prior intelligence regarding the Area of Operations, the previously mentioned uncertainty relating to location, type and quantity of targets on the battlefield is represented in the model as a list of potential Enemy Orders of Battle (EOBs). Again, using information from Figure 6 (number of target clusters designated by the user or commander), several EOBs are generated using intelligence available from higher echelons and entered as input to the model. Table 4 shows one possible EOB.

Four potential enemy EOBs were generated for this research to model the uncertainty associated with target location, type and number of entities for each identified target cluster. As with the number of target clusters in the battlespace, the user can specify any number of enemy EOBs to generate based on the experimental design or analysis being considered. Each EOB has a probability of occurrence that the model considers when determining a robust allocation of sensors to target areas.

Table 4. Enemy Order of Battle (sample)

	Estimated Number of Targets By Cluster									
Target Categories	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Rifleman, RPG, SOF	100	12				75				
Tracked Main Battle Tank			5	7						19
Special Purpose Artillery			4			4				
Wheeled Light Transport				6			11		5	
Tracked Armor Vehicle	125									15
Heavy Wheeled Transport					5	2				
Towed Artillery	30								4	
Wheeled Armor Vehicle				6				5		
Engineer Vehicle		4	4				6		7	
Tracked Missile Launcher						10				

System Characteristics

The final piece of the SMM and methodology consists of four identified characteristics associated with each individual sensor, platform, and package. The four characteristics used were cost, logistical footprint, perishability (opposite of survivability), and latency. Each characteristic is calculated at each level of aggregation, and used at the package level to assess the overall characteristics of the suite of packages employed.

The cost characteristic accounts for simply actual system (i.e. sensor and platform) replacement cost in dollars. Logistical requirement include transportation requirements from actual equipment (hardware) deployment into theater to platform transport throughout the theater of operations. Perishability is associated with the likelihood that a sensor or platform will be damaged or destroyed through enemy action or equipment failure before mission accomplishment. And, finally latency defines a sensor's response time.

System characteristics in the four categories were simply ranked from least to most. Extensive research and effort was not concentrated to characteristic development because many of the sensors, platforms, and systems are still in production and testing phases. The model currently allows the analyst or user to develop up to four characteristics and provide inputs representing the values or weights.

The SMM allows the analyst or decision maker to provide a relative weighting to each characteristic category according to importance in the scenario or outcome. The objective function of the SMM incorporates these characteristics by minimizing their effects while maximizing expected number of targets detected in the search area.

MIXED INTEGER PROGRAMMING MODEL

The Sensor Mix Model is further characterized as a mixed-integer program (MIP). In a MIP, both continuous and integer variables are required to describe, quantify and qualify the inputs and states of the model.

Accurately modeling the sensor/platform-to-target allocation requires the use of non-linear functions to determine the expected probability of target detection. Difficulties arise in attempting to model or incorporate these non-linear measures of effectiveness into a linear optimization model.

In order to overcome the non-linearities, the solution was to enumerate a reasonable number of consolidated packages based on identified basic package configurations (see Table 1). Performance measures for these consolidated packages were pre-computed and provided as inputs for the model. For simplicity of example, this model enumerated only consolidated packages with up to two copies of up to two basic packages, resulting in 175 available consolidated packages for consideration in the model. At this point the MIP solves the optimization problem using integer decision variables that represent the assignment of packages to target clusters.

CURRENT DATA

Data currently available via Army Materiel Systems Analysis Activity (AMSAA) sources provides a lateral range curve and probability of detection for a particular sensor against a specific target type at a specified range. Table 5 provides a notional example of AMSAA data.

Table 5. Example of Sensor Data for Notional Sensor A Detecting Notional Target Type 1

Sensor Type: Sensor A	Target Type: Target 1
RANGE	**Probability of Detection**
100	0.954
200	0.943
300	0.907
400	0.876
500	0.854
600	0.791
700	0.723
800	0.643
900	0.532
1000	0.432
1100	0.310
1200	0.291
1300	0.121

Data similar to Table 5 provides the performance measure for individual sensors. However, performance measures for platforms carrying multiple sensors and consolidated packages (combinations of platforms) are currently unavailable. Using notional sensor performance data and platform performance (sensing velocity, time on station, etc), package performance levels were determined using random search theory, as described earlier.

