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Tactical decision aid for unmanned vehicles in maritime missions

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TACTICAL DECISION AID FOR UNMANNED VEHICLES IN MARITIME MISSIONS

by

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March 2005

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TACTICAL DECISION AID FOR UNMANNED VEHICLES IN MARITIME MISSIONS

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ABSTRACT

An increasing number of unmanned vehicles (UV) are being incorporated into maritime operations as organic elements of Expeditionary and Carrier Strike Groups for development of the recognized maritime picture. This thesis develops an analytically-based planning aid for allocating UVs to missions. Inputs include the inventory of UVs, sensors, their performance parameters, and operational scenarios. Operations are broken into mission critical functions: detection, identification, and collection. The model output assigns aggregated packages of UVs and sensors to one of the three functions within named areas of interest. A spreadsheet model uses conservative time-speed-distance calculations, and simplified mathematical models from search theory and queuing theory, to calculate measures of performance for possible assignments of UVs to missions. The spreadsheet model generates a matrix as input to a linear integer program assignment model which finds the best assignment of UVs to missions based on the user inputs and simplified models. The results provide the mission planner with quantitatively-based recommendations for unmanned vehicle mission tasking in challenging scenarios.

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LIST OF ACRONYMS

AAW	Anti-Air Warfare
AO	Area of Operations
C4ISR	Command, Control, Communications, Computers, Information, Surveillance, Reconnaissance
CCOI	Critical Contact of Interest
CDP	Cumulative Detection Probability
COI	Contact of Interest
CPA	Closest Point of Approach
CSG	Carrier Strike Group
CWC	Composite Warfare Commander
DOD	Department of Defense
ESG	Expeditionary Strike Group
FOV	Field of View
FP	Force Protection
ID	Identification
LCS	Littoral Combat Ship
MIO	Maritime Interception Operations
MOE	Measures of Effectiveness
MOP	Measures of Performance
MUAV	Micro-Unmanned Aerial Vehicle
MUVAM	Maritime Unmanned Vehicle Allocation Model
NAI	Named Area of Interest

NEO	Non-combatant Evacuation Operations
NMETL	Navy Mission Essential Task List
OFT	Office of Force Transformation
RHIB	Rigid Hull Inflatable Boat
RMP	Recognized Maritime Picture
SSC	Surface Search and Coordination
SUAV	Small Unmanned Aerial Vehicle
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle
USW	Undersea Warfare
UUV	Unmanned Underwater Vehicle
UV	Unmanned Vehicle
VTUAV	Vertical Takeoff Unmanned Aerial Vehicle

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EXECUTIVE SUMMARY

This thesis develops an analytical planning aid for allocating UVs to missions then generates data using a spreadsheet model incorporating a random search model and a M/M/k/k loss model, and then solving a linear integer program assignment model. The results are recommendations for unmanned vehicle mission tasking in tactically challenging scenarios.

The Department of Defense and the United States Navy have placed a priority on developing, testing, and implementing unmanned vehicles (UVs) in operations. At the tactical level, this translates to the introduction of more UVs to Expeditionary and Carrier Strike Groups (ESG/CSG). An action officer within the ESG/CSG responsible for allocating UVs will have a challenging task and will benefit from a tactical decision aid that can assist in the planning.

The recognized maritime picture (RMP) is a plot of maritime activity within a defined area supported by search and detection, identification and collection missions. Measures of performance such as probability of detection, percentage of identifications, and collection missions accomplished are quantifiable metrics used to determine the effectiveness of effort expended for these missions.

This research has resulted in a model that provides mission assignment recommendations for UVs conducting RMP missions. The Maritime UV Assignment Model (MUVAM) consists of three parts, the Input Model, the Matrix Generator, and the UV Assignment Program. The Input Model collects operational user inputs on mission types, priority and location, ships in the strike group, UVs on ships, sensors on UVs, and UV locations. The Matrix Generator is a spreadsheet model that uses conservative time-speed-distance calculations, and simplified mathematical models from search theory and queuing theory to calculate measures of performance for possible assignments of UVs to missions. The spreadsheet model generates a matrix as input to the UV Assignment Model, which is a linear integer program to find the best assignment of UVs to missions

based on the user inputs and simplified mathematical models. The MUVAM results are considered recommendations for UV mission planner.

Scenarios common to ESG/CSGs operating overseas were developed in order to exercise the model in circumstances that are a reasonable approximation of real problems. Scenarios include: a heavy traffic scenario, requiring detection and identification, a target rich scenario requiring identification and collection, and a rare high-priority event scenario requiring detection and collection. Results showed that the model provided sensible assignment recommendations to the mission planner in all cases. Further research should include actual test and evaluation with fleet assets, using real data to develop performance parameters that were surrogated in the model, and enhancing the model to address operational availability, maintenance, follow-on operations, re-tasking, and other complexities affecting real-world operations.

I. INTRODUCTION

A. MOTIVATION

The Department of Defense and the United States Navy have placed a priority on developing, testing, and implementing unmanned vehicles (UVs) in operations and set goals for a variety of topics including platforms, sensors, and the intelligence collection process (Roadmap, 2002). The Department of Defense Office of Force Transformation (OFT) envisions future combat systems engaged in fighting first for information superiority and values networking, sensing, and staying power (OFT, 2002). One way of applying these strategic objectives to the tactical level of the Expeditionary or Carrier Strike Group (ESG/CSG) is to examine the use of UVs in developing the recognized maritime picture (RMP).

The broad objectives cited by the OFT, with respect to information superiority, sensor reach, networking and staying power, translate directly to the tactical level. An ESG uses its assets and sensors to develop a common operational picture, also referred to as the recognized maritime picture. The RMP is essential to joint operational planning for maritime operations. This paper focuses on the allocation of unmanned vehicles to support a RMP developed by the ESG/CSG.

An RMP is a plot of maritime activity, within a defined area, that has been evaluated and disseminated to individual units within the area and up to the operational command. Functions that support RMP development include search, identification, and collection missions. A quality or complete RMP is measured by, but not limited to, the percentage of area covered by sensor, percent of correct identifications, time to resolve identification conflicts, and time from intelligence requirement satisfied to reallocation of asset. The use of such measures of performance (MOPs) listed in the Navy Mission Essential Task List (NMETL) provide a quantifiable metric to assess how effective search, identification, and collection efforts are (NMETL, 2001).

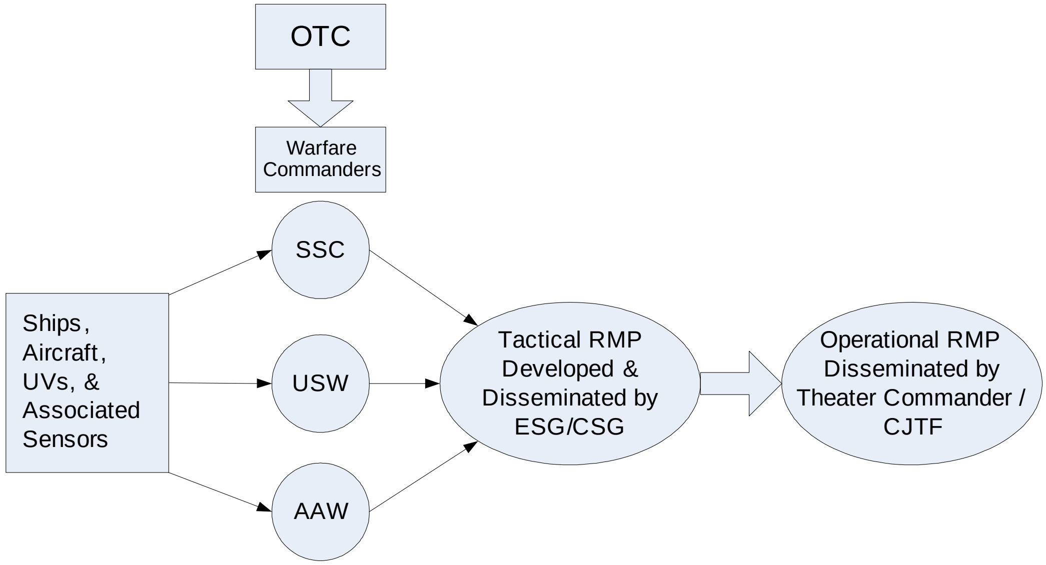

Figure 1. RMP Hierarchy

UV technology is advancing rapidly as previous assets for maintaining an accurate RMP are declining. No fewer than sixty-seven companies or government organizations are developing Unmanned Aerial Vehicles (UAV) (UAV Forum, 2004). The DoD has over 90 UAV's operating with deploying forces and have four times as many programmed for 2010, with projected spending increases from $1 billion to $10 billion (Roadmap, 2002). With the rapid influx of UVs into force operations, it is more difficult to plan missions; therefore a systematic planning methodology is desirable.

B. PROBLEM STATEMENT

More UVs will participate in maritime operations for development of the RMP as organic elements of the ESG/CSG. Whether there is a UV warfare commander as part of the Composite Warfare Commander concept (CWC), or merely a UV element coordinator (UVEC), an action officer within the ESG/CSG will be responsible for allocating UVs in their support of developing the RMP. As a prospective action officer on an ESG/CSG staff, I present the following questions:

(1) What is the best way to employ organic UV assets to support RMP development?

(2) What is the additional planning burden?

C. COMPOSITION

1. Overview

The U.S. Navy's deploying forces transformed from traditional Carrier Battle Groups to Carrier and Expeditionary Strike Groups in 2003. The advent of the ESG/CSG changes the composition of groups of ships and increases the flexibility and responsiveness of expeditionary forces (ESG, 2005). The theater commander or Joint Task Force Commander (JTF), through the Joint Force Maritime Component Commander (JFMCC), requires an accurate representation of maritime operations.

The recognized maritime picture (RMP) is an equivalent term for the common operational picture provided by the ESG/CSG. One of the most valued resources in developing the RMP has been the use of aircraft organic to the ESG/CSG. The introduction of UVs can reduce the demand for manned aircraft if UVs are used to their utmost capability, and their numbers increase. As more UV assets become available, expectations and planning burdens increase. A decision aid that handles large and small numbers of UVs, over a variety of functions and missions, is desirable now and for the future.

2. Force Structure

A typical ESG may be composed of six ships, a large deck amphibious assault ship, LHD or LHA, an amphibious transport dock (LPD), a dock landing ship (LSD), one Aegis cruiser (CG), one Aegis destroyer (DDG), and one LCS (ESG, 2005). For the purpose of this analysis, each ship is assigned a number of UVs which may include Micro-UAVs (MUAV), small UAVs (SUAV), UAVs, vertical takeoff UAVs (VTUAV), and USVs. This study is generic and flexible to allow for future systems, and therefore focuses on UV performance characteristics rather than a specific UV in current or proposed operation.

In a typical scenario, ships within the strike group are assigned a number of UVs. The UVs are classified by type, such as MUAVs, SUAVs, etc. The ships also have a number of sensors for operation on at least one type of UV. Therefore, UVs and sensors can be used in multiple configurations, achieving different capabilities. Although UVs and sensors are described in general terms, some configurations are not compatible with each other for reasons such as size compatibility. For example, Dragon Eye, a Micro-UAV currently in production has total flying weight of 5 pounds. Radar equipment mounted in larger UAVs weighs over 100 pounds (Dragon Eye, 2005). Therefore, an MUAV with radar is not considered a potential UV-sensor configuration.

The scenarios used for this model center on a forward-deployed ESG. The ideal user of this decision aid is an action officer on the ESG staff, in charge of unmanned vehicle operations. Whether there is a UV warfare commander as part of the Composite Warfare Commander concept (CWC), or merely a UV coordinator, this paper assumes that somebody is assigned to coordinate UV allocation and employment. The alternative to these two scenarios is platform-centric (TACMEMO, 2004). Ships are responsible for their warfare areas and use their organic assets to fulfill their warfare missions. This study assumes the group-level resource allocation where the ESG staff monitors and assigns missions for UV controllers to execute. The force-wide responsibility to provide an accurate and appropriate RMP to the operational commander requires adequate oversight on the employment of UV assets.

3. Functions and Missions

Functions and missions critical to RMP development are divided into three categories in this model. They are search and detection, identification, and collection. Detections require assets with sensors to search over a defined area to detect previously "unseen" contacts. Detection for surveillance purposes is "the determination and transmission by a surveillance system that an event has occurred," (Joint Pub 1-02).

Identification is "the process of determining the friendly or hostile character of an unknown detected contact." Collection includes missions such as battle damage assessment (BDA), targeting, and tracking or "birddogging."

> BDA – the timely and accurate estimate of damage resulting from the application of military force, either lethal or non-lethal, against a predetermined objective...
>
> Targeting – the process of selecting and prioritizing targets and matching the appropriate response to them, taking account of operational requirements and capabilities...

Tracking – to point continuously a target-locating instrument at a moving contact (Joint Pub 1-02)

Chapter II details these functions, their performance measures, and a description of the categorization. RMP development includes all the elements of these three categories. A robust resource allocation aid should be able to find the best apportionment of UVs across challenging scenarios, such as heavy traffic, target rich or high interest collection situations.

D. SCENARIOS

1. Heavy Traffic

High density traffic is often a function of geography, such as choke points or shared economic zones for fishing or trade. Examples of such zones an ESG may transit include the Strait of Gibralter, the Strait of Hormuz, or the Strait of Mallacca. High density traffic may also be the result of common access to a large seaport. A scenario considered for this analysis is an ESG transiting through the Strait of Hormuz, north through the Arabian Gulf (Persian Gulf) for tasking such as Marine debarkation into Iraq/Kuwait, and/or non-combatant evacuation operations (NEO).

Figure 2. Map of the Arabian (Persian) Gulf (from www.Expedia.com)

A number of threats exist for an ESG transiting from the Strait of Hormuz to the Northern Arabian Gulf (NAG). Although there are no existing hostilities between the U.S. and Iran, the coexistence of the two navies in a confined body of water is a threat. More likely is the threat of swarm tactics from small craft (GS-Threat, 2002). Vulnerability exists during the transit through the straits and in the NAG in the vicinity of the major ports due to the potential for hostile craft to blend in with commercial and recreation vessels. Safeguarding the ESG while transiting, debarking, and embarking Marines and non-combatants (NEO) is dependent on detecting and identifying as many contacts as possible in a high traffic area. This requires the discovery and sorting of contacts, contacts of interest (COI), and critical contacts of interest (CCOI).

Within the ESG's area of operations (AO), named areas of interest will be designated (NAI). In this analysis, NAIs not only divide up the AO, they are initially broken down by the mission category required by each NAI. For example, a high traffic scenario within the AO will consist of NAI requiring search and detection (SD) missions, and others requiring identification (ID) missions, referred to as NAI-SD and NAI-IDs, respectively. This distinction organizes the problem and facilitates the modeling application.

The high traffic scenario focuses on detection and identification missions. A typical ESG formation features the highest value unit, the LHD in this case, in the center, the LPD and LSD astern, and the combatants sectored 8 nm around the LHD. Although a narrow passage operation may require ships in a group to transit in a tighter formation, this scenario maintains nominal separation to avoid oversimplifying the allocation problem by reducing all the ship platforms to a virtual single launch point of the UVs. NAI-SDs and NAI-IDs are designated throughout the AO.

Figure 3 is a visual representation of an ESG, its AO, and potential NAI designations in a high traffic scenario. The AO is divided into NAI-SDs and NAI-IDs as shown in Figure 3. Six equal NAI-SDs are designated because search and detection assets are required and the areas are beyond the ships' organic sensors. The immediate area around the ESG out to 35 nm is deemed the vital area and is presumed to be within the group's organic surface search radar range. Detections have been made in the vital area, but identifications are required. The rest of the southern NAI-ID and the northern NAI-ID designated as such because they represent a transit lane, a coastal region, or a threat axis where detections have been made by inorganic assets. Despite detection by assets inorganic to the group, the contacts and COIs require identification by the ESG, in order to develop its RMP and ultimately safeguard itself while executing its primary mission.

