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SIMULATING A MARITIME ANTI-AIR WARFARE SCENARIO TO OPTIMIZE A SHIP'S DEFENSIVE SYSTEM

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ABSTRACT

Enemy anti-ship cruise missiles (ASCM) are increasing in capability thereby posing a greater threat to United States Navy ships. Core to a ship's defensive system is a computer-based command and decision element that directs simultaneous operations across a broad set of mission areas. Fortunately, software-only changes to this command element can be evaluated and fielded much more quickly than hardware-based changes; and hence, methods to identify viable software-only changes are needed. This study presents a simulation optimization methodology to identify and evaluate such changes using a notional scenario. First, a raid of ASCM threats against a single ship is simulated and then metaheuristics are used to determine the configuration for a ship's defensive system that maximizes survival. The simulation scenario, a ship's defensive system, and three specific optimization cases are presented. Results are provided for each optimization case to show the defensive system configuration that best ensures the ship's survival.

1 INTRODUCTION

The United States (US) Navy faces rapidly evolving air threats from potential adversaries as advancing missile technologies are fielded. The advancement of long-range anti-ship cruise missiles (ASCM) and anti-ship ballistic missiles, paired with compatible command, control, communications, computers, intelligence, surveillance, and reconnaissance architectures, are enabling adversary nations to execute more complex and threatening missions both near and far from home. ASCM research and development programs are robust and focused on increasing missile speed, range, and employment flexibility in order to penetrate a ship's defensive system. At the core of the ship's defensive system is a computer-based command and decision element capable of simultaneous operations in anti-air warfare, ballistic missile defense, surface, subsurface, and strike missions.

Upgrading ships and the many subsystems that make up their defensive system is one response to countering enhanced adversary threats, but the time to develop and field new hardware is extensive and costly. Changes can be made more quickly to the Anti-Air Warfare (AAW) system software that drives the offensive and defensive performance of these ships (and its subsystems) and implements the tactics, techniques and procedures (TTPs) and Concept of Operations (CONOP) that drive how resources are managed and how the battle is fought. Simulation models can be used to evaluate how changes to TTPs and CONOPs, as well as other software-only changes, will impact the performance of a ship's defensive system against different threat scenarios. However, determining the best set of changes is a non-trivial task since the number of possible combinations of friendly (i.e., *blue*) and adversary (i.e., *red*) configurations and actions is quickly overwhelmed by the curse of dimensionality. In addition, there are often complex effectiveness and efficiency tradeoffs to be considered when evaluating the outcome of a military scenario. Therefore, a means to optimize these simulation models is needed, based on one or more metrics of interest,

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over the very large set of possible changes. This provides a way to identify software-only changes that yield significant capability improvements in countering relevant ASCM threats. These changes can then be deployed to a ship's defensive system more quickly (and cheaply) than hardware changes.

This paper presents a maritime AAW scenario that is analyzed using simulation optimization to determine the best configuration for a ship's defensive system to defeat a specific raid of ASCM threats. The paper is organized as follows. Section 2 describes the maritime AAW scenario, a ship's defensive system, and metrics of interest for optimization. Section 3 presents the simulation optimization methodology to simulate the maritime AAW scenario and determine the defensive system configuration that best counters the ASCM threats. Section 4 reports the results of this simulation optimization analysis, and, finally, Section 5 concludes the paper and details areas for future research.

2 PROBLEM DESCRIPTION

This section describes a notional maritime AAW scenario in which a single ship is attacked by two waves of ASCMs. The ship's defensive system is also described along with its primary operational parameters to prescribe using simulation optimization in Section 3. Finally, measures of effectiveness and one measure of performance (or efficiency) for optimization are defined.

2.1 Maritime Anti-Air Warfare Scenario

The scenario depicted in Figure 1 is a notional maritime AAW scenario that can be simulated using a combat simulation. This scenario consists of anti-ship cruise missile (denoted henceforth as CM) raids on a single ship, where the CMs approach the ship in two separate raids, each raid consisting of 15 CMs. The first and second raids approach the ship from 345° and 325° respectively, indicating a narrow threat sector. Furthermore, the first raid starts from a point 65 nautical miles (nm) from the ship and travels at a speed of 500 kilometers per hour (km/h), whereas the second raid starts from 87 nm and travels at 625 km/h. Both raids approach the ship from an altitude of 300 meters (m). The scenario does not model weather or soft defensive effects such as electronic jamming.