MODEL DESCRIPTION

The discussion of the Sensor Mix Model is divided into two main parts, the Sensor Allocation Model (how 'best' to allocate or assign a given set of sensors to target clusters), followed by the Sensor Mix Model itself (what is the 'best' mix of sensors for a given tactical scenario). Both models use many of the same parameters, inputs, and variables and are defined and described in the following sections. An additional set of constraints is defined for use in the Sensor Mix Model and a second integer decision variable is introduced.

Sensor Allocation Model

This section describes an optimization model that, given a fixed inventory of sensor platforms available, suggests an appropriate assignment of sensor packages to target clusters on the battlefield. The key decisions in the Sensor Allocation Model are which consolidated packages, and how many of each, should be assigned to each target cluster.

The mixed-integer program makes the best overall allocation of packages based on the mix available, taking into account the characteristic weightings of each package, target type weights, and sensor/platform performance. The decision variables for the Sensor Allocation Model are integer and indicate how many sensor packages of a certain type to allocate to a target cluster.

Indices

The indices used to define this model are:

p platform type {'UAV', 'ARV', 'UGS',...}
k package configuration {'K1', 'K2', 'K3',...}
t target type {'INF', 'Main Battle Tank', ...}
c target cluster {'C1', 'C2', 'C3',...}
ch sensor characteristic {'latency', 'cost', 'logistics', ...}
w outcome_scenario {'W1', 'W2', 'W3', ...}
eob enemy order of battle {'EOB1', 'EOB2', 'EOB3', ...}
n number of packages of type *k* to cluster *c* {' N1','N2', ..., 'N10'}

Individual targets of type *t* are identified as being in one of ten target categories for the example in this thesis. The number of target categories can vary based on the user and desired results.

Parameters

The parameters used to define the data for this model are:

Asset Data

$\text{plat\_pkg}_{p,k}$ number of platforms of type required for one package of type
p_avail_{p} number of platform of type *p* available (inventory)
$\text{pkg\_char}_{k,ch}$ value of package *k* contribution to each characteristic *ch*
$\text{cdp}_{c,t,k,w}$ Cumulative Detection Probability for package *k* against target type *t* in cluster *c* in outcome *w*

Table 6 shows the inventory level of organic UA platforms available for mission requirements.

Table 6. Unit of Action Sensor Platform Inventory (From Ref. ORD, 2002).

	Platform Type					
	UAV Class I	UAV Class II	UAV Class III	UAV Class IVa	ARV-RSTA	UGS
Inventory Level	54	36	12	27	27	99

Target Data

$num\_tgt_{t,c,eob}$ number of targets of type t in cluster c for a specific eob

Parameter Weights

wt_tgt_{t} value of detecting target type *t*
wt_char_{ch} platform characteristic weights
pr_eob_{eob} probability of a specific *eob* occurring
pr_out_{w} probability of a specific *w* occurring
alpha_det overall weight for expected targets detected portion of the objective function

alpha_char overall weight for characteristic portion of the objective function

Derived Data

cdpe $_{c,t,k,w,n}$ Cumulative Detection Probability Enumerated for *n* packages of type *k* against target type *t* in cluster *c* in outcome *w*

The model inputs are CDPs (indexed by target cluster, target type, package, and outcome) for one package, and the MIP precomputes the CDPs for assignment of up to ten packages of a single type assigned to a target cluster against a specific target type and indexes them by *n*.

DECISION VARIABLES

Unrestricted continuous variables in the model:

CH_OBJ $_{ch,w}$	value of characteristic weights over all packages assigned to all clusters for an outcome *w*
EXP_TGT $_{t,c,w}$	expected number of targets detected by target type *t* in cluster *c* for outcome *w*
OBJ	objective function value

Integer variables in the model:

KTOC $_{c,k,w}$	Integer Variable: number of packages of type *k* assigned to cluster *c* in outcome *w*

Binary variables in the model:

$$\text{IND\_VAR}\ c,k,n,w = \begin{cases} 1 & \text{if } n \text{ packages of type are assigned to cluster } c \text{ in outcome } w \\ 0 & \text{otherwise} \end{cases}$$

The key decision variables in the Sensor Allocation Model are integer and allow for the selection of which consolidated packages, and how many are assigned to each target cluster.