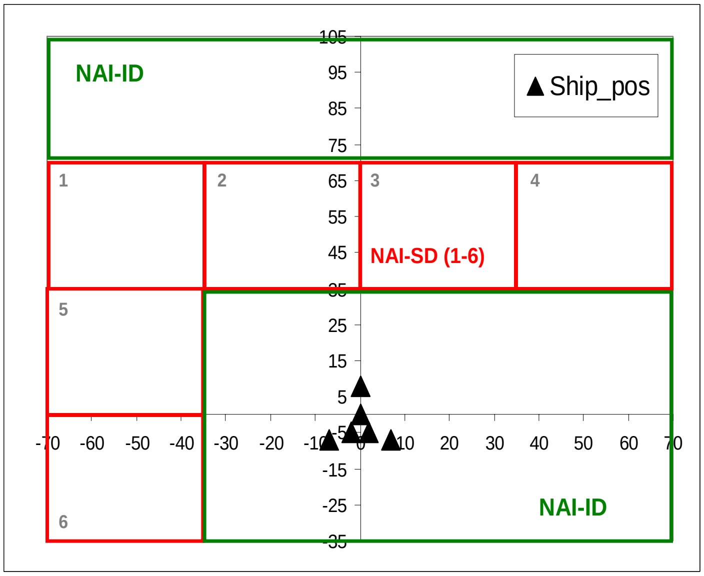

Figure 3. Heavy Traffic Scenario

2. Target Rich

The second scenario is a target rich environment the ESG potentially faces prior to an amphibious landing, when stationed in support of troops already on the beach, or other situations when it remains on station. This scenario reflects recent examples such as forces maintaining station in the northern Arabian Gulf to debark Marines, supporting Marines already debarked, or executing Maritime Interdiction Operations (MIO) (Tarawa, 2005).

Target rich does not equate to all COIs and CCOIs being hostile. It refers to a scenario in which most contacts have been detected, but require identification or collections of opportunity. The commander requires insight into contact intentions to establish the force protection posture for the stationary ESG. The threat should be identified, monitored, and mitigated or prosecuted rapidly, if necessary.

In this scenario, the focus is on identification and collection missions. The ESG formation is relatively static. If there is a specific threat axis, the combatants may be placed between the high value units and the threat. However, in this scenario, it is desirable to examine how large an area can be covered under the target rich conditions. Therefore, NAIs are omni-directional from the defended assets. The scenario consists of COIs in NAI-IDs and CCOIs in NAIs where collection opportunities are expected, referred to as NAI-CPs.

3. High Priority Rare Events

The third scenario consists of multiple NAI-SDs requiring search and detection assets and NAI-CPs with infrequent or rare events. This scenario is the potential progression from the target rich scenario. Most contacts, COIs and some CCOIs have been identified. Now, assets must be made available for high priority collection missions, at a moments notice, despite the infrequency of the collection missions. The ESG disposition and UV asset availability remain consistent in this scenario with respect to the previous two.

Search assets should be operating to detect the as yet unseen COI or CCOI. A planning balance must be achieved. CCOIs must be located before a mission can be launched towards it. If insufficient assets are allocated to searching for the CCOI, then the mission can never be executed. If too many are assets are allocated for search and detection, with the wrong configuration of sensors, collections might not be accomplished despite previous detection and identification.

Table 1 depicts the breakdown of mission categories and the scenarios described. Specifically, it shows the priority of mission category for each scenario an ESG faces when developing the RMP.

Scenario	Mission Category		
	Detection	ID	Collection
Heavy Traffic	X	X	
Target Rich		X	X
Rare High Priority Events	X		X

Table 1. Mission Category vs Scenarios

E. PURPOSE AND SCOPE

The purpose of this thesis is to develop a decision aid, to be used by the ESG/CSG staff, for UV mission allocation, enhancing employment of available UVs to provide broader coverage, and relieving the action officer of a portion of the planning burden. Because force-wide measures of effectiveness are quantifiable, once the success of a UV mission is calculated, an assignment model uses the UV mission data to generate an employment plan. This model answers the operator's questions while addressing the following analysis questions:

(1) What quantity of UVs and missions create a planning burden?

(2) How sensitive is the model to the measures of performance associated with the assets?

The scope of this work is limited to UAVs and USVs. Although UUVs are being developed, the underwater environment is beyond the scope of UV missions being studied (TACMEMO, 2004). The focus of the model is the development of the RMP and associated intelligence collection missions. Only the surface picture is considered in this analysis. Other organic assets, such as helicopters or fixed wing aircraft, are not considered in the development of the RMP for this thesis.

The remaining chapters describe the framework and formulation of the problem, and a detailed description of the model. The results will be analyzed and explained, followed by conclusions and recommendations. Chapter II expands on the functions and missions from operational scenarios derived in this chapter to develop and describe performance measures used to quantify the effectiveness of a UV conducting these missions. Chapter III is a detailed description of the modeling program built from the methodologies described. Chapters IV and V discuss the analysis results and recommendations from implementing the scenarios into the model.

II. METHODOLOGY

A. INTRODUCTION

Chapter I described the ESG composition and scenarios where development of the RMP is divided into detection, identification, and collection functions. Under these functional categories, existing Navy performance measures can quantify the effectiveness of a UV mission (NMETL, 2001). Modeling techniques exist and evaluate expected performance, given parameters associated with the UVs, to calculate the effectiveness for a mission. This enables selection of the appropriate UV package to execute a specified mission.

This chapter discusses the development of detection, identification and collection functions modeled into measures of performance and reviews the techniques used in previous analyses. Theory is shown to reflect doctrine with respect to the application and evaluation of UVs in maritime missions and bridge operational scenarios described in Chapter I with theory and techniques. This is the linchpin to translating UV performance parameters into measures of performance. The measures of performance are then used to determine UV mission effectiveness.

B. FUNCTIONAL AGGREGATION & MISSION DEVELOPMENT

The measures of performance (MOP) used in this analysis are quantifiable for computations of expected values, making them a reasonable means of determining the success of a UV mission (TACMEMO, 2004). Figure 4 shows traceability of MOPs for each type of mission. The CWC concept delegates specific warfare area coordination to staff entities within the strike group. Warfare areas include Anti-Air Warfare (AAW), Undersea Warfare (USW), Surface Search and Control (SSC), and Maritime Interdiction Operations (MIO) (NWP 10-1, 1985). As depicted in Figure 4, SSC and MIO depend on the RMP to conduct their operations.

RMP development is organized into three functions: detection, identification, and collection, which are further decomposed into missions. The missions listed under collection function in Figure 4 are not exhaustive. Further breakdown into goals and objectives leads to the measures of performance (MOPs) shown. Detection, identification, and collection missions use cumulative detection probability, percent identifications made, and percent of collection opportunities realized, respectively (NMETL). The remainder of this chapter explains the selection of these MOPs and how they are used.

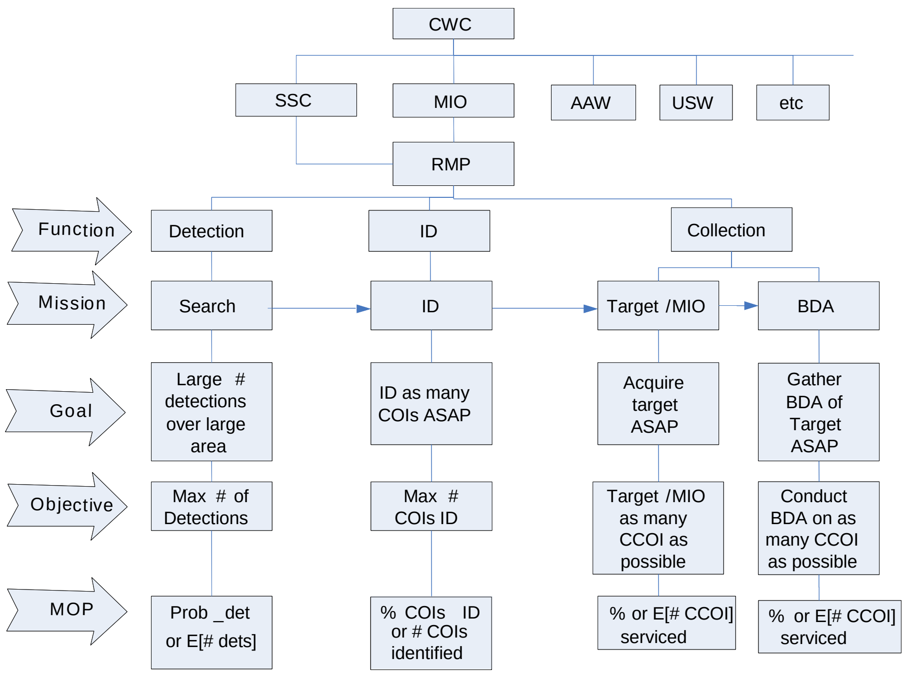

Figure 4. MOP Development

C. DETECTION

A Naval Postgraduate School thesis developed a Sensor Mix Model (SMM) and Sensor Allocation Model (SAM) for UV employment by the Unit of Action (Tutton, 2003). An initial inventory of Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) assets are inputs to the SAM. The SAM determines a performance measure for each target cluster for specified combinations of UVs and sensors. The combinations of sensors and UVs are called packages. A package can be a single UV with one sensor, or multiple UVs with multiple sensors. User inputs include target areas or clusters and targets within the clusters. The SMM uses the output of the SAM to determine how UVs should be employed, and of those assets, what should be organic to the Unit of Action.

Tutton used the random search model to calculate the probability of detecting a variety of targets in defined clusters. These probabilities of detection comprise the SAM output. Parameters such as UAV speed, sensor range, and search area per cluster are inputs into the random search model equations (Tutton, 2003). The probability of detection calculated is an accepted means of measuring the performance of a system or sensor (NMETL, 2001).

CDP is the probability that a platform searching for a contact over a specific time interval detects that contact at least once (Wagner, 1999). Each CDP is determined from UV sensor configuration parameters such as transit speed, mission speed, sweep width, and time on station. These parameters, their derivation, and their relationship to CDP are described in the following section.

Calculation of CDP in this case is based on the random search model. The use of such a model requires three assumptions: (1) random and uniform contact distribution throughout the named area of interest (NAI); (2) the platform's path is random but uniformly distributed; (3) and no search effort falls outside the search area. (Stone, 1975)

The first assumption is reasonable since there is no prior information with respect to contact movement. The second assumption is a reasonable approximation since over time, the UV-sensor configuration effectively covers the assigned search area fairly evenly, but with overlap that is a characteristic of randomness. The third assumption is reasonable since the RMP requirements, by nature, include total search area that is significantly larger than the sensor's effective detection range.

Other search models considered were the exhaustive search model and the inverse cube law model for area search with parallel sweeps. The exhaustive search model is predicated on a stationary target and precise coverage of the area with an ideal sensor with zero overlap and zero gaps. Exhaustive search is considered an upper bound on the effectiveness of searching an area (Washburn, 2002). The inverse cube law is more realistic than exhaustive search, but is based on a very specific geometry for the search pattern (Wagner, 1999). Random search does involve overlap of search effort and is often considered a conservative lower bound for any sensible, realistic search. The difference between the three models is demonstrated by plotting probability of detection versus coverage factor, where coverage factor is a function of the UV sensor configuration performance parameters and is explained in section C.3. For this thesis, the more conservative model is preferred, and so random search is assumed. For random search CDP and expected number of detections are directly related as described in the following sections. Either one can be used as the MOP for the UV detection mission. Maximizing one maximizes the other.

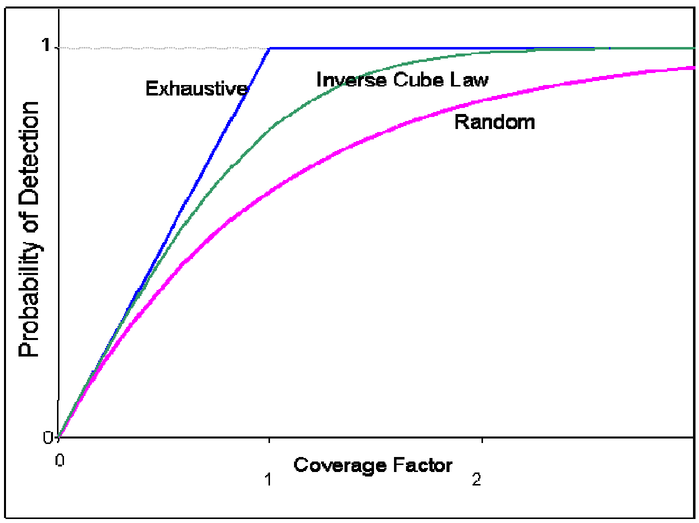

Figure 5. Plots of Probability of Detection vs Coverage Factor; three progressively more conservative methods.

1. Sweep Width

The performance of a UV sensor configuration is summarized in a function called the lateral range curve (Wagner, 1999). Each sensor detects a contact with some cumulative probability of detection when the target is passed at a specified closest point of approach (CPA) distance resulting in a lateral range curve. A lateral range curve is typically a smooth, symmetric plot of cumulative probability of detection vs. CPA range, with probability decreasing as CPA range increases in magnitude. Cumulative probability of detection is typically highest, although not necessarily 1.0, for sensor paths that pass directly over the target, i.e., at a CPA range of zero.

A commonly used scalar measure related to lateral range curves is sweep width. Sweep width is equal to area under the lateral range curve and represents the width of the zone of sensor detection of an equivalent "cookie-cutter" sensor that always sees targets with CPA inside the sweep and never sees targets with CPA outside the sweep. This equivalent cookie-cutter sweep width can be used to represent the performance of a sensor with a more general lateral range function, such as a UV, if the CPA between the UV and target are uniformly random (Washburn, 2002). Expression 1 is the formal calculation of sweep width and Figure 6 shows the relationship of sweep width and the lateral range curve.

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

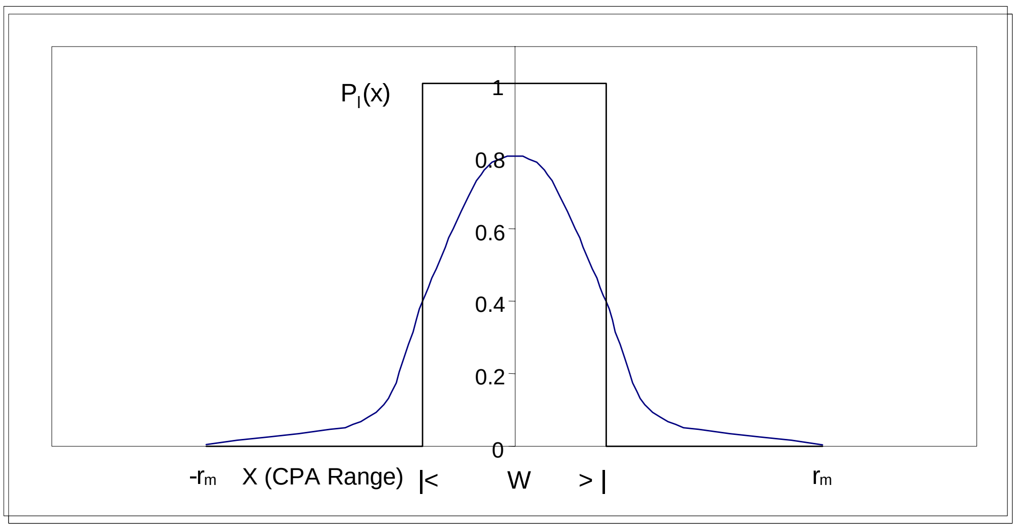

Figure 6. Lateral Range Curve vs Sweep Width (From Ref. Wagner,1999)

2. Time on Station

UV speed and endurance are directly related to the size of the UV, fuel capacity, payload capacity, etc. Transit speed is the speed the UV travels at when traveling from the control ship to the NAI. It is assumed that while transiting from the control ship to the NAI, sensors are passive, providing no valuable information. Once the UV reaches the NAI, it commences operating its sensors and adjusts its speed to the specified speed required for the effective sweep width, called search speed. Total time is the entire time a UV remains operational, including transit time and mission time.