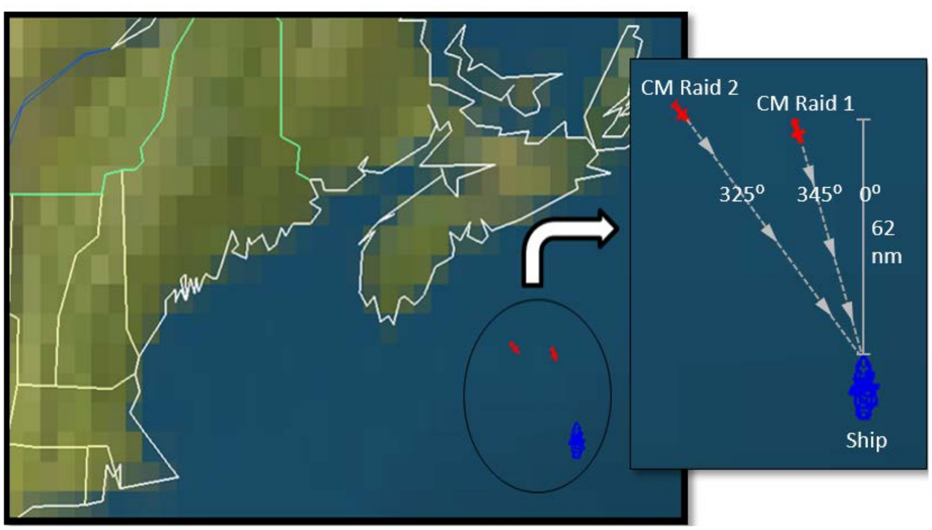

Figure 1: Visual representation of notional maritime AAW scenario.

2.2 Ship Defensive System

A ship's defensive system consists of its sensors that detect and track threats, its weapons that engage and destroy threats, and its crew that command, control, and operate this system. This defensive system originates with the sensor, as it is responsible for the detection of the CMs. In the notional maritime AAW scenario, the ship possesses a single radar sensor, which has a default range of 0 to 90 kilometers (km) (i.e., 49 nm). The sensor has a rectangular field of view and performs independent search with deterministic detection and tracking. Additionally, it has a default azimuth and elevation of 120°, with an azimuth pointing angle of 0° and an elevation pointing angle of 30°. The default sweep rate is set to 3 seconds and the slew rate to 0 deg/s.

To physically combat the encroaching CM threat, the ship is equipped with eight Surface-to-Air Missile (SAM) launchers, four short-range and four medium-range. Furthermore, the ship is equipped with two types of intercept missiles: short-range and medium-range interceptors. As defaults, there are 40 interceptors of each type, and each interceptor type can be launched from its corresponding launcher. Intuitively, the medium-range interceptor can destroy the threat at a greater distance; however, the probability of kill (P_k) is 65% for these interceptors. Likewise, the short-range interceptors destroy the threat at a closer distance but have a P_k of 85%. P_k is the main source of uncertainty in the simulation.

A final component of the ship's defensive system is the human element that reflects the command and control paradigm (such as manual or autonomous), tactics, techniques, and procedures (TTP), operational doctrine (or best practices) and limitations, and crew experience and proficiency.

For this study, sensor, weapons, and crew preparedness parameters were chosen as inputs to vary in a simulation of the maritime AAW scenario. Initial values and ranges for these input parameters were selected based on examining opensource resources such as the US Navy Fact File (US Navy 2019) and adjusted based on initial experimental runs to ensure changes to these parameters had a meaningful impact on the key measures of effectiveness and performance.

The specific sensor inputs that were varied are listed in Table 1 along with their description and the extent to which they can vary in the scenario.

Table 1: Sensor inputs to vary.

Input Name	**Description**	**Min Value**	**Max Value**
Azimuth	Horizontal field of vision	30°	120°
Azimuth Point Angle	Axis of symmetry for azimuth	0°	359°
Elevation	Vertical field of vision	10°	60°
Elevation Point Angle	Axis of symmetry for elevation	5°	60°
Sweep Rate	Time to scan sensor's entire field of view	1 second	30 seconds
Maximum Range	Maximum distance to detect threat	50 nm	120 nm

The sweep rate is a dependent sensor input since it depends on the azimuth and elevation, as increasing the field of vision (FOV) of the sensor will consequently increase the time needed to scan this FOV. For this study, the relationship between sweep rate and the corresponding azimuth and elevation is defined in Table 2 (e.g., it takes the sensor 11 seconds to scan the FOV when its azimuth is 60° and elevation is 40°).