CONSTRAINTS

The model requires two main constraints. The first constraint set ensures that only one package type (regardless of configuration) is assigned to a target cluster.

$$\sum_{k,n} IND\_VAR_{c,k,n,w} \leq 1; \qquad \forall w, c$$

$$KTOC_{c,k,w} = \sum_{n} ord(n) * IND\_VAR_{c,k,n,w} \qquad \forall c, k, w$$

The second constraint ensures that only available platforms are used:

$$\sum_{c,k} plat\_pkg_{p,k} * KTOC_{c,k,w} \leq p\_avail_p; \qquad \forall p, w$$

The next two constraints calculate terms in the objective function.

$$EXP\_TGT_{t,c,w} = \sum_{eob,k,n} num\_tgt_{c,t,eob} * wt\_tgt_t * pr\_eob_{eob} * cdpe_{c,t,w,k,n} * IND\_VAR_{c,k,w,n}$$

$$CH\_OBJ_{ch,w} = \sum_{c}\sum_{k} KTOC_{c,k,w} * pkg\_char_{k,ch} * wt\_char_{ch,w}$$

The final constraint defines the objective as a weighted combination of expected, weighted targets detected and weighted sensor characteristics.

$$OBJ = alpha\_\text{det} * EXP\_TGT_{t,c,w} - alpha\_char * OBJ\_CH_{ch,w}$$

OBJECTIVE FUNCTION

The objective in this model is to maximize the weighted combination of expected number of weighted detections and overall sensor characteristic penalties.

RESULTS

We implemented the model using GAMS with CPLEX as the solver. The results for the model using 10 basic packages uniquely configured into 175 consolidated packages and allocated to 10 target clusters over 4 enemy order of battles, are given in Table 7.

Table 7. Model Results

	CPLEX (version 7.5)
Presolver	417 rows and 23,481 columns eliminated
Problem Size	5528 rows, 52400 columns, 115080 nonzeros
OPTCR = 0.05	< 10 seconds
OPTCR = 0.0	< 10 seconds

(175 Packages versus 10 Target Clusters, 4 EOBs and 10 Target Categories)

CPLEX applies a ‘presolve phase,’ which reduces the size of the MIP. The parameter OPTCR is a relative measure of optimality, and provides a bound on how far from the best possible answer the solution is (OPTCR = 0.05 requires the solution to be within 5% of optimal). The smaller the OPTCR, the more time needed for the solver to find a solution.

Table 8 is an example of Sensor Allocation Model output. For example, the SAM allocated three copies of package 1 to target cluster 1 and two copies of package 1 to target cluster 3. Table 9 breaks down the assignment of consolidated package 118 to target cluster 4 into basic package components and total assets allocated.

Table 8. Sensor Allocation Model Sample Output

Package ID \ Clusters	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
P1	3		2							
P17		5								3
P25					10				1	
P97						4				
P10							2	7		
P118				4						

Table 9. Assignment of P118 to Target Cluster 4

Assignment \ Basic Pkg	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P118			2					1		

Consolidated Package 118:

Basic Package Combinations: (See Table 1)
Package 3: UAV Class III x 1
Package 8: UAV Class III x 1
UAV Class IVa x 1
Total Assets Allocated to Cluster 4:
UAV Class III x 8
UAV Class IVa x 4

CONCLUSIONS

This research has resulted in the development of a model for optimally allocating sensor packages to target clusters on a battlefield A sensor package consists of a combination of platforms each carrying one or more sensors. The model ensures that platforms have sufficient range, time on station, and performance level for each enemy order of battle per target cluster so the maximum expected number of target detections occurs.

The Sensor Allocation Model, with a fixed mix or inventory- of sensor platforms, allocates consolidated packages to target clusters. The model takes into account uncertainties in sensor performance and uncertainties in target location, type and quantity. The model precomputes values for what would otherwise be non-linear model components (e.g. consolidated package performance for expected target detections).

Integer variables represent the assignment of consolidated packages to target clusters resulting in a mixed integer linear program. An instance of the allocation model, with 10 basic packages, 10 target clusters, 4 enemy order of battles and 175 consolidated packages solved in less than ten seconds on a Pentium III processor.

RECOMMENDED MODEL REFINEMENTS

Data Improvements

Classified sensor data is available from AMSAA sources. The AMSAA data was reviewed to determine type and format available and a surrogate data set was generated to mirror the classified data and to develop our models. The assumption was made in development of the optimization models that platform and package performance data would become available as further experimentation and research is conducted. The availability of such data would eliminate the need to surrogate the data in ways such as those described in Chapter 3, Section I (Metric Development) and in paragraph 2 (Dependence Factors) below. As additional sensor platform and package data becomes available, additional refinements and improvements to the models will be required.