Time on station is easily determined once the transit speed, search speed, total time, and distance to the NAI are given. A Euclidean distance formula determines the distance from the control ship to the center of the NAI. Transit speed, search speed, and endurance are provided for each UV-sensor configuration. Time on station is determined by:

$$Time\ on\ \ Station = t_{total} - (2 * \frac{D}{v_t}) \qquad (2)$$

where T_{total} is total operational time, D is the initial distance between the UV and the center of the NAI, and V_t is transit speed.

3. Coverage Factor

Coverage factor is a function of the preceding performance parameters and the search area. Fixing the total area of each NAI, the mission speed, time on station, and sweep width, a coverage factor is calculated. It is the ratio of the search effort expended in the NAI by the given UV-sensor configuration during its time on station, divided by the NAI area (Wagner, 1999).

$$Coverage\ \ Factor = \frac{v_s W t_{os}}{A} \qquad (3)$$

where v_s is the UV configuration search speed, W is the sweep width of the configuration, t_{os} is the time on station, and A is the total area of the NAI. Coverage factor can exceed 1.0 but still leave some targets undetected because of the nature of random search.

4. CDP

It has been shown (Wagner, 1999), that the cumulative probability of detection for random search for a stationary target in a defined area of interest can be expressed as

$$F_d(t_{OS}) = 1 - e^{-\frac{vWt_{os}}{A}} \qquad (4)$$

The key performance parameters affecting the CDP for UVs conducting detection missions are search speed, time on station, sweep width, and search area. When deciding whether or not to assign a particular UV-sensor configuration to an NAI, these performance parameters are the planning factors. A decision aid utilizing these planning factors to determine a good assignment of UVs to missions reduces the planning burden.

5. Expected Number of Detections

With the random search model, the detection rate is a constant, $\frac{v_s W}{A}$, and the expected number of detections during the time on station, t_{os} is $\frac{v_s W t_{os}}{A}$. The relationship between CDP and the expected number of detections, $E[\#dets]$, for random search, is expressed in the following equation:

$$CDP_{PKG,NAI} = 1 - e^{-E[\#dets]_{PKG,NAI}} \tag{5}$$

It is also noted that with the random search model, the expected number of detections is identically equal to the coverage factor. Thus maximizing coverage factor is the same as maximizing expected number of detections and equivalent to maximizing CDP. In Chapter III, expected number of detections is used as the MOP for the UV detection mission because it conveniently allows the formulation of a linear objective function for the UV assignment model. For that model, $E[\#dets]$ is a parameter and is called $det_{i,j}$, the expected number of detections by package i searching in NAI j.

D. IDENTIFICATION TASKING

A maritime application of UV analysis is an agent-based model for Unmanned Surface Vehicles (USV) (Steele, 2004). Results provide insight on increasing USV sensing and endurance capabilities while not necessarily increasing the production or quantity of USVs in tactical and operational settings. Steele's work looked at identification and force protection (FP) missions. It is an example of the use of expected performance measures to explain the effectiveness of USVs conducting ISR and FP missions. The performance of identification missions were measured with the proportion of enemies detected. Factors such as the USV's speed, sensor range, and quantity were inputs to evaluate the effectiveness of the USV in specified scenarios.

One method for addressing the identification functions is to use a traveling salesman problem (TSP) algorithm. TSPs, in general, involve a salesman and a number of houses to visit. The objective is to minimize the total distance traveled, or time required, while visiting all the houses. It is reasonable to view the identification requirements as one large TSP spread out over the entire AO. One study compared and contrasted the results of an orienteering problem using a stochastic algorithm, a deterministic algorithm and a center of gravity heuristic (Golden, 1987).

The orienteering problem is analogous to identification tasking in that competitors are required to visit a subset of control points from the start point, they accrue varying magnitudes of points at each control point, and must return to the start point before time expires with as many points as possible. Control points are analogous to contacts requiring identification, the contacts all have equal point values in this case, and the UV must return before running out of fuel. The percent of contacts successfully visited determines the UV's "score."

Similar to the detection modeling approach, a more conservative MOP is desired. Using any of the aforementioned algorithms in a TSP model calculates a precise MOP that may not allow for any deviation from the assigned route. Another reason for using an alternative method to model identification tasking is the ability to assign and operate UVs in groups of two or more for a single NAI. The uncertainty in the performance parameters also lend toward a more conservative calculation of the measures of performance. Therefore, maintaining a large, but partitioned AO and a straight forward calculation of the MOPs gives a solution capable of handling a more robust, larger RMP.

Navy doctrine provides another reason for not using a TSP algorithm, stating that when conducting identification missions on multiple contacts, operators can become disoriented. It suggests using waypoints as a means of keeping the operator oriented (TACMEMO, 2004). The use of waypoints in lieu of direct transit from contact to contact precludes the optimality sought in the TSP algorithm. For simplicity a more direct and conservative method should be used to calculate the MOPs. A conservative application of time and speed parameters of the assets, over the Euclidean distance between contacts can be used to determine the percent of contacts identified, or % ID.

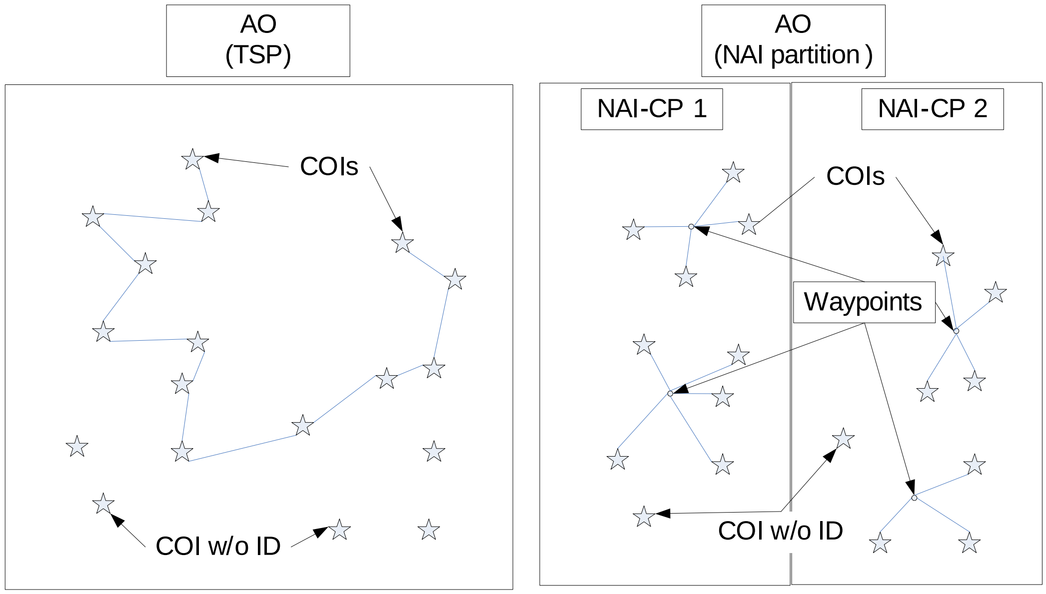

Figure 7. Identifying contacts over the entire AO using TSP algorithm vs partitioning AO and using waypoints and a conservative estimate to calculate proportion of contacts identified.

A finite set of contacts with known positions require identification, referred to as #COIs. Each configuration has a transit speed (v_t), identification speed (v_{ID}), and endurance (t_{total}). The same calculation in Equation 2 is used to determine the on station time for a configuration and a given NAI. Within an NAI, up to three waypoints are designated for the percent ID calculations, in addition to reducing operator orientation problems. The NAI is limited to three waypoints to reduce the scope of the problem. Using distance between contacts and their closest waypoint, the total distance required to be traveled is calculated. This model assumes a conservative approach that the operator has to travel back to a waypoint between each contact visited. This yields the following equation for each NAI

$$D_{NAI} = 2 * \sum_{COI} \sqrt{(X_{WPT} - X_{COI})^2 + (Y_{WPT} - Y_{COI})^2} \qquad (6)$$

Using the approximate position of each COI (X_{COI}, Y_{COI}), the Euclidean distance from the waypoint closest to each COI (X_{WPT}, Y_{WPT}) is calculated. The total distance required by a configuration is conservatively determined to be twice the sum of all the distances to the respective waypoint. This is a conservative modeling approach and is revisited in the analysis.

The conservative approximation of the number of contacts identified by a configuration is equal to the ratio of time available to the configuration (t_{total}), over the time required to travel D_{NAI} multiplied by the number of COIs (#COIs). Equation 7 expresses this ratio.

$$ID_{CON,NAI} = \frac{t_{total}}{D_{NAI}/v_{ID}} * \#COIs \qquad \forall CON, NAI \tag{7}$$

The number of identification for a package is equal to the cumulative sum of the percentage of contacts identified by each configuration in the NAI-ID multiplied by the number of contacts in the NAI-ID, expressed in Equation 8.

$$ID_{PKG} = \#COIs * \sum_{CON} \%ID_{CON,NAI} \qquad \forall NAI \tag{8}$$

The conservative calculation of D_{NAI} lends toward a modeling approach that is ultimately an over-estimate of the time required to travel between contacts and COIs. However, the excess time accounts for the time required to make multiple passes of a contact to gather all the required information. It also addresses the potential for UV operators to use waypoints when visiting multiple contacts, thus avoiding disorientation (TACMEMO, 2004).

In Chapter III, the conservative approximation of the number of contacts identified is used as the MOP for the UV identification mission in the UV assignment model. For that model, this conservative approximation is used as a parameter called $id_{i,j}$, the expected number of identifications made by package *i* for NAI *j*.

E. COLLECTION

Collection events are random events that occur over time. It is assumed that the likelihood of these events occurring during a short time interval is very small. Therefore, collection events are considered rare events and can modeled as a Poisson process (Devore, 2000). Although, a BDA mission may be correlated to a targeting mission, the arrival of these events over time is infrequent enough, that collectively, they are assumed independent. Another justification for this assumption is that it is conceivable to conduct coordinated attacks in which an asset outside the ESG attacks a CCOI, but the ESG is tasked to conduct BDA.

The varied natures of these events are uncoordinated. Timelines that support BDA or targeting or intelligence collections of opportunity (COLLOP) are independent of each other. While there may be periods of time when their rate of activity are each greater than during others, there is no interdependence among these three efforts. This enables superposition of these event streams and lends itself to the aggregation of collection missions into a single collection function, with a common MOP and is diagrammed in Figure 8. The independence among events in non-overlapping time increments implies the "memoryless" or Markovian property for time until an event occurs (Ross, 2003).

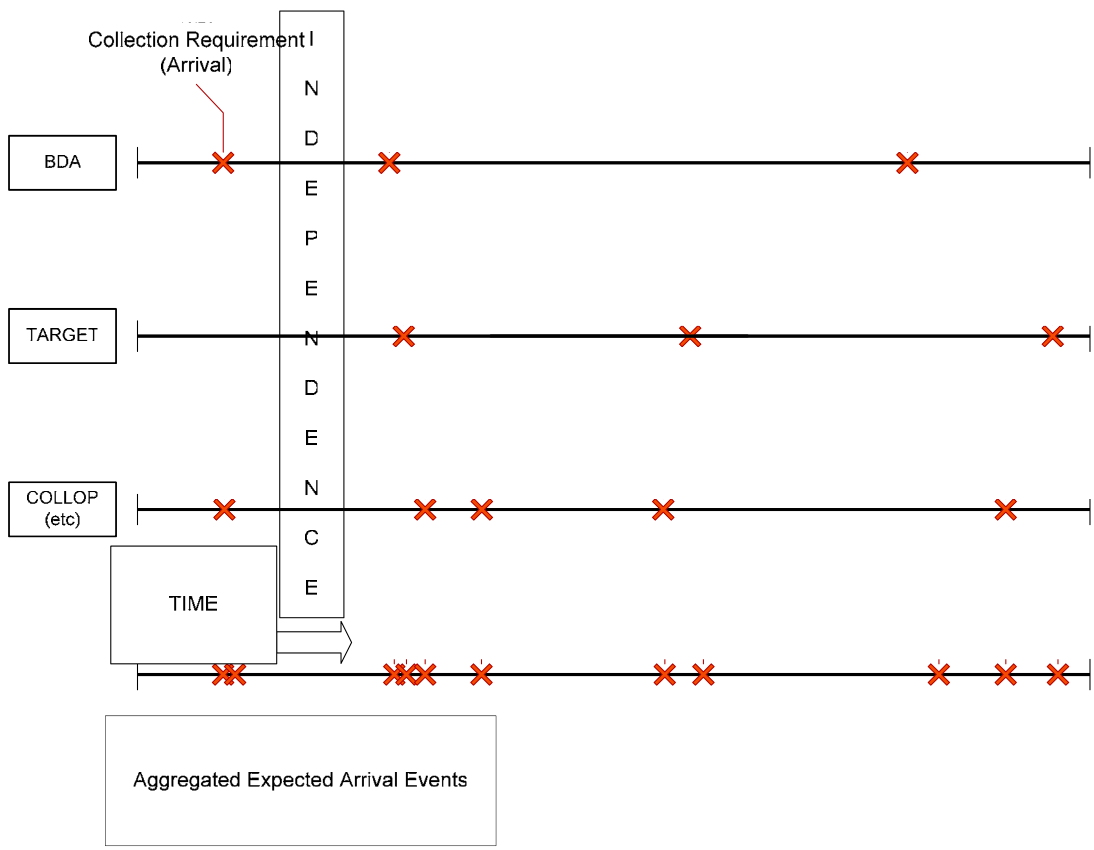

Figure 8. Aggregation of Collection Arrival Rates

As collection events "arrive" in the AOR, they must be "serviced" by a sensor within the ESG. If a set of UVs are designated as the collection servers, at any given time the UVs are in one of a defined set of states. They are either idle on station, or busy collecting information on a recently arrived contact. The proportion of time in each state can be calculated. A Markov chain holds the property that the future is independent of past events. A Markov chain, with arrivals, servers, and service times with some service and interarrival distribution, is considered a queuing process (Ross, 2003). Service of a collection event may take a very short time, such as capturing video for BDA, may take longer, such as targeting, or may be very long, such as bird-dogging. For convenience, service time, i.e., the amount of time a UV spends collecting information on a target, is assumed to be exponentially distributed.

Accordingly, collection missions can be quantified as an $M/M/k/k$ loss system, according to Kendall notation. The two M's refer to the fact that both interarrival and service distributions are exponential, thus Markovian, the first k is the number of servers in the system and the second k refers to system capacity. Any customers that arrive when there are already k customers being served are lost (Allen, 1978). Therefore, the infrequent and aggregated collection requirements are independent, random events. With the assumption of exponentially distributed inter-arrival and service times, the arrival rate and service rate are expressed as:

$$\mathrm{E}\left[\text{arrivals per unit time}\right] = \lambda \tag{9}$$

$$\mathrm{E}\left[\#\text{ services per unit time}\right] = \mu \tag{10}$$

For collection missions we are interested in the proportion of time when all sensors are busy, because any collection opportunity that arrives during this time will not be served. If a customer arrives for service, can not be served immediately, and departs without being served, the customer is said to renege. In the collection mission context, reneges occur when the system is in a state where all servers are busy. Other states include those when no servers are busy, one server is busy, two servers are busy, and so on through the k^{th} server being busy. The proportion of time the system is in the state where k servers are busy, is equal to the percentage of time a renege occurs.