Table 2: Sensor sweep rates (in seconds) for (azimuth, elevation) pair.

	Elevation					
Azimuth	**10°**	**20°**	**30°**	**40°**	**50°**	**60°**
30°	1	2	4	8	13	20
45°	2	3	5	9	14	21
60°	5	6	7	11	15	22
75°	8	9	10	12	18	24
90°	12	13	14	15	20	26
105°	16	17	18	19	23	28
120°	20	21	23	25	27	30

The weapon inputs that were varied are listed in Table 3 along with their description and the extent to which they can vary in the scenario.

Table 3: Defensive weapon inputs to vary.

Input Name	Description	Min Value	Max Value
Max Medium-range	Maximum distance the medium-range intercept missile may engage threat	60 nm	90 nm
Min Medium-range	Minimum distance the medium-range intercept missile may engage threat	20 nm	40 nm
Max Short-range	Maximum distance the short-range intercept missile may engage threat	15 nm	30 nm
Min Short-range	Minimum distance the short-range intercept missile may engage threat	5 nm	10 nm
Medium-range Inventory	Number of medium-range intercept missiles	0	80
Short-range Inventory	Number of short-range intercept missiles	0	80

The experience and proficiency of the ship's crew is critical to operational effectiveness. To explore crew preparedness in the simulation, this study used an operator delay parameter defined as the time needed by the crew to assess the detection of a CM by the sensor and then decide to engage the CM with an intercept missile. Logically, more experienced crews will take less time to process and engage a threat given the same tracking information from the sensor. Therefore, this operator delay parameter was set to 60 seconds for a low experience crew, 40 seconds for a medium experience crew, and 20 seconds for a high experience crew.

2.3 Measures of Effectiveness and Measure of Performance

This study uses two measures of effectiveness (MoE) and one measure of performance (MoP) for optimization as follows:

- MoE 1: *Probability of Raid Annihilation* (P_{RA}) – the probability the ship survives the CM raids, (i.e., the probability all CMs are detected, tracked, engaged, and destroyed).
- MoE 2: *Closest Range* – the distance from the ship at which the closest CM is destroyed (this measure is only meaningful (non-zero) when all CMs are destroyed).
- MoP 1: *Weapons Expended* (*WE*) – a count of the number of intercept missiles used to engage CMs.

These key measures translate to meaningful optimization objective functions. Specifically, any of the two MoEs (P_{RA} and *Closest Range*) would be maximized (more is better) whereas the MoP (*WE*) would be minimized (less is better). The MoEs relate to the operational effectiveness of the ship's defensive system whereas the MoP relates to the resource expenditures of the defensive weapons. Operationally speaking, effectiveness of the ship's defensive system is the primary goal (existential in nature) and efficiency is a secondary goal (resource preserving in nature).

3 SIMULATION OPTIMIZATION

This section presents a simulation optimization methodology that uses the maritime AAW scenario to determine the ship's defensive system configuration that best counters the CM raids. The simulation is first described followed by the optimization objective functions and constraints. This section concludes with a description of the method used to solve the simulation optimization problem.

3.1 Simulation of the Maritime AAW Scenario

The Extended Air Defense Simulation (EADSIM) is a many-on-many simulation of air, missile, and space warfare that models fixed and rotary wing aircraft, tactical ballistic and cruise missiles, sensors, satellites, and command & control structures. Furthermore, EADSIM is widely-used across the US Department of Defense (DoD) and contains several configurable data inputs related to sensors, weapon systems, and rules of engagement. The simulation code is managed by the US Army Space and Missile Defense Command and is currently used by 390 total agencies worldwide. See Teledyne Brown Engineering, Inc. (2019), the support contractor for EADSIM, for additional details.

EADSIM has an unclassified scenario representing a missile attack against an established air base. Using the air base as a proxy for a ship, which assumes the ship's speed is negligible relative to the CMs, this scenario was adapted to represent a maritime AAW scenario to simulate the ship's defensive system in EADSIM and evaluate the different MoEs and MoP for a ship against a CM raid. Specifically, for the maritime AAW scenario, the sensor, defensive weapon, and crew preparedness parameters described in Section 2 were chosen as simulation inputs to vary in EADSIM.