Dependence Factors

The combination of sensors mounted on a single platform assumed a positive, or enhanced, overall platform performance. This positive dependence factor was applied to all sensor combinations. Further research may indicate that multiple sensors mounted on the same platform do not enhance performance in all situations and may possibly cause degradation in platform performance in some instances.

In similar fashion, combinations of platforms to form basic and pre-configured packages also assumed an enhanced performance level. Additionally, no particular criteria were used in determining basic pre-configured packages. The development of a methodology to optimize over individual platform performance to develop optimal package configurations should be considered for refining the model’s package performance metric.

VV&A

Verification, Validation, and Accreditation have not been conducted on this model. TRAC-Monterey is in the process of developing the Dynamic Allocation of Fires and Sensor (DAFS) simulation. The output from the SAM can be used as input to the DAFS model. Validation would be accomplished by comparing the performance (in DAFS or other simulations) of sensor allocations suggested by the SAM to those derived by other means.

Target Clustering

The manner in which target clusters were identified for the model is perhaps too simplistic. Target clusters were based on proximity to nearby targets on the battlefield. A more effective method of clustering targets may include a statistical algorithm that groups targets by similarities or dissimilarities based on a series of inputs. A more refined method of identifying search areas and grouping targets could be incorporated to improve the model.

Sensor Characteristics

Four sensor characteristics (logistics, cost, perishability, latency) were identified through discussion and review of several Objective (Future) Force documents. The descriptions used for these terms are rather nebulous and difficult to quantify in meaningful measurements. As the Objective (Future) Force concept continues to develop, additional characteristics or methods to quantify the impact to operations can be identified and incorporated into the model.

SUGGESTED FURTHER RESEARCH

Many possibilities can be pursued to extend the model presented in this research. This study only addresses the allocation of organic Unit of Action sensor assets. However, our basic methodology easily adapts to echelons above or below the UA level. Minor modifications are needed to include joint assets at the higher echelons, and different mission requirements at both levels would have to be considered.

Another more challenging project would be to create a dynamic model significantly improving the utility of the Sensor Allocation Model. There are two components for consideration in the development of a dynamic model. The inclusion of multiple time periods would take into account equipment or platform resupply, attrition rates, maintenance, follow-on missions, and new launch sites.

The second more difficult component would involve the allocation of a package to a higher priority or just-identified target area. This reallocation would also apply to reallocation to a secondary target area if the allocation to the original target area was no longer required (i.e. mission change, combat damage assessments show target area clear, etc).

Further extensions of the model would allow for consolidated packages to search multiple target areas. This could be modeled based on a prioritization of target clusters and involve platform time on station. A more difficult scenario would allocate a consolidated package to search a primary target cluster, then “decompose” the consolidated package into basic package configurations. The resulting basic packages would then be reconsolidated into newly formed consolidated packages and optimized for allocation to secondary target clusters. New variables will be necessary to indicate package location, remaining time on station, and distance to secondary search area.

LIST OF REFERENCES

"Concepts for the Objective Force." United States Army White Paper, 2002.

"Fusion Concept Development." [FCD] briefing, February 2003.

"Future Combat System Development." [FCSD] March 1999. Online. Internet. 17 March 2003. Available: http://www.fas.org/man/dod-101/sys/land/fcs.htm.

"Joint Vision 2020." United States Army White Paper, 2000. Online. Internet 06 June 2003. Available: http://www.dtic.mil/jointvision/jv2020.doc.

Klein, Lawrence A., Sensor and Data Fusion Concepts and Applications, Volume TT 14, 1993.

McCarl, Bruce A., GAMS User Guide, 15 December 2002.

"Mission Needs Statement for FCS." [MNS], 31 October 2002.

Objective Force Organization & Operational Concept for the Unit of Action. [UA O&O] Change 1 to TRADOC Pam 535-3-90, 25 Nov 2002.

Operational Requirements Document for the Future Combat Systems. [ORD] Change 1 Final, UAMBL, Fort Knox, KY, 25 Nov 2002.

Rardin, Ronald., Optimization in Operations Research. 1998.

Stone, Lawrence D., Theory of Optimal Search, 1975.

"The Army Vision." 1999. Online. Internet. 26 May 2003. Available: http://www.army.mil/Vision/Documents/OjectiveForce.ppt.

"UAMBL Overview Briefing." [UAMBL]. United States Army Mounted Battle Lab, July 2002.

Wagner, Daniel., Naval Operations Analysis., 3rd Edition, 1999.

Washburn, Alan R., Search and Detection, 3rd Edition, 1996.