The proportion of time, P_k, that all k servers are busy, so that an arriving customer is lost is determined using Erlang's loss formula (Allen, 1978):

$$P_k = \left\{ \frac{\frac{(\lambda/\mu)^i}{k!}}{1+(\lambda/\mu)+\frac{(\lambda/\mu)^2}{2!}+\ldots+\frac{(\lambda/\mu)^k}{k!}} \right. \tag{11}$$

where k is the total number of servers.

Similar to the aggregation of λ over collection missions, homogeneity is assumed among UV configurations. Under this assumption, μ for a package of non-homogeneous configurations is calculated as the mean of the configurations in the package, and is expressed as:

$$\mu_{pkg} = \frac{\sum_{config \in pkg} \mu_{config}}{\#configs_{pkg}} \tag{12}$$

μ_{pkg} is the average of the μ for each configuration in the package. Using μ_{pkg} and the aggregated λ_{NAI}, P_k is determined. The percentage of collection opportunities realized is the complement of the percentage of reneges (1-P_k), an MOP for the collection mission.

Another MOP for the collection mission is the expected number of collections realized or expected number of events serviced. This is equal to the packages' time on station multiplied by the expected number of arrivals per hour (λ_{NAI}) multiplied by the percentage of opportunities realized (1-P_k). In Chapter III, this is used as the MOP for the UV collection mission in the UV assignment model. For that model, this MOP is used as a parameter called $collop_{i,j}$, the expected number of collections made by package i in NAI j.

Now that the problem is framed and methodologies used to address it, the actual model used to assist UV mission planning can be built. Chapter III is a detailed description of this model.

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III. MUVAM

A. INTRODUCTION

Chapter I introduces three operational scenarios that an ESG may encounter and discusses the detection, identification, and collection functions it performs to develop the RMP. The success in executing these functions are evaluated using metrics such as cumulative detection probability, percent identifications made, and percent of collection opportunities realized. Chapter II explains how the MOPs are evaluated using the random search model, conservative time-speed-distance calculations, and the M/M/k/k loss system from queuing theory. Once evaluated, the MOPs are metrics for measuring the effectiveness of UV mission planning. This chapter describes how the process is captured in a mathematical model called the Maritime UV Assignment Model (MUVAM).

The MUVAM requires user input pertaining to the group's UV assets, combines them with parameters specific to the assets, and develops performance measures as input for an optimization-based allocation program. It is divided into three programs. The first is a spreadsheet model for asset and mission inputs. This feeds a second spreadsheet for processing the data into measures of performance. The third program uses optimization software to assign assets to missions. Figure 9 depicts the processes, the models, and their relationships.

This chapter is broken into three sections: a description of the common inputs among the three functional areas, the computations specific to each functional area, and finally, the optimization portion of the model.

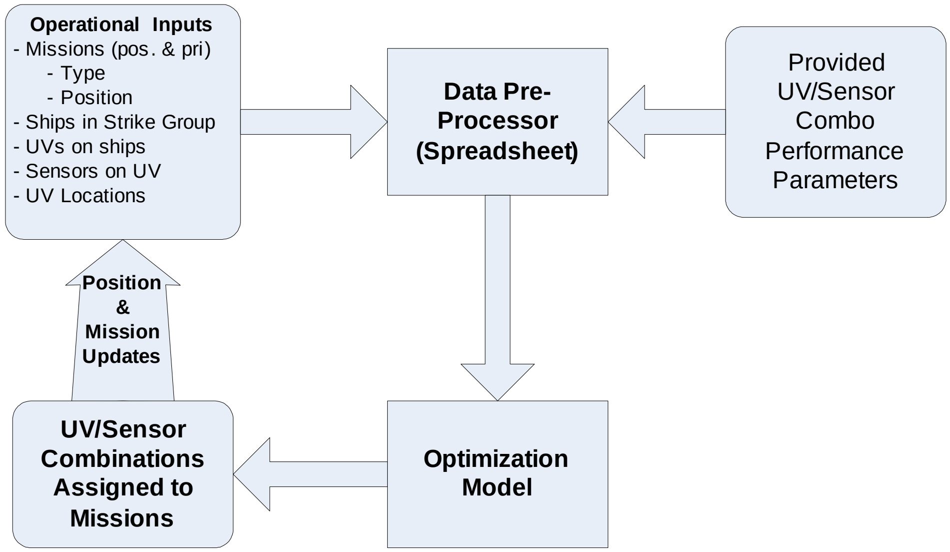

Figure 9. Model Overview

B. COMMON INPUTS

1. Assets

Asset allocation requires input of the ESG/CSG ship composition, including each ship's complement of UVs. In this scenario, there are six ships, five UV and five sensor types in a notional ESG comprised of an LHD, an LPD, an LSD, an Aegis DDGs, and an LCS (ESG, 2005). The UV types are Micro-UAVs (MUAV), small UAVs (SUAV), UAVs, vertical takeoff UAVs (VTUAV) and USVs. Ship and UV complements are shown in Table 2.

Ship #	1	2	3	4	5	6		
Ship ID	LHD	LPD	LSD	CG	DDG	LCS		
1	0	2	3	3	3	3	MUAV	14
2	1	1	1	1	1	1	SUAV	6
3	1	1	1	0	0	0	UAV	3
4	2	2	0	0	0	1	VTUAV	5
5	2	1	1	1	1	1	USV	7
per Ship	6	7	6	5	5	6	35	Total Assets
Availa ble	3	2	2	2	4	2	15	Available

Table 2. UV and Ship Inputs (light blue shading denotes user input)

Rationale for UV-Ship complements is varied. One assumption is that UVs are spread out among the ESG, and not singularly assigned to one of the larger amphibious ships. Availability of USVs is based on current prototypes such as the Spartan Scout, a stock seven meter rigid hull inflatable boat (RHIB) with remote controls and sensors mounted on it (Steele, 2004). Two standard seven meter RHIBs are used on DDGs. The assumption for this model is that on each DDG, one of the standard RHIBs is replaced with a USV of similar size to the Spartan Scout. The LPD, LSD, and LHD, because of their well decks, can carry and operate more than one USV.

MUAVs are distributed among the combatants in greater numbers. They are omitted from the LHD due to the assumed command, control, and coordination issues between such a small unmanned platform and the larger, manned aircraft operations associated with a helicopter carrier. SUAVs are spread evenly among all ships except the LCS. The SUAV is omitted from the LCS in recognition of the projected size of the LCS. UAVs are limited to one each on the L-class ships due to the cost of the UAVs and the larger flight deck area on these ships. VTUAVs are placed on the L-class ships because of the capacity of the ships and potential for use by the Marines in addition to maritime applications. Assignment of the VTUAVs is less critical since they can launch and recover on any of the ships.

2. Sensor Aggregation

UV platforms of varying types are assigned to ships within the ESG. Each ship also has a pool of sensors to mount on the different platforms. A platform with one or more sensors is a configuration. One or more configurations comprise a package. For the purposes of this analysis, configurations are limited to one or two sensors per platform, and packages are limited from one to three configurations. Figure 10 depicts the development of packages from UVs and sensors, to their configurations, and finally, configurations combining to form packages. Table 3 lists the possible configurations developed from UVs and sensors and based on current technology, payloads, and sensor weights (UAV Forum, 2004).

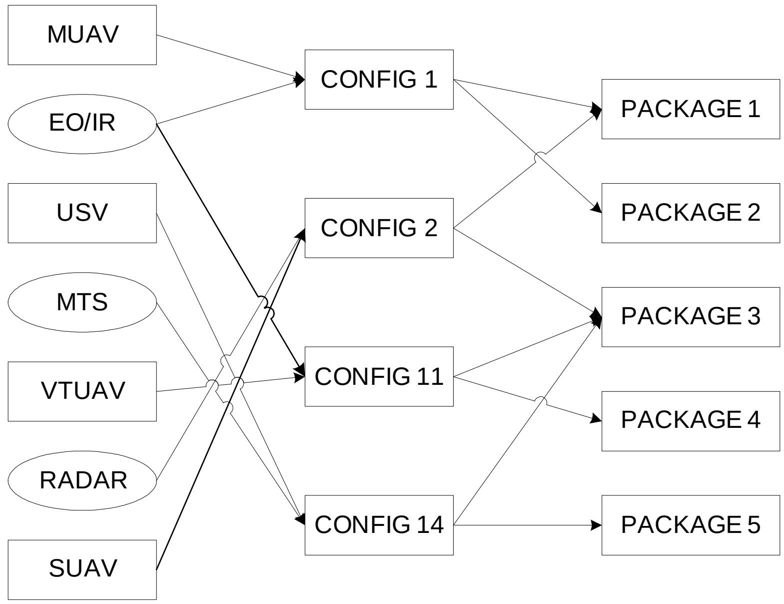

Figure 10. UV and Sensor Aggregation

Ship ID	**UV Type**	**Sensor ID #**	**Sensors**
1	**MUAV**	**1**	**Radar**
2	**SUAV**	**2**	**EO/IR**
3	**UAV**	**3**	**SIGINT**
4	**VTUAV**	**4**	**Lasar Designator**
5	**USV**	**5**	**MTS (EO/IR/LD)**
Configurations			
Config #	**UV Type**	**Sensor1 ID #**	**Sensor2 ID #**
0	**0**	**0**	**0**
1	1	2	
2	2	1	
3	2	2	
4	2	2	4
5	3	2	
6	3	2	3
7	3	1	2
8	3	1	5
9	3	2	4
10	3	1	4
11	4	2	
12	4	2	4
13	4	5	
14	5	5	1
15	5	5	3

Table 3. UV-Sensor Configurations

To develop the packages, the user inputs available UVs whose initial locations are the same as their assigned ship's location. The user then enters the current configuration for each UV. A worksheet for each ship's complement of configurations uses combinatorial math to determine the potential number of packages for each ship's configurations. However, the user must enter the specific packages to be considered for the specific operation.

For example, the LHD has an inventory of six UVs with only three presently available for mission planning. The "Ship1 Pkg Entry" worksheet calculates the maximum possible packages from three UVs to be seven. In general,

$$\text{Max \# Packages for } n\,UVs = \binom{n}{3} + \binom{n}{2} + n \tag{13}$$

The user then inputs which of the seven possible packages to be considered. For example, in Table 4, Package 1 consists of an SUAV (UV_Type 2) in configuration number three, a UAV (UV_Type 3) in configuration number eight, and a VTUAV (UV_Type 4), in configuration number 11. The user selects this package by entering a one in the appropriate cells under the configuration columns in the Package 1 row. Continuing down the column of packages, Package 2 consists of only one UV, namely the SUAV in configuration three, and is denoted with the one entered in the cell.

Ship Name	**LHD1**	**Ship_ID**	**1**					
Number UVs	**3**		**Enter Package configurations. No more than three UV's per package.**					
Potential Packages		**7**	**Ensure no duplicates. Column A lists max # of possibilities**					
				Platforms				
Config #	3	8	11					
UV_Type	2	3	4					
Package_ID								
1	1	1	1					
2	1							
3		1						
4			1					
5		1	1					
6	1	1						
7	1		1					

Table 4. Sample of "Ship1 Pkg Entry" worksheet (light blue shading denotes user input)

An easier approach would just utilize all the potential packages. Allowing the user to input the packages facilitates scaling the size of the problem down with simple rationale, such as a Micro-UAV traveling at 40 knots may not be a good candidate to operate in a package with a UAV at operating 100 knots. Once entries are made for each ship, a macro consolidates the package list into one table. Table 5 is a sample of a consolidated package list.

Package ID	Ship	Config of UV #1	Config of UV #2	Config of UV #3
1	1	11	8	3
2	1	3	0	0
3	1	8	0	0
4	1	11	0	0
5	1	11	8	0
6	1	8	3	0
7	1	11	3	0
8	2	13	0	0
9	2	8	0	0
10	2	13	8	0
11	3	1	0	0
12	3	1	0	0
13	3	1	1	0
14	4	4	0	0
15	4	15	0	0
16	5	1	1	1
17	5	14	0	0
18	5	1	1	0
19	5	1	1	0
20	5	1	1	0
21	5	1	0	0
22	5	1	0	0
23	5	1	0	0
24	6	1	0	0
25	6	1	0	0

Table 5. Complete package list for mission planning

C. DETECTION

1. Mission Inputs

The user divides the area of operations (AO) into independent partitions based on the mission required to be performed in each geographic areas called named areas of interest (NAI). NAIs for search and detection (SD) missions are referred to as NAI-SDs, as described in Chapter I. Potential exists for mission requirements to overlap NAI. The model treats NAIs independently and disjoint, therefore, overlap does not need to be considered when evaluating the value of assigning a package to overlapped NAIs.

NAI-SDs are entered by the user in a spreadsheet table. The center of the square NAI is entered as an X, Y grid coordinate along with its width. Area is calculated as the width squared. Table 6 is taken from the NAI-SD input into the spreadsheet.

User Inputs

	Center Position			
Number	**X**	**Y**	**Width**	**Area**
1	-52.5	52.5	17.5	1225.0
2	-17.5	52.5	17.5	1225.0
3	17.5	52.5	17.5	1225.0
4	52.5	52.5	17.5	1225.0
5	-52.5	17.5	17.5	1225.0
6	-52.5	-17.5	17.5	1225.0
7	52.5	17.5	17.5	1225.0
8	52.5	-17.5	17.5	1225.0

Area = Width^2

Table 6. NAI-SD Input, Indexing, and Area Calculation in Excel (light blue shading denotes user input)

2. Parameters

Each configuration has assigned performance parameters relevant to CDP calculation. These parameters include total mission time, transit speed, search speed, sweep width. The assumption is that when a strike group receives a UV-sensor configuration, these parameters are characteristic to the equipment. This assumption is maintained for all three mission areas.

The speed parameters are common enough the assumption and expectation is reasonable. Speed and total mission times used in Table 7 are derived from commonly accepted speed and time ranges (TACMEMO, 2004). The sweep width values are more difficult to derive and their approximation for this analysis are explained below.

	Sensors	Index		IP Altitude (ft)	FOV	Foot Print (ft)	W (nm)
MUAV	Radar	1	MUAV	500	30	350	0.04
SUAV	EO/IR	2	SUAV	2000	30	1500	0.18
UAV	SIGINT	3	UAV	4000	30	3000	0.35
VTUAV	Lasar Designator	4	VTUAV	3000	30	2000	0.24
USV	MTS (EO/IR/LD)	5	USV	NA	NA	NA	5

Configurations					V_xsit	V_search	V_ID	V_collop	t_total
Config #	UV Type	Sensor1	Sensor2	(nm)	(knots)				(hrs)
0	0	0	0	0	0	0	0	0	0
1	1	2		0.04	40	30	20	20	2
2	2	1		0.18	70	50	40	40	4
3	2	2		0.18	70	50	40	40	4
4	2	2	4	0.18	70	50	40	40	4
5	3	2		0.35	90	80	70	70	6
6	3	2	3	0.35	90	80	70	70	6
7	3	1	2	5	90	80	70	70	6
8	3	1	5	5	90	80	70	70	6
9	3	2	4	0.35	90	80	70	70	6
10	3	1	4	5	90	80	70	70	6
11	4	2		0.24	100	80	70	50	4
12	4	2	4	0.24	100	80	70	50	4
13	4	5		0.24	100	80	70	50	4
14	5	5	1	5	15	10	10	10	6
15	5	5	3	5	15	10	10	10	6

Table 7. Parameters needed for MOP calculations for each configuration

Nominal sweep widths used are shown in Table 7, under the column “W”. Sweep widths used in this analysis range from 0.04 nm to 5 nm depending on the sensor and UV configuration and geometry, as generically considered in doctrine (TACMEMO, 2004). The values under the columns titled Initial Pass (IP) Altitude, Field of View (FOV), Foot Print, and Width (W) are based on sensor field of view and geometry recommended for the four UAV types (TACMEMO, 2004). Using Initial Pass Altitude and field of view yields an approximate diagonal footprint. Sweep width is calculated using Pythagorean's theorem. This is a simplified approximation for general asset allocation. Real world mission planning should use actual sweep width data provided by manufacturers or government testing.