To evaluate the MoEs and MoP, the key EADSIM outputs collected for each simulation were the number of CMs killed (of the 30 CMs launched), number of medium and short-range intercept missiles launched at CMs (i.e., *WE*), and the simulation times when the last CM is successfully destroyed from both raids, denoted T_{LS}, for time of last success. T_{LS} was used as a proxy measure for the *Closest Range* MoE since time is easier to extract from EADSIM than range. This is a suitable proxy since time can be expressed as a distance given the velocity of the threatening CM. In the results, T_{LS} = time of last success in CM raid 1 + time of last success in CM raid 2, which, when minimized, means the simulation time when the last CM was destroyed was as early as possible in both raids. Therefore, T_{LS} should be minimized because earlier success times means the CMs are killed sooner, or further from the ship.

3.2 Optimization Objective Functions and Constraints

To determine the ship's defensive system configuration that best counters the CM raids within the maritime AAW scenario, the following three optimization cases were considered:

- Case 1: Maximize P_{RA}.
- Case 2: Minimize T_{LS} (thereby maximizing the *Closest Range* MoE) subject to P_{RA} = 1. This case demonstrates a preemptive multi-objective optimization problem (Ehrgott 2005) where P_{RA} is the primary objective function and then T_{LS} is the secondary objective function. Therefore, given P_{RA} = 1 (i.e., the ship survives the raid), the next goal is to destroy the closest CM as far away from the ship as possible, which equates to minimizing T_{LS}.
- Case 3: Minimize T_{LS} and minimize *WE*, subject to P_{RA} = 1. This case demonstrates a classic multi-objective optimization where the objectives T_{LS} and *WE* are equally important, and hence, there is a tradeoff to consider between these two objectives (Ehrgott 2005). This introduces the concept of Pareto optimality where the optimal set is expressed as a frontier (called the Pareto frontier) of solutions that balance the tradeoff between the objectives. In this case, a solution is Pareto optimal if for any other solution in which T_{LS} decreases (increases), *WE* increases (decreases).

The cases above describe the optimization objective functions, which are constrained by real-world operational or resource limitations. This study included two constraints that are now described. The first constraint is that the layers of defense must overlap to ensure a ship can defeat threats once a CM is in range of intercept. Therefore, for a defense layered with two intercept missiles (i.e., a short-range interceptor and a medium-range interceptor), the maximum range of the short-range interceptor must be at least as far as the minimum range of the medium-range interceptor. That is, the engagement layers between the layers of defense must overlap as shown in Figure 2. This is mathematically denoted by Max Short-range $\geq$ Min Medium-range.

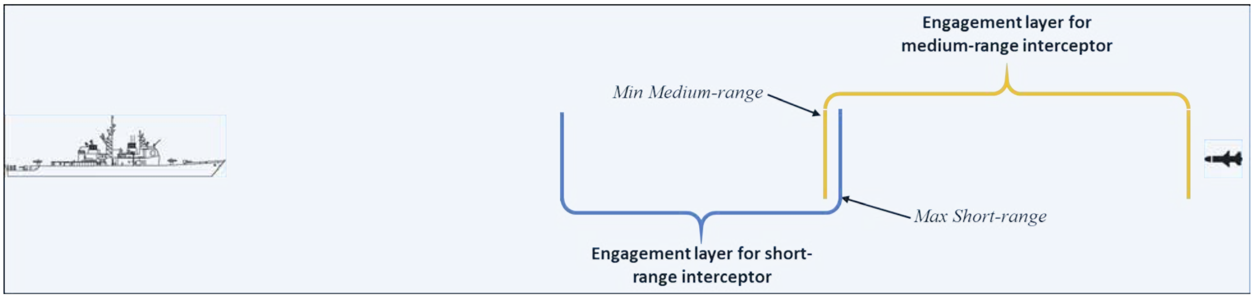

Figure 2: Notional defense layers for a naval ship.

