# Optimization of ISR Platforms for Improved Collection in Maritime Environments

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## ABSTRACT

Maritime Domain Awareness (MDA) requires the ability to accurately identify, track, and understand the rationale of the behavior of vessels given the surrounding contextual environment. Reasoning about such behaviors can ultimately lead to a better understanding of whether the behaviors are normal or anomalous. In order to adequately improve the quality and overall confidence of the output of the reasoning process that leads to the conclusions regarding the nature of vessel behaviors, a system must be provided with sufficient, high quality, track data from which such conclusions could be made. The nature of maritime data, particularly in specific environments, and the fact that Intelligence, Surveillance and Reconnaissance (ISR) assets in future network-centric systems are likely to be heavily requested due to the complexity and number of non-traditional missions, necessitates that these resources be effectively utilized across the mission space in order to maximize overall collection and hence derive good quality tracks for actionable tasking of limited resources.

This paper will describe the development of ISR allocation optimization algorithms for the maritime domain, leveraging modeling and simulation capabilities from the Interactive Scenario Builder (ISB) decision support tool. The ISB is a 3D tactical decision aid and mission planning system that provides insight into, and visualization of, the RF environment. The ISB is used in the Joint Information Operations Command and in Navy IO Centers (Hawaii, Georgia, Norfolk, San Diego, and Whidbey Island). The optimization algorithms being developed within the ISB take into consideration "areas of interest" such as high interest vessel movements, shipping lanes, fishing areas, military exercises, ports of particular interest, area of high piracy, cargo, or past shipping incidents. These events help focus where specific ISR collection resources need to be positioned. The other type of event includes "difficulty measures" such as signal limitations or enhancements caused by Meteorology and Oceanography (METOC) conditions. Such affects may lead to a reduction in effective surveillance and tracking caused by spatial-temporal gaps in signal collection. The optimization techniques will enable the optimal positioning of ISR assets to maximize signal coverage, as well as enable the tracking of assets at the signal scan-on-scan level, in complex and uncertain maritime tracking environments by optimizing over areas of interest, difficulty measures and ISR asset performance characteristics. This paper will describe the technical details associated with the optimization techniques, early development and integration results within the ISB and lastly future development activities.

## 1.0 Introduction

Current sensor placement strategies are primarily manual, and are not robust to dynamic changes in the environment. MDA efforts rely on the analysis and identification of vessel electronic emissions including ELINT and Automated Identification Systems (AIS) intercepts. There are hundreds of thousands of vessel intercepts worldwide daily. Environmental conditions impact electronic signals, for example, through decreases in Signal-to-Noise Ration (SNR) or through increasing the propagation distance. Taken together, this constitutes the “difficulty measures”. In order to decide where to allocate resources under the difficulty measures, there must also be a sound rationale (i.e., interest measures) of where to place scarce resources. The novelty of our approach is the optimization of the placement of the ISR resources, concurrently factoring in the difficulty and interest measures. This capability will provide unique operational relevance by supporting activities such as blue force positioning for protection, red force identification and location, Global War on Terror (GWOT) and MDA.

The goal is to develop a toolkit that finds an optimal allocation of sensor resources within the maritime domain, in the sense of maximizing the expected value of the information obtained. In order to maintain a state of optimal utility, this allocation will need to be refined or updated based on two types of events in the battlespace. The first type of event will include “interest measures”, such as high interest vessel movements, key shipping lanes, fishing areas, military exercises, ports of particular interest, area of high piracy, cargo, and past shipping incidents. These events help focus where specific ISR collection resources need to be positioned. The other type of event includes “difficulty measures” such as limitations or enhancements caused by Meteorological and Oceanography (METOC) conditions. This may lead to a reduction in effective surveillance and tracking caused by spatial-temporal gaps in signal collection. The toolkit will support the warfighter by enabling the optimal repositioning of assets in maritime tracking environments by simultaneously optimizing across areas of interest, difficulty measures and ISR asset performance characteristics.