3. Implementation

Coverage factor for a single UV-sensor configuration is determined from the configuration's speed, sweep width, time on station, and the size of the area being searched. The Matrix Generator uses lookup functions to retrieve these parameters from the Input Model for each NAI and package combination. Coverage factor for each configuration in a package is calculated by multiplying the configurations search speed (v_s), sweep width (W) and time on station (t_{OS}) together and dividing by the entire area of the NAI-SD. The sum of these values is equivalent to the expected number of detections by the package under the assumption of random search. Table 8 is a sample from the Matrix Generator of parameters taken from the Input Model for a package comprised of three configurations and the subsequent calculation of the expected number of detections.

NAI	Pkg	Index	Config	NAI_Area	W	v_{xsit}	v_s	t_{total}	d_{xsit}	t_{OS}	v_sWt_{OS}/A	E[# dets]
1	1	1	11	1225	0.24	100	80	8	74.2	6.52	0.102	1.536
1	1	2	8	1225	5	90	80	6	74.2	4.35	1.420	1.536
1	1	3	3	1225	0.18	70	50	4	74.2	1.88	0.014	1.536

Table 8. Sample calculation of the expected number of detections for a given package and NAI-SD

The Matrix Generator uses a macro to create the entire table of NAI-SD and package combinations. Another macro reformats the table into an n package by m NAI-SD matrix of expected detections, called the search matrix. The search matrix is saved as a comma separated values file to facilitate importing it into the optimization program.

After the optimization program finds the best assignments, the results for the detection tasking can be interpreted three equivalent ways. The first interpretation is optimum search and detection *coverage*. The second, assuming random search, is maximum expected number of detections, and the third is that the assignment provides the best overall cumulative probability of detecting a random target. Converting expected number of detections to $CDP_{PKG,\ NAI}$, is accomplished with the following equation:

$$CDP_{PKG,NAI} = 1 - e^{-E[\#dets]_{PKG,NAI}} \tag{14}$$

D. IDENTIFICATION TASKING

1. Mission Inputs

Similar to detection missions, identification (ID) missions require user-established NAIs, referred to as NAI-ID, for input. Instead of entering the grid coordinates and radius of the NAI-ID, the user must select up to three waypoints within the NAI-ID, and enter their grid coordinates as well as the expected number of contacts in each NAI-ID, as shown in Table 9.

		Waypoint					
NAI #	**Wpt #**	**X**	**Y**	**Radius**	**Area**	**# COIs**	**D_WPT**
1	**1**	0	0	65	0.0	50	0.0
	2	0	60		0.0		60.0
	3	60	30		0.0		127.1
							194.2

Table 9. NAI-ID and Waypoint Input Table

The user then enters the grid coordinates, X_{COI} and Y_{COI}, into the COI Input worksheet within the Model Inputs spreadsheet. The distance to each waypoint is calculated and the minimum value is determined in the last column of Table 10

	Total COIs:	50						
Counter	NAI #	COI	X_COI	Y_COI	D_WPT1	D_WPT2	D_WPT3	MIN D_WPT
1	1	**1**	5	-20	20.62	80.16	74.33	20.62
2	1	**2**	5	0	5.00	60.21	62.65	5.00
3	1	**3**	25	-20	32.02	83.82	61.03	32.02
4	1	**4**	25	0	25.00	65.00	46.10	25.00
5	1	**5**	18	-8	19.70	70.34	56.64	19.70

Table 10. COI Input and minimum waypoint distance calculation

2. Parameters

Parameters used are taken from the same table used in detection missions. Configurations are taken from the same inventory, transit speed is the same, but the mission speed is referred to as v_{ID}. Again, platform speeds are as generally accepted (TACMEMO, 2004). No other parameters are used as the conservative time-speed distance calculation has each UV traveling to the position of the contacts.

3. Implementation

The Matrix Generator spreadsheet retrieves the parameters and data with respect to the packages, total contact-waypoint distance (D_{NAI}), and identification speed (v_{ID}) for each package, and total mission time (t_{total}). The formulas described in Chapter II are implemented in the Matrix Generator as shown in Table 11.

NAI	Pkg	Index	COIs	Config	V_{XSIT}	V_{ID}	t_{total}	D_{NAI}	t_{NAI}	% ID	$E[\# IDs]_{CON}$	$E[\# IDs]_{PKG}$
1	1	1	24	11	100	80	8	1200.6	15.0	0.533	12.8	26.4
1	1	2	24	8	90	80	6	1200.6	15.0	0.400	9.6	26.4
1	1	3	24	3	70	50	4	1200.6	24.0	0.167	4.0	26.4

Table 11. Sample calculation of the expected number of identifications for a given package and NAI-ID

These calculations are implemented in the ID worksheet in the model's Matrix Generator spreadsheet. As the parameters are copied into the Matrix Generator, the calculation of $E[\# \; IDs]_{PKG}$ is done for each package and NAI-ID combination and generates a table for *n* packages and *m* NAI-ID; in an *n* x *m* matrix. Similar to translating the expected number of detections into CDP, the expected number of IDs for a package assigned to an NAI-ID is translated into the desired MOP of % ID by dividing the expected number of identifications by the total number of contacts for a given NAI-ID.

E. COLLECTION

1. Mission Inputs

Collection missions are entered into the Input Model spreadsheet similar to detection missions and are referred to as NAI-CPs. The grid coordinates and widths are entered. Also, the expected arrival rate value (λ) is entered for each NAI-CP. λ is entered as the expected number of collection opportunities to enter the NAI per hour. To be consistent with the assumption that collection events are rare events, this arrival rate value is typically less than 1 per hour. Table 12 is an example of an NAI-CP table from the Input Model spreadsheet.

User Inputs

	Center Position				
Number	**X**	**Y**	**Width**	**Area**	**λ**
1	12.5	30	12.5	625.0	0.1
2	-12.5	30	12.5	625.0	0.1
3	-35	30	10	400.0	0.1
4	-35	10	10	400.0	0.1
5	-35	-10	10	400.0	0.1
6	35	30	10	400.0	0.1
7	35	10	10	400.0	0.1
8	35	-10	10	400.0	0.1
9	20	90	20	1600.0	0.1
10	-20	90	20	1600.0	0.1

Table 12. NAI-CP Inputs with Position, Width, and Expected Arrival Rate Inputs

2. Parameters

Critical parameters for collection missions include total mission time, transit speed, collection speed, and expected number of service completions per hour, again using generally accepted values (TACMEMO, 2004). The expected number of service completions per hour is a nominal value chosen based on notional sensor characteristics and the assumption that they are significantly larger than arrival rates as shown in Table 13 compared to λ values in Table 12.

Configurations				V_xsit	V_collop	t_total	
Config #	UV Type	Sensor1 ID #	Sensor2 ID #	(knots)		(hrs)	$1/\mu$
0	**0**	**0**	**0**	**0**	**0**	**0**	**0**
1	1	2		40	20	2	0
2	2	1		70	40	4	0
3	2	2		70	40	4	5
4	2	2	4	70	40	4	4
5	3	2		90	70	6	4
6	3	2	3	90	70	6	3
7	3	1	2	90	70	6	3
8	3	1	5	90	70	6	3
9	3	2	4	90	70	6	4
10	3	1	4	90	70	6	3
11	4	2		100	50	8	4
12	4	2	4	100	50	8	3
13	4	5		100	50	8	2
14	5	5	1	15	10	6	2
15	5	5	3	15	10	6	2

Table 13. Parameters critical to calculating the % Collection opportunities realized.

3. Implementation

The percent of collection opportunities realized is calculated as the complement of the percent collection events reneged due to busy UVs. As discussed, a queuing model can represent this system by computing performance using the expected rates of occurrence and service rates. The average rate of collections of opportunity by a package, μ_{pkg}, must be adjusted for non-homogeneity among configurations within a package before being put to use. This is accomplished with lookup functions and averaging in the package consolidating worksheet of the Matrix Generator. Collection speed and time on station are also averaged in the package consolidation worksheet to account for non-homogeneity.

When not servicing a collection within the NAI-CP, UVs simply dwell idle on station. Events occur over time according to a Poisson process, and the location is assumed to be random throughout the NAI-CP. To account for the undetermined location of the UVs relative to the CCOIs, the μ_{pkg} is adjusted and referred to as μ_{total} and is calculated as

$$\mu_{TOTAL} = \left[\frac{1}{60 * \mu_{PKG}} + \frac{d_{NAI}}{V_{PKG}} \right]^{-1} \tag{15}$$

where d_{NAI} is the maximum distance across the NAI-CP (hypotenuse), V_{PKG} is the average speed of the package and the factor of 60 adjusts the μ_{PKG} from minutes to hours.

The expected number of arrivals during a packages' time on station obtained by multiplying the time on station for the package by λ, the expected number of arrivals per hour. The proportion of time all UVs in a package are busy collecting, P_k, is calculated using Equation 11, the complement of which is 1- P_k, the proportion of collection opportunities realized. The expected number of events served is equal to the proportion of collection opportunities realized (1-P_k) multiplied by the expected number of arrivals.

NAI	Pkg	k	$1/\mu_{pkg}$	$V_{\text{—collop}}$	t_{total}	d_{xsit}	t_{os}	d_{NAI}	$1/\mu_{tot}$	μ	λ	E[# arrivals]	P_k	E[# services]
1	1	3	4.0	86.7	6	102.0	3.6	49.5	0.638	1.568	0.365	1.329	0.0017	1.327
1	2	1	5.0	70.0	4	102.0	1.1	49.5	0.790	1.265	0.108	0.118	0.0790	0.108
1	3	1	3.0	90.0	6	102.0	3.7	49.5	0.600	1.667	0.373	1.393	0.1830	1.138

Table 14. Sample calculation of the expected number of events serviced for a given package and NAI-CP

A macro generates a complete table for all packages and NAI-CP combinations. Another macro reformats the table into a matrix of *n* packages by *m* NAI-CP for entry into the assignment model. Again, the expected number of services is translated into the preferred MOP, proportion of collection opportunities realized, for packages assigned to NAI-CPs.

F. ASSIGNING ASSETS TO MISSIONS

The Model Input and Matrix Generator spreadsheets organize and process assets and missions into measures of performance. This section describes the UV Sensor Assignment model. Using optimization software and given the matrices developed for detection, identification, and collection missions, this model assigns the packages to NAIs.

The mixed-integer program makes the best overall allocation of packages based on the available mix of packages, the priority of function (detection, ID, or collection), function and NAI characteristics, and sensor/platform characteristics. The decision variables of the UV assignment problem are binary, either assigning package *i* to NAI *j*, or not.

1. Indices

The indices used to define this model are:

i	UV package configuration	Set I: {'p1', 'p2', 'p3',…}
j	NAI index	Set J: {'a1', 'a2', 'a3',…}
k	UV index	Set K: {'u1', 'u2', 'u3',…}
det_j	search NAIs, subset of *J*	
id_j	ID NAIs, subset of *J*	
collop_j	collection NAIs, subset of *J*	

2. Data

In addition to the matrices for each mission type, the following data is required to prevent identification missions from drawing all the assets.

COI_{id_j} the number of COIs located within NAI *id_j*

3. Parameters

The parameters used to define this model are:

$det_{i,j}$	expected number of detections by package *i* searching in NAI *j*, $j \in det\_j$
$id_{i,j}$	expected number of identifications made by package *i* for NAI *j*, $j \in id\_j$
$collop_{i,j}$	expected number of collections made by package *i* in NAI *j*, $j \in collop\_j$
$uvassign_{i,k}$	binary assignment UV *k* to package *i*
α	priority factor for search mission category
β	priority factor for identification mission category
γ	priority factor for collection mission category

4. Decision Variables

The binary decision variable in the model is:

$X_{i,j}$	assignment of UV package *i* to NAI *j* (binary)

5. Constraints

The model constraints are:

$\sum_{i} X_{i,j} \leq 1$	$\forall j$	PKG/NAI
$\sum_{j} X_{i,j} \leq 1$	$\forall i$	NAI/PKG
$\sum_{i,j} uvassign_{i,k} * X_{i,j} \leq 1$	$\forall k$	PKG/UV
$\sum_{i} X_{i,id\_j} * id_{i,id\_j} \leq COI_{id\_j}$	$\forall id\_j$	IDLIMIT

$X_{i,j} \in (0,1)$ BINARY

The first constraint ensures that not more than one package is assigned to the same mission in an NAI. The second constraint ensures that no package is assigned to more than one NAI. The third constraint ensures no UV is assigned to more than one package. The fourth constraint prevents an over-allocation of assets to identification missions. Relaxations of the first constraint may be necessary when there are more assets than NAIs to avoid underutilization of resources.

6. Objective Function

The objective in this model is to maximize the performance of the group's UV assets over a prioritized set of missions in a set of named areas of interest.

Maximize OBJ

$$\text{OBJ} = \alpha \sum_{i,j \in \text{det\_j}} \text{det}_{i,j} X_{i,j} + \beta \sum_{i,j \in \text{id\_j}} \text{id}_{i,j} X_{i,j} + \gamma \sum_{i,j \in \text{collop\_j}} \text{collop}_{i,j} X_{i,j}$$

G. IMPLEMENTING MUVAM

Implementing the scenarios discussed in Chapter I provides insight as to the usefulness of MUVAM. The goal of this input-output model is to assist the UV mission planner by providing useful recommendations for allocations of UVs to missions. Sensitivity analysis on constraints within the model determine if MUVAM is a balance between a model producing appropriate allocation solutions to very specific scenarios, or one that produces solutions to a wide variety of scenarios, but fail to make operational or analytical sense.

Chapter IV implements basic scenarios testing the model against the functional areas: detection, identification, and collection. The insights provided from the initial runs are used to facilitate the implementation of the more complex scenarios. The face validity of the model is determined by getting optimal results to a reasonable approximation of real problems.

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IV. ANALYSIS AND RESULTS

A. INTRODUCTION

Having introduced three operational scenarios, discussed the detection, identification, and collection functions, defined the corresponding metrics, explained how they are evaluated using applicable modeling theory, and detailed development and implementation of the Maritime UV Assignment Model (MUVAM), UV allocation is ready to be analyzed.

This chapter investigates the results of running the three operational scenarios in the MUVAM. Prior to implementing the heavy traffic, target rich and high priority rare event scenarios, the model requires applicable testing of the three functional areas: detection, identification and collection. The results of these functional tests and scenarios in the model provide insight into the capability of the model to handle the more complex operational scenarios. Comparing the analytical results against operational expectation and experience demonstrates the utility of the model for its intended user. The analysis is meant to establish face validity, supporting the notion that solutions provided by this model yield effective allocations of UVs to missions.

B. DETECTION

The functional test of the detection portion of the MUVAM used the same AO as the operational scenarios (140 nm by 140 nm). Although NAIs are not required to be the same dimension, the AO is divided into 16 equal sized NAI-SDs for ease of comparison. The ESG is centered on the origin of a grid with maximum X and Y at 70 nm and 105 nm, respectively, and the minimum X and Y at -70nm and -35nm, respectively, as shown in Figure 11. The potential packages are derived from 15 UVs of each type, from each ship. The packages used in the MUVAM analysis are the same as depicted in Tables 5.