The second constraint varies the number of intercept missiles in the scenario. In all optimization cases, the total number of intercept missiles is limited by a given *total inventory*. The number of interceptors for each defense layer can vary so long as the sum of the inventories for each defense layer is equal to the given total inventory. Returning to a defense layered with two types of intercept missiles, the number of short-range interceptors plus the number of medium-range interceptors must equal the given total inventory. This is mathematically denoted by *Short-range Interceptors inventory* + *Medium-range Interceptors inventory* = *total inventory*. In the EADSIM scenario, the given *total inventory* is equal to 80 intercept missiles. As shown in Table 3, the inventory for either interceptor type is permitted to equal any integer value between 0 and 80 (in step sizes of 4), provided the total weapon inventory is equal to 80. Ultimately, this constraint on weapon inventory allows the optimization to determine the impact of the quantity of medium and short-range interceptors without also varying the total weapon inventory, since the intent was not to limit overall resources within the scenario (i.e., varying the total weapon inventory in the optimization would introduce another layer of complexity).

3.3 Solution Implementation

Using EADSIM to simulate the maritime AAW scenario, an optimization program was used to determine the input settings that maximize the ship's ability to defeat a cruise missile raid. Specifically, the inputs, outputs, MoEs and MoP, and three optimization cases were explored. The optimization program selected is called OptDef, which interfaces with an optimization engine called OptQuest, both of which are developed by OptTek Systems, Inc. (2019). OptDef has a custom graphical user interface that integrates with EADSIM and OptQuest is a recognized commercial solver for simulation optimization.

Figure 3 depicts the iterative solution process by which the optimization program updates simulation inputs in EADSIM, executes EADSIM, and then collects simulation results. The optimization program provides a set of simulation inputs to EADSIM, where a set of simulation inputs includes one value within the minimum and maximum range for each sensor and defensive weapon variable given in Tables 1 and 3 in addition to an operator delay time. The program then executes EADSIM and collects the resulting number of CMs killed, *WE*, and T_{LS} as output. The optimization program then determines a new set of simulation inputs using metaheuristics. Specifically, the metaheuristic combines distinct sets of inputs that have yielded the best simulation outputs found in the search thus far to create a new distinct set of inputs to simulate. This new set of inputs for EADSIM then results in another set of outputs, and this process is repeated iteratively until some stopping criteria is reached (e.g., the total number of simulation runs to execute, a specified time to search, or a given number of search iterations without finding an improving solution are common stopping criteria). Once the stopping criteria is met, the optimization program returns the defensive system configuration that optimizes the objective function of interest subject to the constraints discussed in Section 3.2. For the multi-objective optimization cases, there may be several defensive system configurations that result in a set of non-dominated output values, which estimates the Pareto frontier.

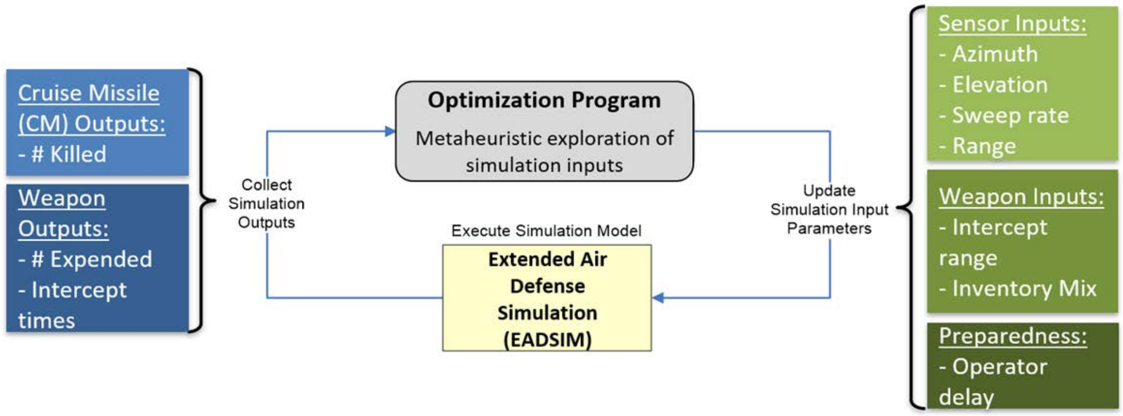

Figure 3: Simulation optimization solution process.