## 2.0 Sensor Allocation Tool Architecture

The proposed architecture is depicted in Figure 1. The overall workflow consists in the user first creating a scenario consisting of platforms and threats (and their anticipated or projected movements) within the ISB environment. When constructing a scenario, the different types of sensors on the various platforms must also be specified as well as their operating characteristics. Two kinds of optimization techniques are available through the ISB plug-in interface, namely, optimization of signal coverage and optimization of track continuity. Each optimization uses appropriately developed metrics for the evaluation of the effectiveness of the optimization. The signal coverage optimization technique attempts to optimize the placement of platforms in order to maximize a signal coverage metric associated with the targets of interest, while the track continuity technique attempts to minimize the amount of time that a target cannot be tracked. The box titled “Optimize Scenario” in Figure 1 implements both techniques with a different evaluation scheme. . The track continuity optimization technique utilizes an evaluation from EWSim (“EWSim Scan-to-Scan Evaluation” box in Figure 1), which provides a scan-on-scan modeling capability from emitter-to-receiver, in order to assess the optimized solution in terms of gaps in track continuity. The algorithms and metrics are described in later sections.

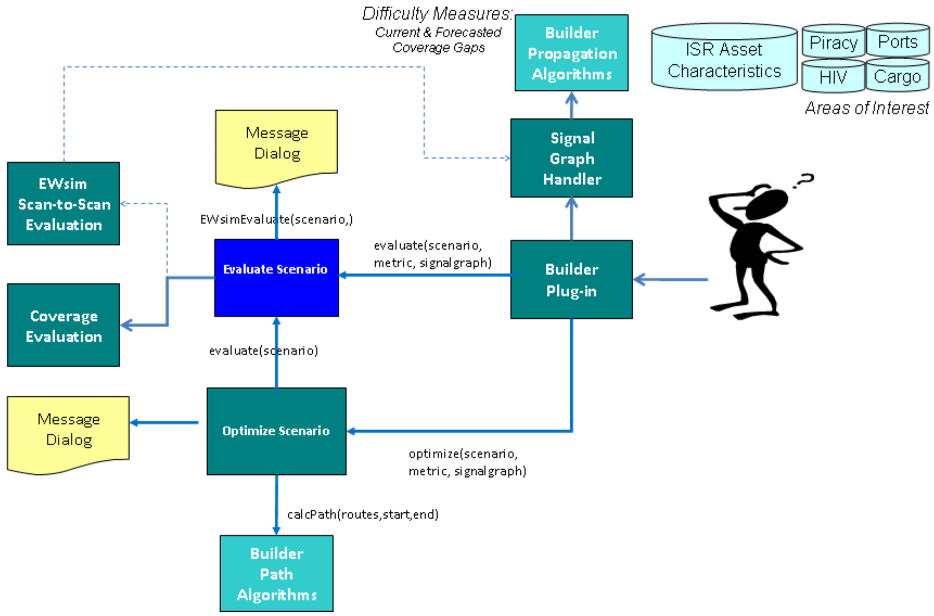


**Figure 1: Sensor Allocation Tool Components**

## 2.1 The Interactive Scenario Builder

The ISB is a software application and programming framework for building radio frequency (RF) scenarios and analyzing propagation within a simulated environment (Figure 2). Its two primary uses are easy scenario construction with a globe based interface and making propagation models accessible to the DoD community without requiring expertise in electromagnetic modeling. The ISB project started in the seventies as a FORTRAN tool for RF engineers at NRL. It later became a C application targeting SGI machines, but was still intended for lab use. The utility of a graphical RF analysis tool for planners at the tactical and operational levels led to an attempt to install ISB on SGI machines afloat. The software wasn't easily deployable though, and had significant usability problems, but still found utility at various commands that realized that the ISB provided advances in predicting and visualizing the performance of radar, communication and EW systems. In light of changing requirements for more widespread use, an effort to make the tool more accessible to the DoD community by rewriting the ISB in Java began in 2002. The result is the current ISB, the version 3 line, of which the most recent release is version 3.2.3 from May 2009.