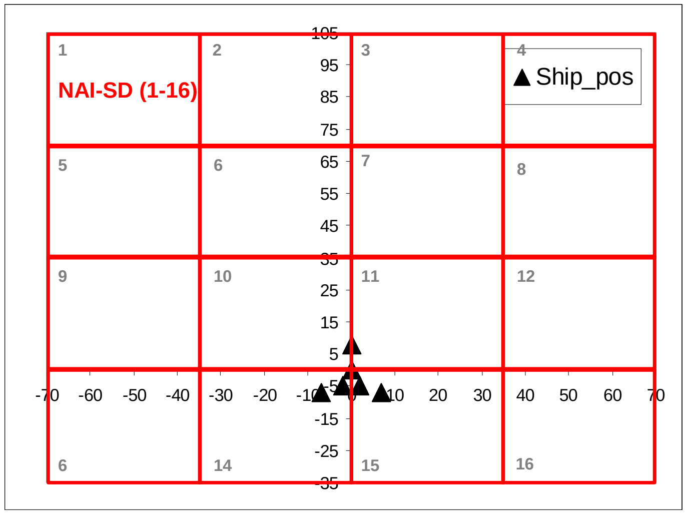


Figure 11. Baseline AO with ESG and 16 NAIs

The initial results of the model produce analytically sound search and detection missions, but does not reflect operationally sound mission planning. The areas of interest closest to the ESG are allocated the most assets. Analytically, this reflects the relationship between CDP and time on station: the closer the NAI is to the ESG, the more time on station the sensor has, and the CDP increases. The four NAI-SDs adjacent to the ESG are all assigned assets as well as the next five of six NAI-IDs moving away from the ESG along the X and Y axis. Figure 12 is a graphical representation of the detection only results.

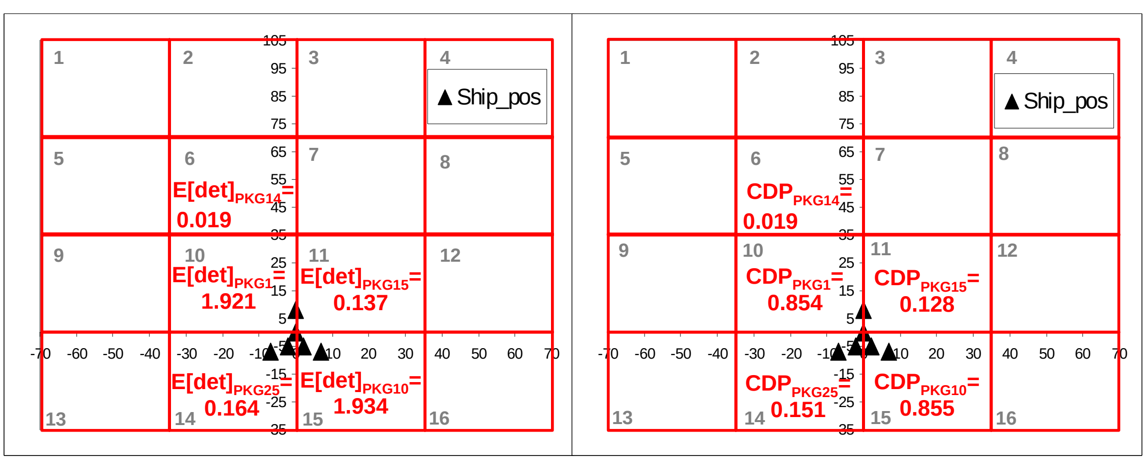


Figure 12. CDP_{PKG} in 5 of 16 NAI-SDs, using 8 of 15 UVs from 25 packages

In this circumstance, not all the assets are allocated. The seven UVs not allocated are MUAVs and USVs confirming analytical and operational considerations with respect to the limitations of these types of UVs. Operationally, MUAVs such as Dragon Eye, are used for short range, short duration, over the visible horizon collections (Dragon Eye, 2005). Two USVs are allocated to search and detection missions in this scenario. The results of the model are consistent with fleet experience, depicting both USVs and MUAVs as ill-suited for broad area search missions (TACMEMO, 2004). The results of this initial run prove that for detection functions, the model appropriately allocates assets, ignoring poor mission candidates, while allocating suitable assets for broad area search missions.

The next run does not include MUAVs and USVs and eliminates the requirement for detection in the NAI-SDs adjacent to the ESG (10, 11, 14, and 15). Shipboard sensors, such as radar, perform search coverage within the vital area, defined here as a radius of 35 nm from the ESG. The results lend credence to the validity of the detection function of the MUVAM, allocating assets to three NAI-SD previously unsearched, while another is assigned a higher performing UAV, as shown in Figure 13. All the assets are assigned and further increases in sensor coverage require more UVs suited for search and detection missions, including SUAVs, UAVs, and VTUAVs. Figure 13 summarizes the MUVAM results of detection only over the entire AO with the exception of the NAI-SDs assigned to the vital area.

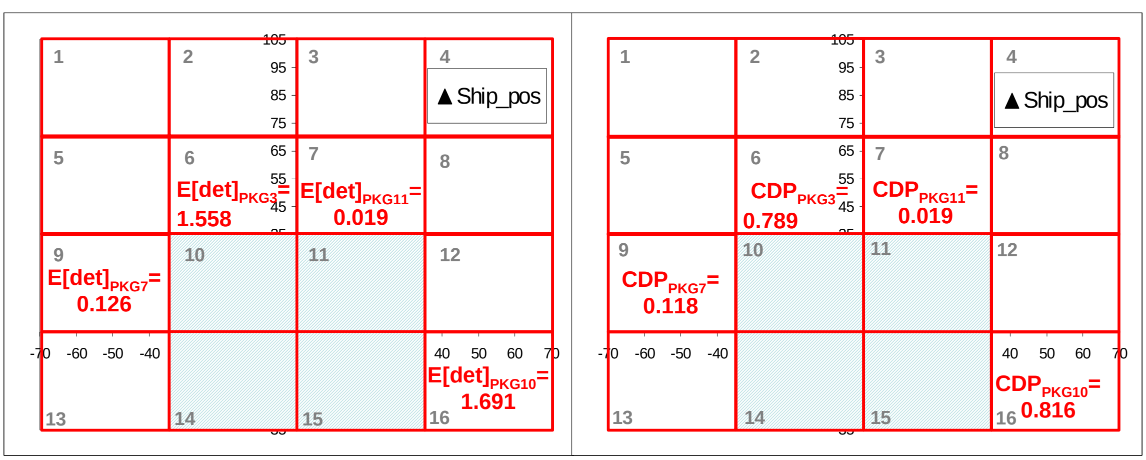


Figure 13. Additional NAI-SDs searched (7,9,16) with vital area covered by ship sensors and MUAVs and USVs are removed from available inventory

Relaxing the requirement for UV search in the vital area and removing from the available inventory ill-suited UVs from detection tasking enables examination of the assignment constraints to discern whether the model assigns more packages to fewer NAI-SDs, achieving higher CDPs in the assigned NAIs. Relaxing the constraint that limits the number of packages assigned to an NAI (PKG/NAI) allows the model to assign all the packages to the closest NAI and the total CDP may equal one, which is a waste of resources. Figure 14 shows the change of assignments when the PKG/NAI constraint is relaxed to two. Figure 15 shows the results when the constraint is relaxed to three. No assignment changes result from further relaxations.

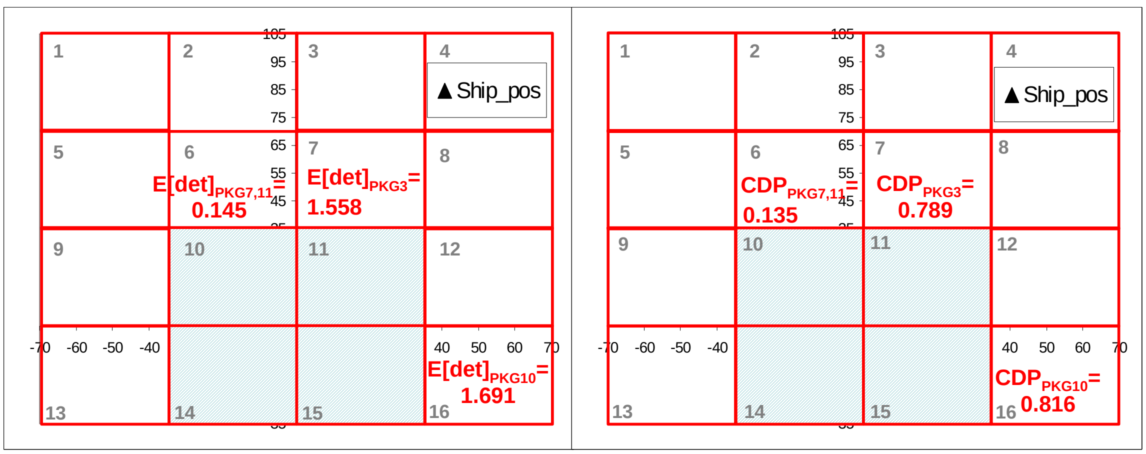


Figure 14. PKG/NAI constraint to ≤ 2, PKG 3 shifts to NAI 7, PKGs 7 & 11 shift to NAI 6. CDPs increase but number of NAIs with some coverage decreases by one

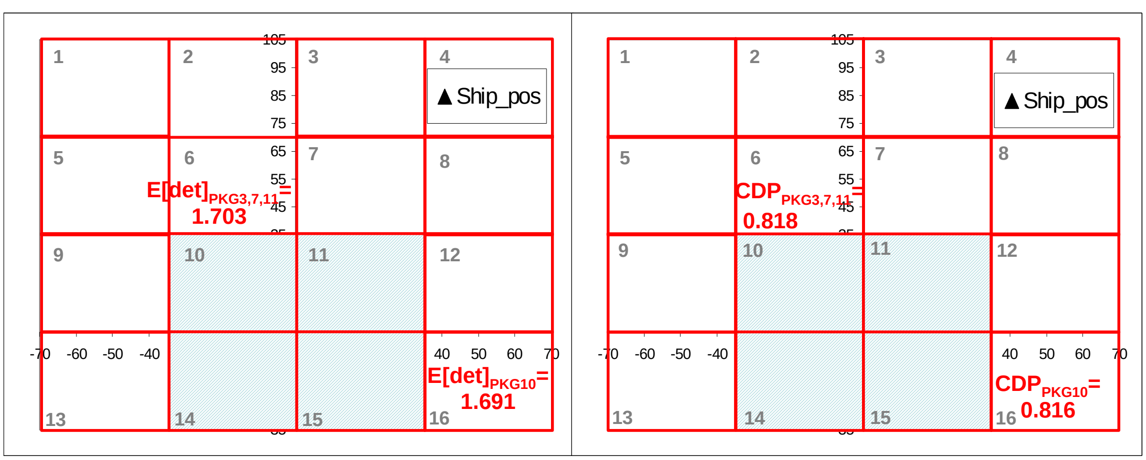


Figure 15. PKG/NAI constraint to ≤ 3, PKG 3 shifts to NAI 6, CDP increases in NAI 6 but number of NAIs with some coverage decreases by one

Other adjustments to the model include increasing the number of UVs per package from three and allowing packages to be formed among UVs from different ships within the ESG. The Input Model omits production of such package combinations, limiting the scope of the problem and achieving a balance between UV allocations resulting in assignments of UVs to fewer NAIs with high CDPs and assigning UVs to more NAIs with lower CDPs.

Excluding the vital area and eliminating MUAVs and USVs from the available inventory is a sensible step for assigning the right platform to the right job. The detection tasking allocation aspect of the MUVAM yields consistent, acceptable results. The balance between the quantity of NAI-SDs a moderate-to-low level of coverage (low CDP), versus few NAI-SDs with higher CDPs is achieved by iterating through relaxations of the PKG/NAI constraint. The detection portion of the model accurately portrays operational scenarios requiring detection assets while providing the user with detailed and quantitatively acceptable information for optimal search mission planning.

C. IDENTIFICATION

The same baseline scenario used to test the detection portion is used to test the identification portion of the MUVAM. Additional inputs include dividing the AO into two NAI-IDs and creating 80 contacts uniformly distributed over the AO. A random number generator in Microsoft Excel™ and a linear equation provided the contacts and their grid coordinates. The contacts were generated repeatedly until an equal number of contacts were obtained in both NAI-IDs, thus avoiding potential bias towards one versus the other.

The results of the first run are plotted in Figure 16. The first takeaway from Figure 18 is that NAI-ID 2 has a higher percentage of identifications made. The reason is likely due to a difference in package capability. However, other explanations must be ruled out to determine face validity of the identification portion of the model. The arbitrary placement of the waypoints could produce disparity between performances in the NAIs. Rather than allowing the user to enter the waypoints, an optimal waypoint placement was accomplished with a simple linear program Microsoft Excel's™ Solver function. The objective is to minimize D_{NAI} while changing the X, Y coordinates of the waypoints, yielding optimal placement.

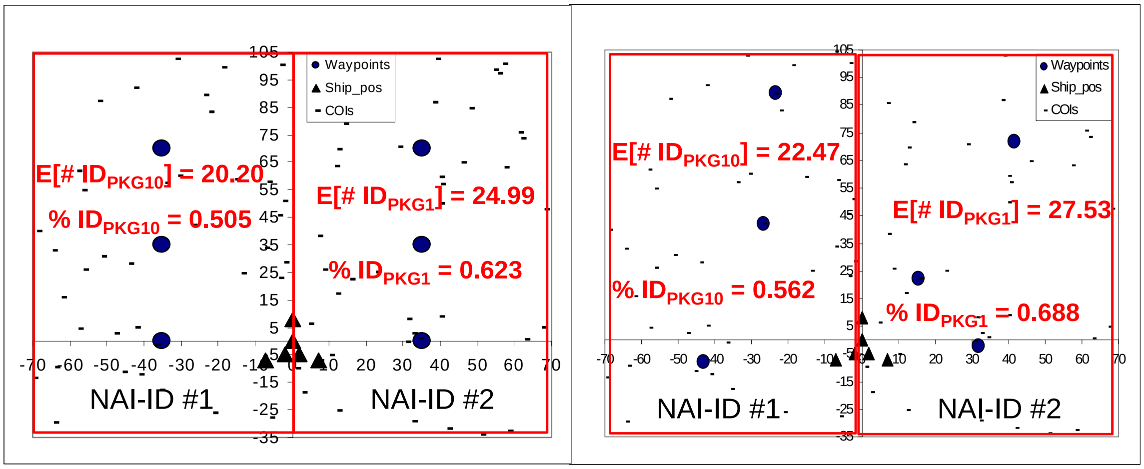
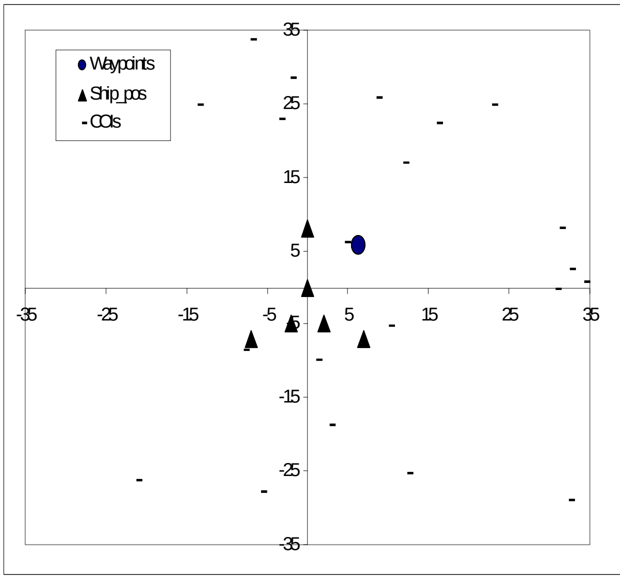


Figure 16. Two iterations of ID of 80 COIs Uniformly distributed throughout AO. Left side uses arbitrary waypoints, right side uses optimal waypoint placement

Optimal waypoint placement yields higher % ID in both NAI-IDs and demonstrates that UV package capabilities are the driving factor affecting different results between NAI-IDs of the same size, number of contacts and contact distribution. The packages assigned to conduct the identifications consist of SUAVs, UAVs and VTUAVs. Similar to the detection functions, the assignment of MUAVs and USVs are questioned. Tactically, they are suitable for identification tasking. As discussed previously, the Dragon Eye is an example of an MUAV successfully identifying a variety of objects within its effective range (Dragon Eye, 2005). Therefore, it may be beneficial to divide the basic identification scenario into three NAI-IDs, where the third NAI-ID consists of the contacts in the vital area (<35 nm) of the ESG and only MUAVs and USVs are assigned to identify contacts. This is similar to the adjustment made to the detection portion of the MUVAM.