The term metaheuristic refers to a class of optimization solution algorithms used to solve difficult problems; however, metaheuristics do not always find an optimal solution. Unlike simple heuristics, like a greedy or hill-climbing heuristic, metaheuristic algorithms combine multiple strategies to form a higher-level algorithm with more sophisticated solution generating properties (Reeves 1995). A simple greedy heuristic may quickly converge to a local optimum but will not find the best solution in a nonconvex solution space. Metaheuristic techniques have strategies that allow them to escape local optima (solutions that are optimal for their immediate neighborhood) and search for a global optimum (solutions that are optimal over the entire solution space). Commonly known classes of metaheuristic algorithms include techniques such as tabu search, scatter search, and genetic algorithms (see Glover 1986; Glover 1977; Glover and Laguna 1997; Glover et al. 2000). The primary metaheuristics employed by the optimization program in Figure 3 are scatter search and tabu search.

4 ANALYSIS AND RESULTS

This section details the specific simulation optimization analysis performed to identify the ship defensive systems that significantly improve P_{RA}, T_{LS}, and *WE* for the three previously described optimization cases.

Each optimization case had the same scenario setup as described in Section 2.1, including the inputs and outputs specified above. The three optimization cases used the same EADSIM engagement output report that was built from 30 Monte Carlo (MC) replications (a sufficiently large number given the study scope) for each described simulation run (i.e., set of inputs). To illustrate, as depicted in Figure 3, the optimization program provides EADSIM with a set of values for each input parameter defined in Tables 1 and 3 and an operator delay time. For this given set of input values, EADSIM executes 30 MC replications and then returns the outputs (based on the 30 MC replications) back to the optimization program. For example, a $P_{RA} = 0.8$ for a simulation run in the optimization program means all CMs were killed in 24 of the 30 MC replications. The optimization program then sends another set of input values to EADSIM in an attempt to find a set of inputs to produce a larger P_{RA}, and this cycle iterates until a stopping rule is satisfied.

Before analyzing the specific optimization cases, it's worth considering the complexity of solving this simulation optimization problem. For this maritime AAW scenario in EADSIM, there are 11 independent input variables that can vary according to the ranges defined in Tables 1 and 3 coupled with operator delay. Considering all feasible combinations of values for these independent variables, there are over 55 trillion simulation runs to evaluate if one was to enumerate the feasible decision space. To put this in context, for this EADSIM scenario with 30 MC replications for each simulation run, it took nearly 7 hours (6h:56m:10s) to run 4,493 simulation runs using 15 cores on a 24 core, 48GB RAM desktop computer. Thus, assuming a rate of 5,000 runs in 7 hours, it would take over 8,886 millennia to enumerate the decision space. Even doing a full factorial design of experiment (DoE) with only three values for each input variable would require 177,147 simulation runs, which would take over 10 days assuming the same computational rate. Clearly, the curse of dimensionality takes a heavy computational toll as the number of input variables grows. Fortunately, advanced optimization methods make explicit enumeration of the decision space unnecessary for nearly all practical problems. As demonstrated below, optimization enhances the utility of complex simulation models making it possible to find optimal or near-optimal system configurations with a relatively small number of simulation runs.

4.1 Case 1 (Maximize P_{RA})

Case 1 maximizes P_{RA} (a P_{RA} = 1 indicates all 30 CMs were destroyed in each of the 30 MC replications). The optimization program executed 4,400 simulation runs, each with a different input and found a set of inputs yielding a P_{RA} = 1 after only 75 runs. Figure 4 displays the P_{RA} for each simulation run (denoted as iterations) as an individual point (or dot) on the graph. The blue line on the graph indicates the best P_{RA} found to date as the iterations progress (e.g., iteration 75 is the first simulation run to have a P_{RA} = 1). 1,746 of the 4,400 simulation runs resulted in a P_{RA} = 1 indicating many alternative optimal defense system configurations. Figure 4 shows both the diversification (wide exploration across the decision space) and intensification (focused search in promising areas of the decision space) in the optimization search. Diversification is indicated by seeing simulation runs with P_{RA} across the range of 0 and 1. Moreover, the graph shows a significant number of iterations where P_{RA} = 0, which indicates many "bad" areas of the decision space were also searched (in case one of these "bad" areas is in fact a "good" area). Alternatively, intensification is indicated in the graph by the streaks of iterations with similar P_{RA} values, especially where P_{RA} is close or equal to 1. This indicates a focused search in the "good" areas of the decision space.