With the version 3-baseline efforts for improved usability and deployment, there also came a desire to make the tool accessible to third party software developers. This goal was met by designing the application with an extensive plug-in framework. The system is designed as an amalgamation of related services that communicate over a central bus and are accessible by a universal registry. The application consists of a few of the most critical services and packages, but most of the functionality within ISB is implemented using the plug-in framework and is distributed with the application as part of the standard installation. Plug-ins can add new platform types, new equipment types, or can create entirely new object types that can be saved with the scenario file and otherwise appear seamlessly as part of the application.

One of the key capabilities that the ISB offers is it's suite of propagation models. The propagation models are implemented by another DoD owned software tool called EMPIRE. EMPIRE provides a common programming interface for accessing a number of propagation models, including:

- Advanced Propagation Model (APM)
- HF field strength model from SSC-San Diego,
- Standard propagation model (also referred to as FFACTR)
- Millimeter Wave Propagation model (MMWPROP)
- Radio Physical Optics (RPO) model
- Variable Terrain Radio Parabolic Equation (VTRPE) model
- The Terrain Integrated Rough Earth Model (TIREM)
- Irregular Terrain Model (ITM).

Through EMPIRE, the same interface for specifying terrain, ground dielectrics, atmosphere, foliage, rain rate, and other factors apply to all supported propagation models. The ISB builds on EMPIRE's common programming interface, adding a globe interface for building scenarios, viewing terrain, maps, entering other propagation factors, calculating the impacts of Electronic Attack (EA) on radar and communication performance and displaying propagation results as color plot overlays on a globe.

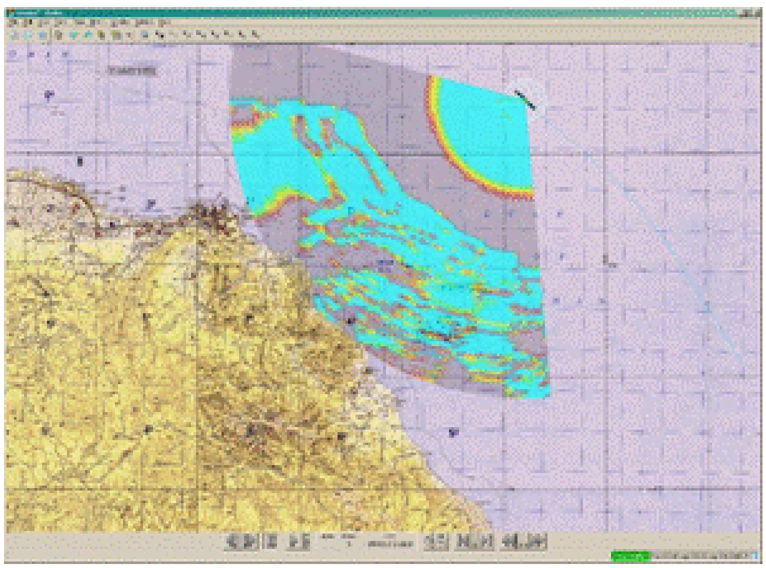

**Figure 2: ISB Screenshot**

One of the most complicated factors affecting RF propagation predictions is the effect of varying atmospheric conditions on an RF signal as it travels through space. To help understand this, the ISB has a range of ways to enter atmosphere profiles and pass them to EMPIRE for assessment of their impact on propagation. Ducting can be manually defined by specifying the humidity, duct height, and strength. Conditions can be estimated based on a large data set of average conditions from the past twenty years, as compiled by the National Center for Environmental Prediction. Current conditions and short term forecasts can be fetched automatically from web services provided by Fleet Numerical Meteorological and Oceanographic Center (FNMOC) or from the Air Force Weather Association (AFWA). The forecast data can be used to create Monin-Obukhov atmosphere profiles. Some of the interesting parameters available from these services are electromagnetic duct base height and strengths, surface wind speed, and temperature. The data comes from COAMPS, MM5, and WRF models.