The list of available packages is reduced from the original 25 packages to 14 developed from six MUAVs and three USVs. The NAI-ID encompassing the vital area contains 21 contacts from among the randomly generated 80 contacts. The model uses only one optimally situated waypoint at position (6.4, 5.8). Figure 17 is a close up of the ESG, the vital area, the waypoint, and the contacts.



Pkg ID	Ship	Config of UV #1	Config of UV #2	Config of UV #3	E[#IDs}
1	3	1	0	0	4.53
2	3	1	0	0	4.53
3	3	1	1	0	9.07
4	4	15	0	0	4.53
5	5	1	1	1	13.6
6	5	14	0	0	4.53
7	5	1	1	0	9.07
8	5	1	1	0	9.07
9	5	1	1	0	9.07
10	5	1	0	0	4.53
11	5	1	0	0	4.53
12	5	1	0	0	4.53
13	6	1	0	0	4.53
14	6	14	0	0	4.53

Figure 17. Close up view of vital area, MUAV and USV packages, and their E[#IDs] for the vital area. Shaded packages were allocated by the UV Assignment Model resulting in a cumulative % ID = (4.53+13.6)/21=0.863

Relaxing the PKG/NAI constraint is appropriate for assigning MUAVs and USVs to ID missions in the vital area. Navy doctrine and the previous results for detection demonstrate this practice (TACMEMO, 2004). Therefore, the best way to assign MUAVs and USVs to identification missions within the vital area is to run the model with the PKG/NAI constraint relaxed to the number of MUAVs and USVs. Setting the IDLIMIT constraint to the number of contacts requiring identification within the vital area maximizes the number of identifications made without exceeding the number of required identifications, subsequently avoiding quantitatively excessive assignments.

Testing the identification portion of the MUVAM demonstrates the utility of the model. Although the model does not directly handle the limitations of MUAVs and USVs to identification missions within the vital area, it is flexible enough to provide planning guidance to the user. Identification mission planning in the vital area merits independent considerations to determine how many assets are required to identify a desired percentage of contacts. The user can run the MUVAM for all the identification requirements in the vital area, assign MUAVs and USVs, then run the model for the remaining UVs and contacts to determine the number of assets required to achieve the desired percent identification. Adjusting the manner in which real problems are input into the MUVAM, maintains its balance and flexibility of being a model that is detailed enough to provide useful UV mission planning guidance for real problems, without being limited to a narrow range of specific scenarios.

D. COLLECTION

Collection functions are analyzed similar to the previous two. The entire inventory of available packages is entered into the model for collection missions over the entire AO. NAI-CPs are derived from the AO the same as the detection NAI-SDs, 16 equally sized squares. The expected number of collection events in each NAI-CP per hour is 0.1 (arrival rate-λ). Expected service time per collection opportunity is listed for each configuration in Table 12.

The expected number of services does not provide meaningful information without comparison to the expected number of arrivals; therefore a plot of the proportion of time collection opportunities are realized is shown in Figure 18. The takeaway from this plot of package assignments to NAI-CPs is that not all UVs are utilized. The six UVs not utilized are MUAVs. In NAI-CP 10, package 4, an SUAV is assigned.

Using insight gleaned from the previous two baseline scenarios, it may be beneficial to implement MUAVs and USVs strictly in the vital area prior to assigning more capable assets. Figure 19 depicts these results. The failure to utilize all the available UVs is the result of UVs that cannot reach NAI-CPs and it also reflects the one PKG/NAI constraint. Running the same problem with the constraint relaxed to up to three packages per NAI-CP yields the results shown in Figure 19.

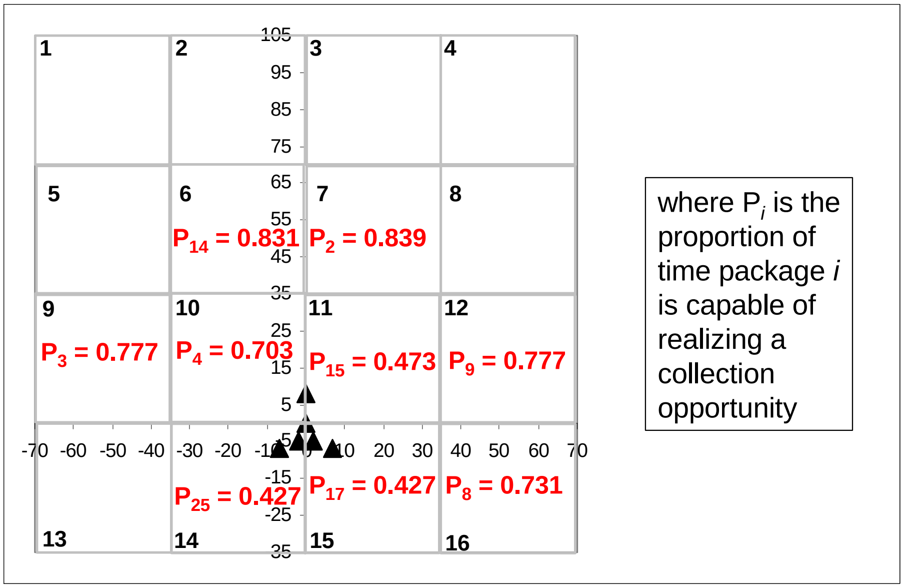


Figure 18. MUVAM results for collection mission over entire AO. 9 of 15 UV allocated, non-allocated assets are all MUAVs

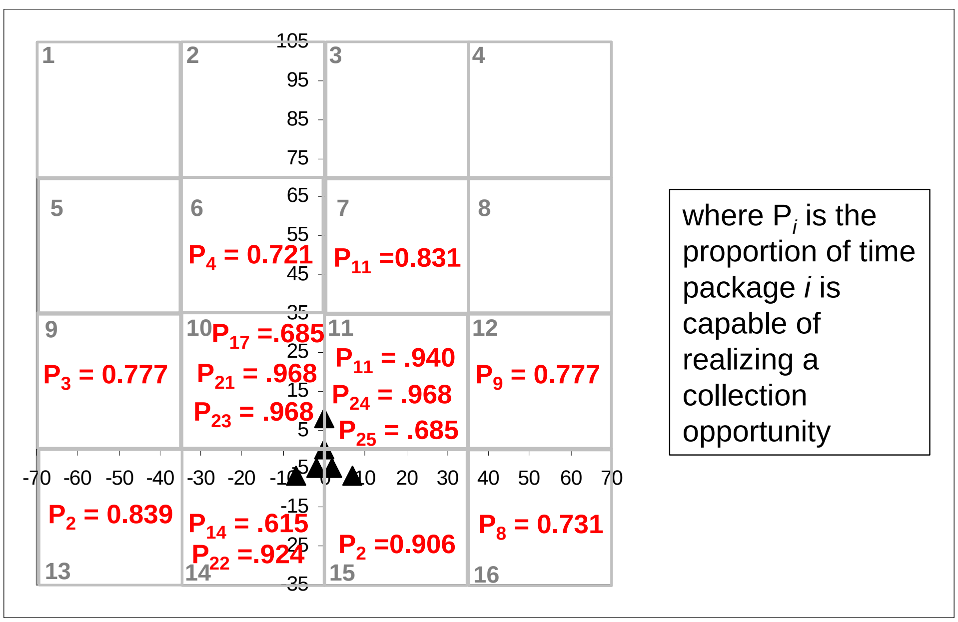


Figure 19. Second iteration of collection missions over AO with NAI/PKG constraint relaxed ($\leq$ 3) and MUAVs and USVs assigned to vital area before the rest of the NAI-CPs

Similar to identification with respect to strictly allocating MUAVs and USVs to missions within the vital area, the collection portion of the MUVAM appears to appropriately assign MUAVs and USVs to the vital area, freeing up more capable UVs for tasking further from the vital area center. Since this is a smaller scale scenario, close attention is given to this condition as the scenarios are combined and become more robust. Now that each function area has been run through the model, the operational scenarios discussed in Chapter I are implemented with the insights gained.

D. HEAVY TRAFFIC SCENARIO

The information gained from running the model for detection and identification functions provides a starting point for running the model under the heavy traffic scenario described in Chapter I. The heavy traffic scenario focuses on detection and identification in the AO, where specified areas require search and detection assets, and contacts require identification throughout the AO, but some areas within the AO have higher concentrations.

The scenario is initialized with 80 contacts, in the same size AO discussed previously. The contacts are generated randomly using a uniform number generator function and linear equations. To mirror the heavy traffic scenario described in Chapter I, 40 contacts were generated uniformly throughout the AO, 20 are concentrated in region above the line Y = 70, and the last 20 are concentrated in the vital area plus the area east of the vital area. There are three NAI-IDs; one for the vital area and two NAI-SDs divide the remainder of the AO equally by area. NAI-ID 1 has 24 contacts, NAI-ID 2 has 32 contacts, and NAI-ID 3 has 24 contacts. The NAI-SDs (1-6) are located in the portions of the AO without concentrated contacts. Figure 25 depicts the layout of the NAI-SDs and NAI-IDs, as well as the contacts.

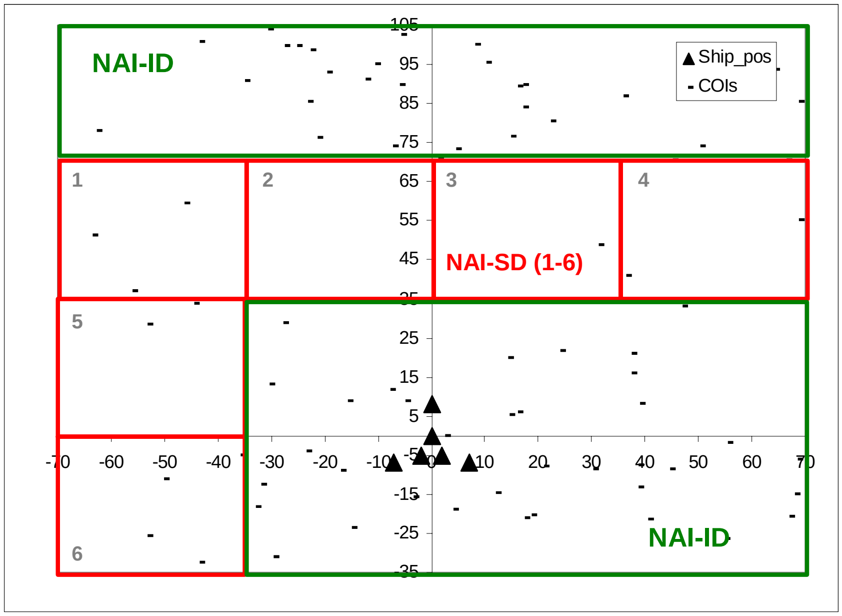


Figure 20. Heavy Traffic Scenario and NAI designation.

Running the model, MUAVs and USVs are not used for search missions; and when used for identification missions, their operations are restricted to the vital area. These outcomes are intuitively and quantitatively consistent. Segregating the vital area and its contacts from the AO and running the MUVAM with only packages comprised of MUAVs and USVs appears to deliver the best allocation of assets. The PKG/NAI constraint is completely relaxed since these UVs are dedicated to identification missions within the vital area. The MUVAM allocates six packages consisting of three USVs and four MUAVs to identify 93% of the contacts in the vital area.

The six NAI-SDs and two NAI-IDs are now run through the model with the remaining packages. Relaxations of PKG/NAI constraint are run and analyzed resulting until the best result is determined to be PKG/NAI ≤ 3. The result is depicted in Figure 21.

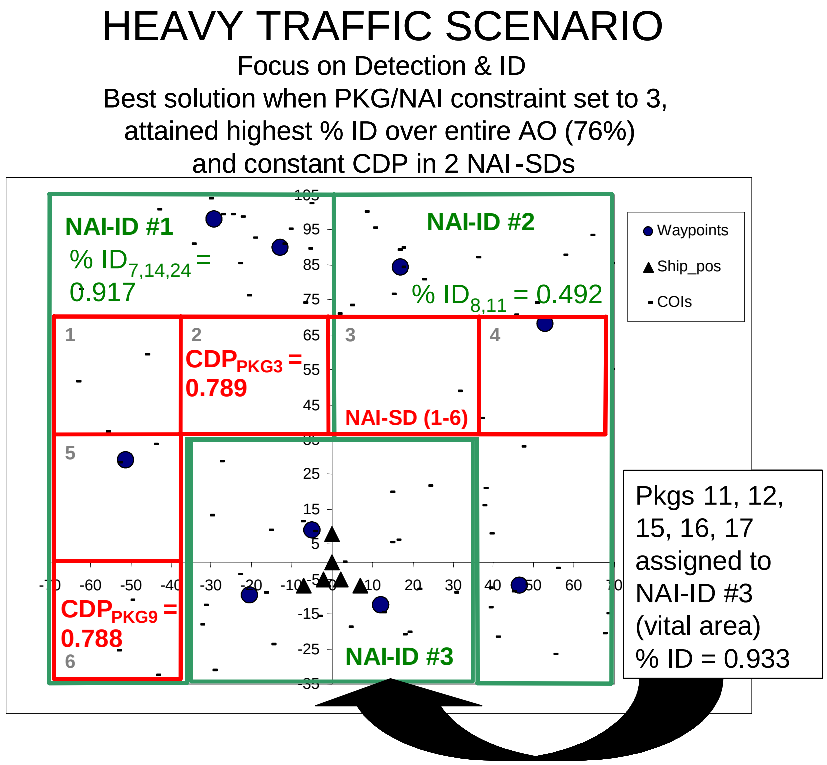


Figure 21. Heavy Traffic Scenario Results

Allocation of UVs for detection is consistent throughout model runs regardless of constraining the numbers of packages per NAI and confirms that the limitations of the available package inventory are binding on detection allocations. Under this premise, the user is inclined to use the remaining inventory of UVs to attain the most identifications possible. Knowing the exact number of contacts in each NAI-ID and the percentage of identifications made in each NAI-ID, the total number of identifications over the entire AO is calculated.

The allocation attaining the highest overall percent identifications in the entire AO is the most desirable under the conditions of this scenario. Possible complications of this result include the introduction of critical contacts, or some high priority identification requirement among the existing contacts. The MUVAM does not directly address these types of events, however the conservative distance calculation driving the percent identification conceivably accounts for unplanned requirements. Figure 22 is a plot of the relationship between allocation in NAI-IDs 1 and 2, and the percent identification over the entire AO (% ID of AO).