The ISB's graph package is another part of the framework that is available to the optimization algorithms. It has classes to represent nodes, edges, and graphs, classes for building graphs as a discretization of spherical or Euclidean space, and classes for finding shortest paths using Dijkstra's or $A*$ algorithms. The

*A** algorithm is basically Dijkstra's algorithm with the addition of a heuristic that predicts the distance from a given hypothetical path to the end point. If the heuristic *h(x)* returns zero for all nodes *x*, *A** becomes analogous to Dijkstra's breadth first style algorithm. A few standard heuristics are provided within the framework--including the Manhattan distance heuristic (for use where diagonal travel between nodes is prohibited), a heuristic based on Euclidean distance, and one based on distances on the surface of a WGS84 ellipsoid. Consumers of the path finding API can also provide their own heuristic implementations by implementing the appropriate interface. Graph and algorithm visualization tools are also provided, making it easy to display a created graph on the globe and view potential paths and search frontiers that expand as *A** progresses (Figure 3).

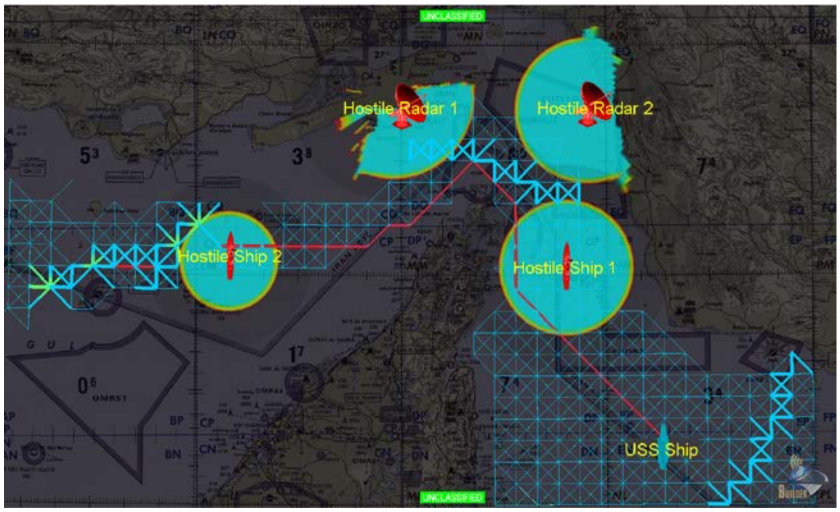


**Figure 3: Visualization of A* Search Frontier**

The ISB serves as the integration framework for the other two components of the sensor allocation tool: EWSim and Optimization algorithms, both of which are integrated as ISB plug-ins. The optimization algorithms are launched through custom menu actions (Figure 4). They use the current ISB scenario configuration to populate a EWSim scenario. The EWSim scenarios are run multiple times to build statistical models of receiver capabilities against varying initial emitter scan and pulse states. The EWSim software uses ISB's propagation interface for attenuation prediction.

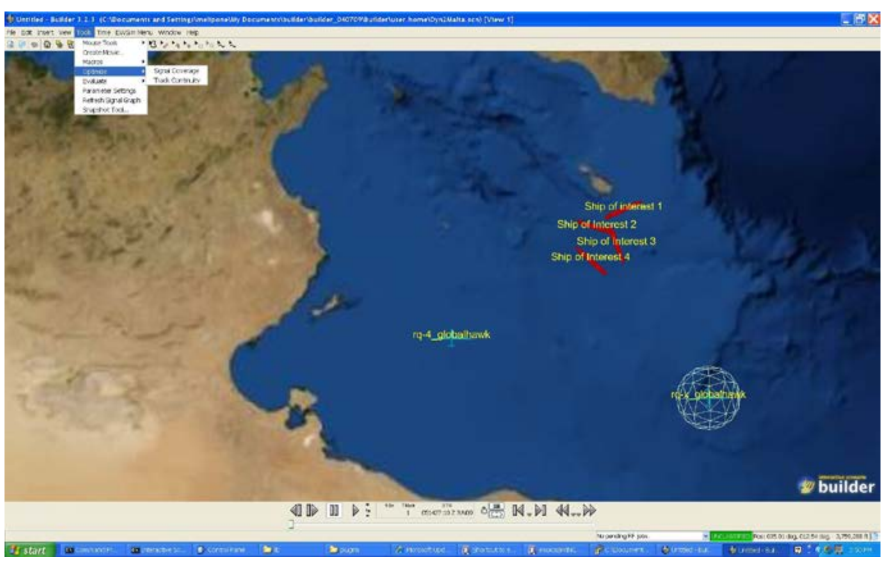


**Figure 4: Optimization Plug-in within ISB**

The sensor allocation project expanded the API for interacting with EMPIRE by adding a layer responsible for calculating, caching, persisting, and otherwise tracking results of loss computations between transmitter and receiver nodes. The central entity provides a simpler interface for accessing propagation loss than the prior interface. It also provides an opportunity for storing loss results centrally, which allows persistence of loss within saved scenarios. The interface that the sensor allocation tool uses to access this centralized RF environment combines the graph and RF packages by constructing a graph of RF signals (Figure 5). Nodes each have a geographic coordinate, but also have a set of signals--one from each transmitter in the scenario. Nodes are linked with eight neighbors—North, South, East, West, and the diagonals. The signals at each node represent the RF environment at an instance in time, so as the planning horizon moves the signals in the graph are updated. The strength of the signals at each node indicates the suitability of the position as a sensor station or center of orbit--the stronger the signals within a band of interest at a node, the more desirable the position for sensor placement. When routing sensors between regions of the graph, a shortest path algorithm like *A** combined with an edge weighting scheme based on the quality of signals available along each edge can select paths that travel between nodes with better signal reception. The resulting path will route sensors along paths with high quality signals on their way to station. The graph can also be visualized, which allows for visual inspection of the signals in a studied area.

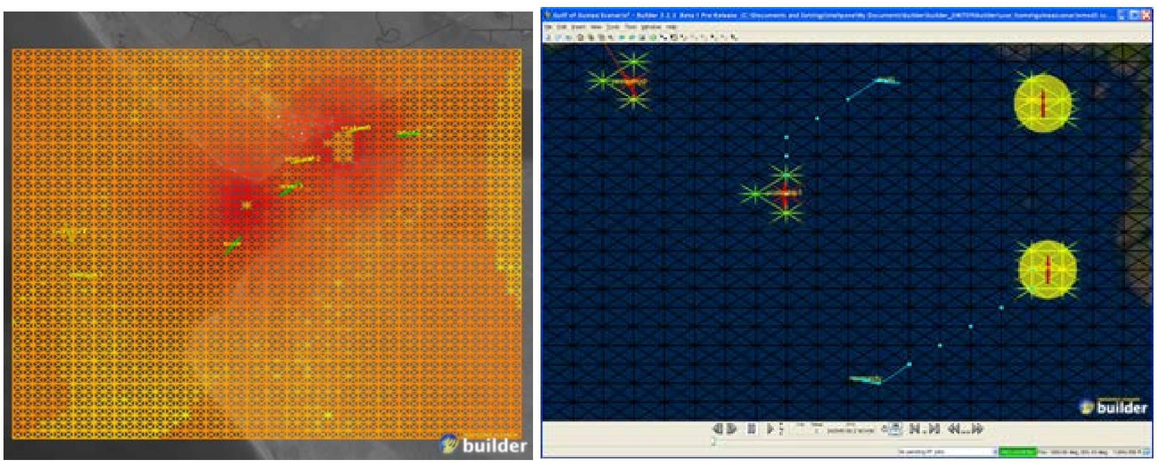

**Figure 5: (L) Example of a Signal Graph (R) Computed Route within Signal Graph**

## 2.2 Electronic Warfare Simulation (EWSim)

EWSim is an agent-based simulation of electronic warfare platforms and systems and their interactions with each other and their environment. While the ISB excels as a platform for developing scenarios and in modeling the physics pertinent to EW problems (such as RF propagation), EWSim bring depth to the modeling of ES sensors and RF emitters. Specifically, EWSim models signals at the pulse level and the collection of those signals as the result of discrete dwells in time of ES sensors.