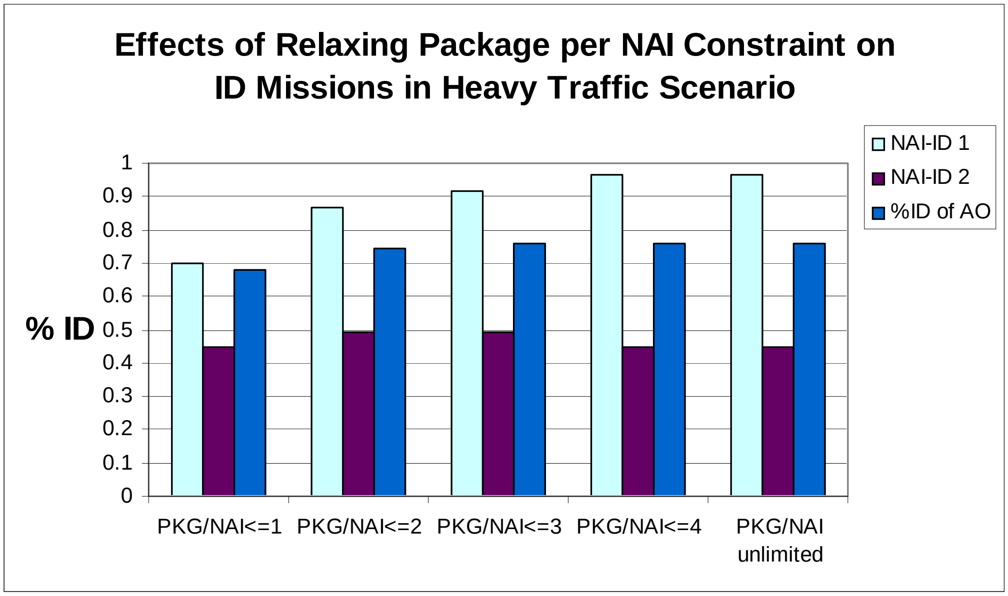


Figure 22. Results of progressive relaxation of PKG/NAI constraint

In Figure 22, the NAI-SDs and NAI-ID #1 are omitted because they are essentially constant for each PKG/NAI constraint. Beyond PKG/NAI ≤ 3, the plot shows no appreciable change in % ID of the AO. The tradeoff between NAI-ID #1 and NAI-ID #2 when relaxing the constraint from three to four is appreciable. Enhancing the model to make an allocation distinguishing between the two options is too specific to a particular scenario. This type of distinction is better left to the user, thus proving the utility of the model in driving the scenario and allocation problem to this point.

The MUVAM provides useful UV allocation guidance under the heavy traffic scenario. Previous insights regarding MUAV and USV tasking in the vital area provide the framework for a process to input scenario and asset specifics into the MUVAM to achieve useful results. The scenario and modeling results are a reasonable approximation of the real problem. This is evident in the accurate and consistent results for the detection allocations and attainment of the maximum number of identifications over the entire AO.

E. TARGET RICH SCENARIO

The information gained from implementing the model for collection and identification functions provides a starting point for the target rich scenario described in Chapter I. The target rich scenario focuses on collection and identification in the AO, where specified areas require collection assets, and contacts require identification throughout the AO.

The AO and contact distribution are identical to the heavy traffic scenario, as well as the three NAI-IDs. The NAI-IDs have 24, 32 and 24 contacts, respectively. There are seven NAI-CPs of equal size lining the northern and eastern edges of the AO (Figure 23). Following the same process used in the heavy traffic scenario, MUAVs and USVs are implemented into the model for allocation only in the vital area. Once the allocation of the vital area is determined, the remaining assets are implemented into the model for allocation to the remaining NAIs.

Figure 23 displays the results. Critical to this scenario is that there are only eight UVs in the available inventory, two of which are a USV and MUAV. The most capable packages, consisting of three and two UVs respectively, accomplish a combined 96.3% of the identification missions (packages 1 and 10). The remaining UV, an SUAV, is assigned to NAI-CP 6 for collection missions. This makes intuitive and analytical sense since NAI-CP 6 is the closest NAI to the host platform. The tendency to favor identifications of contacts in known positions makes operational sense in that it is not preferred to utilize resources towards infrequent events rather than a detection that has already been made. The model is consistent with analytical and operational expectations. It is also consistent with the notion that the inventory of assets and their limited capabilities is reducing the ability to meet all the mission requirements.

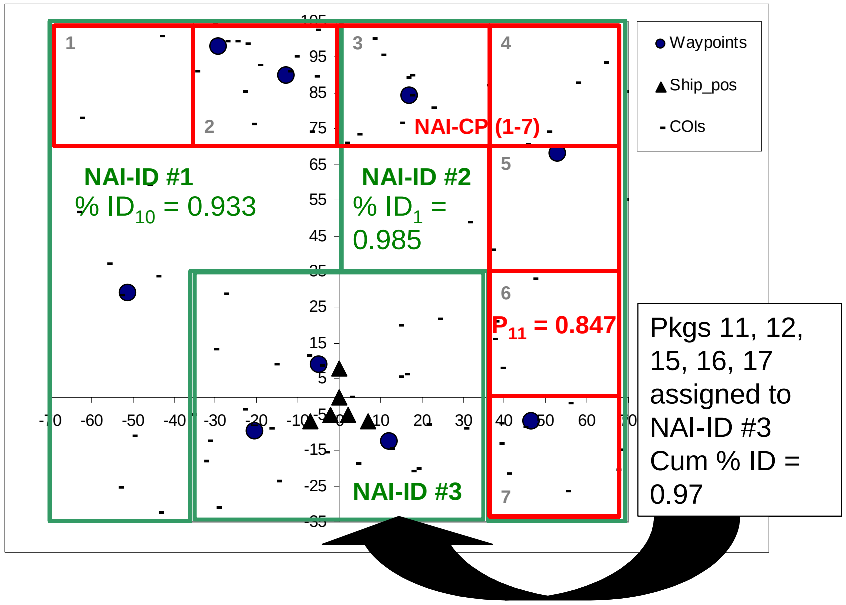


Figure 23. Target Rich Scenario Results

F. HIGH PRIORITY RARE EVENTS SCENARIO

The final scenario for analysis using the MUVAM concerns the rare, high-priority event scenario described in Chapter I. The same AO is considered in this scenario as in all the previous implementations, except detection and collection functions are the main effort. The vital area is not considered for asset allocation because detections in the vital area are made with ship's sensors. The northernmost section is designated as collection areas and is divided into equal NAI-CPs, similar to previous scenario implementation. The remaining portions of the AO are divided into eight equal sized NAI-SDs. Figure 24 depicts the layout of the AO and NAI-CPs and NAI-IDs described.

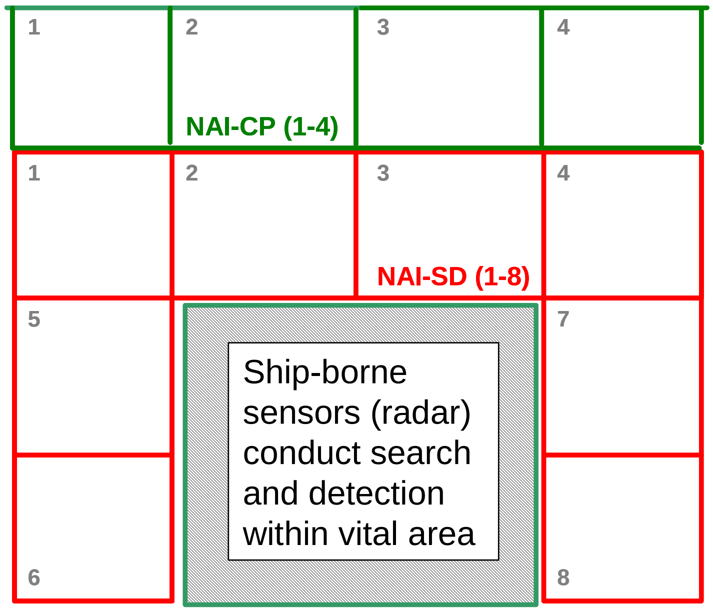


Figure 24. Rare High-Priority Events Scenario

Since search and identification in the vital area are omitted from this scenario, there is no need to implement MUAVs and USVs through the scenario separately. In this case, they are considered for allocation with the rest of the package inventory. The results did not allocate any MUAVs or USVs to any NAIs, confirming previous observations regarding the utility of these platforms beyond the vital area and their marginal suitability for detection missions. It also lends credence to the MUVAM being a reasonable approximation of a real problem.

The results shown in Figure 25 are consistent with previous results. UVs are allocated to very few NAI-SDs due to the lack of configurations in the available inventory with preferred performance parameters. The MUVAM assigns assets to collection functions because the expected numbers of events serviced are consistently higher than most expected number of detections in the same set of packages. Regardless of the preference, the MUVAM still provides information to the user with respect to the capabilities and expected results from a set of available packages and a balance is created between a model that is overly sensitive to specific scenarios and one that is capable of providing useful results for real problems.

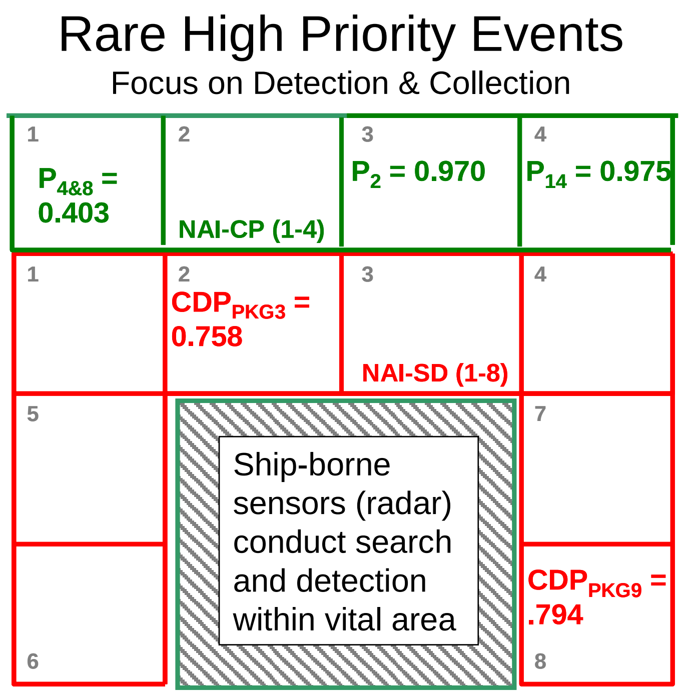


Figure 25. Results of High Priority Rare Events Scenario

Previous scenarios implemented in the MUVAM resulted in better asset allocations while iterating through PKG/NAI constraint relaxations. The rare, high priority event scenario saw very little change or increase in objective function value. The results are displayed in Table 15. Package 14 is allocated to NAI-CP 2 in the first iteration, but is assigned to NAI-CP 4 in the second, achieving a higher proportion of time capable of collection. Package 4 subsequently shifts NAI-CP 4 to NAI-CP 1 increasing the operational effectiveness.

	NAI/PKG<=1	NAI/PKG<=2	NAI/PKG<=3	NAI/PKG<=4
NAI-CP 1	0.152	0.403	0.403	0.403
NAI-CP 2	0.959	0.000	0.000	0.000
NAI-CP 3	0.970	0.970	0.970	0.970
NAI-CP 4	0.251	0.975	0.975	0.975
NAI-SD 2	0.758	0.758	0.758	0.758
NAI-SD 8	0.794	0.794	0.794	0.794

Table 15. Minimal change as PKG/NAI limit relaxed

G. FINDINGS

For the scenarios considered, the MUVAM has been found to be flexible and detailed enough to recommend operationally sound allocation of UVs to critical missions. Several interesting results were discovered during initial test runs of the model, such as the non-allocation of MUAVs and USVs beyond the vital area. Examination of the cause of those results provides important insight concerning UV payload and speed limitations. Another interesting result of the sensitivity analysis of the results concerned the constraint limiting the number of packages allocated per NAI. Although it seemed reasonable to force the assignment model to spread the UV packages out over the various NAIs, it was found that that did not attain the best results for a specific scenario.

V. CONCLUSIONS

This chapter discusses overall conclusions of the analysis and provides recommendations for future studies and validation of the MUVAM. Recommendations address possibilities for future versions of the MUVAM, including user interface, MUAV and USV performance in the vital area, as well as the sensitivity of the PKG/NAI constraint in the optimization portion of MUVAM. Any changes to the model should continue to maintain the balance of flexibility and detail that the MUVAM has thus far demonstrated.

This research has resulted in a model that provides analytically-based mission planning guidance for UVs conducting maritime missions. The MUVAM provides the ESG/CSG action officers a tool enabling effective assignment of UV inventory to a set of mission critical functions. The model consists of three parts, the Input Model, the Matrix Generator, and the UV Assignment Program.

The Input Model requires two general user inputs, the asset inventory, and scenario data. Given the input of available assets, UV platforms and sensors combine into configurations with predetermined parameters characteristic to the equipment. As many as three UVs of various configurations from a single ship combine to form packages. Missions are categorized into one of three functions for entry into the model: detection, identification, and collection. Scenarios implemented for this analysis included a heavy traffic scenario focusing on detection and identification, target rich scenario focusing on identification and collection, and rare high-priority events scenario focusing on search and collection.

The Matrix Generator spreadsheet uses the data in the Input Model to calculate measures of performance (MOP) for an inventory of UVs and a given scenario. The MOPs are calculated using the random search model, conservative time-speed-distance calculations, and queuing theory. These analytical approaches address detection, identification and collection functions, respectively. The spreadsheet generates n packages by m missions sized matrices as input into UV Assignment Program.

The UV Assignment Program is an optimization program that assigns UV packages to named area of interest (NAI) within a user defined scenario. Constraints include preventing the model from assigning the same package to more than one NAI, preventing the same UV from being assigned to multiple packages, and assigning only one PKG/NAI. The last constraint was found to be too restrictive when the scenarios were implemented into the model. Access to the source code facilitated relaxing the constraint and conducting sensitivity analysis.

The analysis of implementing the baseline scenarios into the model proved that the optimal solutions generated by the MUVAM are operationally useful UV allocations to a reasonable approximation of the real problem. The results of the model implementation were tactically and analytically appropriate for each function. Examples of this type of face validation are the specific insights made pertaining to MUAV and USV tasking, as well as allocation of assets in the vital area. MUAVs and USVs, due to their limited speed and combat radius, are ill-suited for detection, and must be specifically allocated for identification and collection within the vital area. The missions in the vital area must be implemented into the MUVAM separately from missions beyond. These conditions were evident from the model output and intuitively make sense from an operational viewpoint.

A. RECOMMENDATIONS

Recommended improvements for the MUVAM include development of a database oriented input portion for developing packages. The scope of the analysis intentionally prohibited packages consisting of more than three UVs, and did not allow packages of UVs across different ships in the ESG. Excel, although widely available and familiar, is somewhat cumbersome for entering the assets and developing the packages. The need to layer the inventory for recall by the Matrix Generator spreadsheet was a priority over a more user friendly interface.

Upgrading the entire model to handle MUAV, USV, and vital area planning would increase the utility of the model. During the analysis, these aspects of planning were done manually and progressively for each iteration of the scenario. Similarly, the relaxation of the PKG/NAI constraint was carried out manually for each iteration. Reformulating the linear integer program assignment model to change that fixed upper bound into a general integer variable would be more efficient.

Developing the MUVAM into a dynamic model would be beneficial to see how the theories used hold up against changes to the scenario. Implementing the model into a simulation or tactical wargame can show its usefulness beyond initial planning processes. Although conservative methodologies were used in the model, factors such as weather, changing mission priorities, and equipment failures were not addressed directly. The inclusion of time periods in a dynamic model will addresses these considerations as operational availability, maintenance, follow-on operations, and re-tasking.

Future research should include using real data on UVs, sensors performance, and actual missions conducted to support development of the RMP. Implementing the data into the model and comparing the actual allocation and results against the allocations developed by the MUVAM would provide further evidence of its validity. Ultimately operational test and evaluation in real ESG/CSG operations will determine the utility of the MUVAM. This study's main contribution is that well-established search theory, math programming and queuing theory techniques can be used to generate quantitatively-based recommendations for unmanned vehicle mission tasking in tactically challenging scenarios.

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