Radars in EWSim are composed of fundamental building blocks of multiple transmitters, antennas, and beams (including 3D radiation patterns), where a radar may have multiple modes, employing one of these modes at a time. A radar mode specifies its signal parameters and antenna scan characteristics, as well as which components (transmitters, antennas, and beams) are active in that mode.

ES sensors in EWSim are composed of multiple receivers, antennas, and beams. They operate in a manner similar to radars in that they can have multiple modes, each of which specifies the behavior of each component in that mode. However, whereas RF transmitter modes specify signal generation characteristics, the modes of RF receivers which are components of the ES systems specify “dwell schedules", the manner in which particular frequency bands will be searched in time. Each dwell requirement specifies a number of parameters for that dwell, the most significant being the dwell duration and revisit rate (specifying, in effect, an average duty cycle for revisiting a band).

The combination of radar antennas scanning in space and ES sensors scanning in frequency sets up what is commonly known as the scan-on-scan problem, where the likelihood of an ES sensor collecting pulses in a dwell depends on the RF band covered by the dwell and the orientation of the radar antennas at the time of the dwell. Figure 6 illustrates the time to intercept and validation of the EWSim ES sensor model in the extreme limits of full and mainbeam-only illumination.

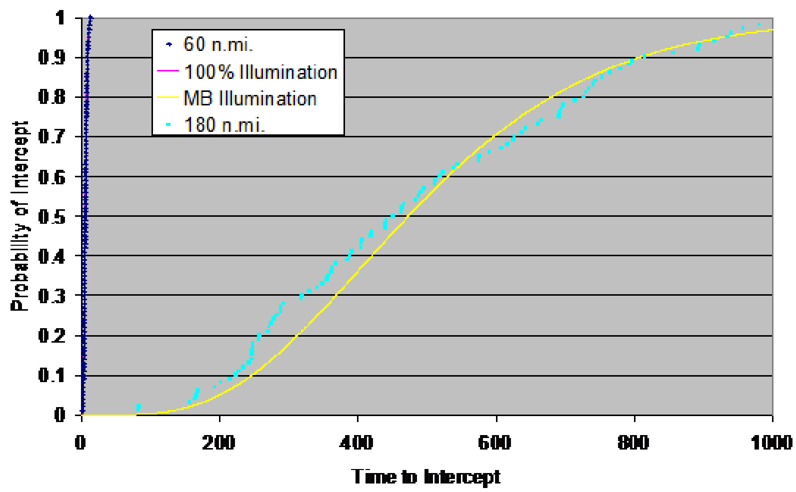


**Figure 6: EWSim Detection Model**

EWSim's ability to model scan-on-scan problems enables us to address higher order metrics such as track-continuity since we can maintain a history intercepts for each dwell. Clearly, the goal when using such a metric is to minimize or even eliminate target collection gaps.

## 2.3 Platform Optimization Algorithms

Platform allocation optimization is a complex problem that involves (1) the optimization of path planning for the platforms and (2) the coordination of the platforms themselves. Previous work has included team models of unattended ground sensor networks [Yilmaz] and cooperative path planning of unmanned aerial vehicles (UAVs) [Shima]. By discretizing the geospatial search space, platform allocation optimization can be solved as a combinatorial optimization problem similar to resource allocation problems where the targets are waypoints on a grid. The "Hungarian" algorithm [Kuhn] for weighted bipartite matching solves resource allocation problems such as role assignments for multi-agent systems in polynomial time. The algorithm consists of transforming a weighted adjacency matrix of *agents* × *tasks* into equivalent matrices until the solution can be read off as independent elements of an auxiliary matrix. Optimality is no longer guaranteed if the problem is over-constrained, i.e. there are more tasks to be assigned than agents. While the "Hungarian" algorithm provides a fast computational solution, it does not reflect the coordination aspects of the platform allocation problem where the continuous nature of an ESM signal propagation and the capability of the platforms to carry several sensors tuned to different frequencies make it possible to detect several targets simultaneously. Evolutionary computation is a stochastic gradient search optimization paradigm where a fitness function and composability of solution heuristics guide the search for optimal solutions in population-based algorithms. The fitness function enables the incorporation of coordination quality criteria such as the absence of interference or redundancy, or the overlap of several non-conflicting task assignments in the evaluation of a candidate solution. Our optimization approach is based on evolutionary computation and will use the "Hungarian" algorithm to provide a baseline for experimental evaluation.

We adopt a "life-cycle" approach where an approximation is obtained in the discretized problem space with the particle swarm optimization (PSO) algorithm [Kennedy] and then refined in the continuous problem space with differential evolution (DE) [Storn]. The PSO algorithm is an evolutionary computation algorithm based on the social learning metaphor and the reinforcement of past success whereby an agent, represented by an *n*-dimensional vector, adapts its solution from the solution of one of its neighbors and past performance. It is characterized by its simplicity and efficiency due to its small population size. Differential evolution is an efficient evolutionary computation methodology for continuous real-valued vectors based on a principled evaluation of the mutation heuristic for exploring the search space. A mutation step size (magnitude and direction) is computed from weighted differences with randomly selected individuals in the population and applied first to produce a new candidate vector which is then recombined with the original candidate vector.

The signal of the transmitters, from the platforms of interest, is propagated along a signal graph built from a geospatial grid (section 2.1). The PSO algorithm evolves (1) the platforms to be included and (2) the grid intersection points of the signal graph as destinations. The platforms to be included are represented as Boolean switches enabling the corresponding grid intersections. In addition, valid destinations points for a platform must have receivable signals and be reached within the planning horizon specified for the scenario. Other constraints, including terrain and geopolitical considerations, will be incorporated for real-time use. The *A** algorithm (native to ISB) is subsequently used to compose a route from a platform to a candidate destination using the grid intersections waypoints and a distance metric as its cost function. Once the PSO algorithm has converged, the paths obtained from a sampling of successful candidate solutions are refined through differential evolution.

The different metrics for the fitness function (Section 3.0) will be combined together through multi-objective optimization to achieve the different objectives of platform allocation, namely, maximization of signal coverage at the planning horizon and observed track continuity throughout the scenario.

## 3.0 Evaluation Metrics

Several metrics come into play for sensor allocation optimization. We have identified two main metrics, signal coverage and track continuity, to reflect the static and dynamic aspects of platform allocation. Given a signal graph (section 2.1) for the propagation of signals at a certain planning horizon, a signal coverage metric *p* combines performance goals *g*, absence of overlaps *c* in detecting signals, and resources *r* for *n* platforms into a harmonic mean to evaluate coordination as follows:

$$p = \frac{3grc}{gr + rc + cg}$$

where:

$$g = \frac{\text{transmitters detected}}{\text{transmitters}} \qquad c = \frac{\text{transmitters detected}}{\sum_{i}^{n} \text{transmitters detected}} \qquad r = r_1 r_2$$

$$r_1 = \frac{\text{maximum total distance}}{\text{total distance} + \text{maximum total distance}} \qquad r_2 = \frac{\text{platforms}}{\text{enabled platforms} + \text{platforms}}$$

and where transmitters are the possible signal sources of interest, platforms are the number of possible platform assets and maximum total distance is a relative notional metric by which to evaluate platform total path distance.

A track continuity metric ***t*** will be obtained from EWSim (section 2.2) results to minimize gaps in surveillance throughout the scenario:

$$t = \frac{\sum_{r}\sum_{T} gaps}{rTD}$$

where $r$ is the number of stochastic runs by EWsim, $T$ is the number of target platforms, *gaps* are the track detection gaps (in kms) for target $T$, and $D$ is the total track distance of the target platforms to be covered.

## 4.0 Development and Experimentation Plan

Additional areas that are expected to be investigated include the development of enhancements to the ISB user interface to enable a user to specify regions of interest (or exclusion zones) that must be included in the optimization, and including any necessary timing constraints to ensure assets arrive in the given region(s) within the appropriate time window. With regard to this issue, we will need to address basic scheduling issues within the optimization process. We also expect to incorporate several interest measures such as piracy areas or ports of particular interest and the affect of METOC (e.g., winds) on the routing of the aerial platforms.

In relation to track data, we expect to integrate live vessel data feeds into the ISB environment. When integrating this data, it will be useful to develop some basic track predictive capabilities so that the optimization techniques are able to optimize the allocation of platforms in real-time toward the predicted (in space and time) track positions. Although other programs are developing more elaborate and complex models to enable more accurate predictions, our predictive capability will be more rudimentary in order to demonstrate how this type of information can be utilized in an overall platform allocation tool.

Other metrics are of interest to the problem of platform allocation optimization will also be developed. An area coverage metric taking into account the different heights of the sensors, terrain, weather and refraction within the RF spectrum is necessary for planning possible collections. A stealth metric where sensors are able to collect signals without being themselves detected will also be developed as well as a surprise metric, where targets are approached from different directions. These metrics will be especially important when expanding the set of scenarios to land-based environments.

We are currently developing MDA-related scenarios using Subject Matter Experts from the Naval Reserve community, and also expect to leverage these reservists to help us improve the operational relevance of our algorithmic solutions through studies and evaluation.

The Special Capabilities Office under the Deputy Under Secretary of Defense (DUSD) for Advance Systems and Concepts (AS&C) has expressed interest in the platform allocation technology, particularly from the perspective of improved tracking of maritime targets to support the counternarcotics trafficking in the Caribbean and Eastern Pacific. We expect to continue dialogue in this regard to better understand how our tool can provide planning support.

## 5.0 Future Research Challenges

A key enabler of a sustainable military force is the notion of a tiered system (Figure 7). A tiered system is an integrated, multi-tier intelligence system encompassing space and air-based sensors linked to close-in and intrusive lower tiers. The lower tiers (e.g., UAVs) are not only the critical source of intelligence; they can also serve as a key cueing device for other sensors. There is active research and exploration within the US DoD to understand the technical challenges in building tiered systems.

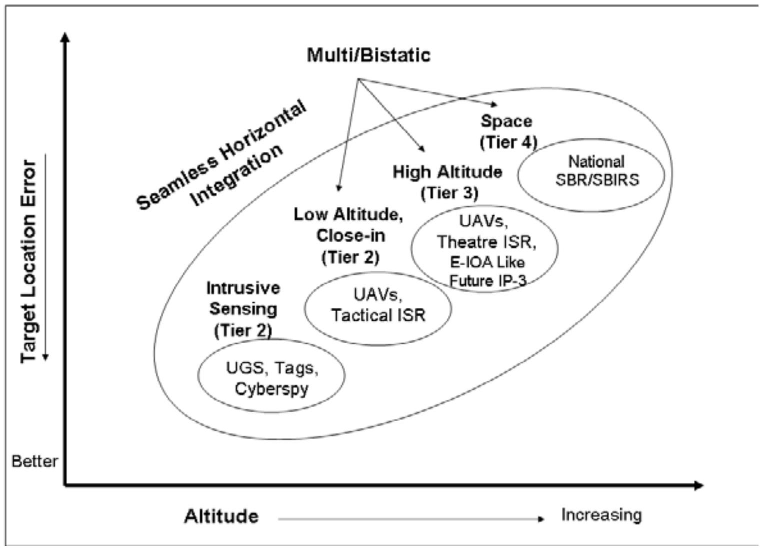


**Figure 7: Tiered Systems**

While we have considered the development of optimization algorithms for platforms at the lower tiers, the technology could be expanded to include the incorporation of space-based assets. Given the diversity of the platforms and assets envisioned in a tiered systems, and the fact that coordination must be achieved both in the horizontal and vertical planes in order to maximally take advantage of the capabilities that are offered by the platforms at each tier, and the environments in which the components of a tiered system will operate; it is not likely that a single optimization approach or even a static family of approaches would work across all cases. It is more reasonable to expect that systems should learn which approaches work well and under which circumstances, and adapt appropriately—this will be the key challenge in building robust, distributed tiered systems!

## 6.0 Acknowledgements

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