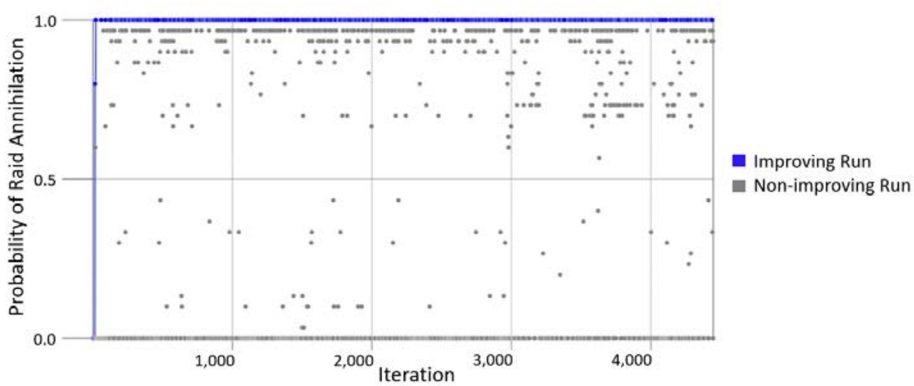

Figure 4: Case 1 optimization progress.

4.1.1 Results

Case 1 successfully demonstrates that for this scenario, by modifying a few key sensor and defensive weapon inputs, a P_{RA} of 1 is attainable (i.e., it is possible to destroy all CMs). A P_{RA} = 1 is best achieved with a high experienced crew and an even mix of short-range and medium-range interceptors.

The significance of the interceptor quantities was found using variable sensitivities analysis that considered linear and non-linear effects such as linear regression, mutual information, and regression trees. This is an intuitive result since the medium-range interceptors can hit a CM further away from the ship, allowing the CMs to be destroyed earlier. However, the short-range interceptors have a higher P_k. Therefore, attaining a P_{RA} = 1 is best achieved when there are both types of intercept missiles.

The crew experience level was seen to be impactful in the regression tree analysis, which is a tool to segment the decision space into combinations of variable value ranges that yield good or bad results. The regression tree was configured to split by crew experience level in order to show the contrast in P_{RA} between the different crew experience levels. When the simulation had a low experience crew, the average P_{RA} was 0.08. Likewise, when the simulation had a medium experience crew, the average P_{RA} was 0.101, and, finally, when the simulation had a high experience crew, the average P_{RA} was 0.709. While it was possible to achieve a $P_{RA} = 1$ with all three crew experience levels, a vast majority of the simulation runs that destroyed all CMs were obtained with a high experience level. The figures and data analyses described above and throughout Section 4 come from the OptDef optimization program.

4.2 Case 2 (Minimize T_{LS})

Case 2 minimizes the time of the last success (T_{LS}) as the secondary objective subject to the constraint that the primary objective function is optimal (i.e., $P_{RA} = 1$). P_{RA} is the most important effectiveness measure, as improving *WE* or minimizing risk by making T_{LS} as small as possible are insignificant if P_{RA} is not equal to 1, since this means the ship was hit by at least one CM. Therefore, once $P_{RA} = 1$ is achieved, then it becomes important to improve these other measures. Recall T_{LS} is a composite variable that sums the time at which the last CM was shot down in the first and second raid. By minimizing this sum, it effectively keeps both CM raids as far from the ship as possible. This is intended to minimize the inherent risk associated with a CM gaining a closer proximity to the ship. This optimization case was run for 2500 simulation runs, and the minimum T_{LS} was achieved on simulation run 890 with a time of 739.99 seconds. Figure 5 shows T_{LS} for each simulation run (again denoted as iterations) as individual points on the graph. The points are further differentiated by color, as red points now show solutions at which an infeasible solution was attained due to the additional constraint on P_{RA}. That is, the red points are the simulation runs with a $P_{RA} < 1$. The gray points are feasible solutions that fail to improve the current best value for T_{LS}, whereas the blue points represent feasible solutions that improved the objective value. As before, the blue line indicates the best T_{LS} value found to date as the simulation progresses. Many simulation runs had no result for T_{LS}, and hence, no point is displayed. Figure 5 additionally highlights diversification as there is a large range of values attained for T_{LS} over the entirety of the optimization. Furthermore, intensification is also indicated by the distinct clusters of points that closely follow the blue line.

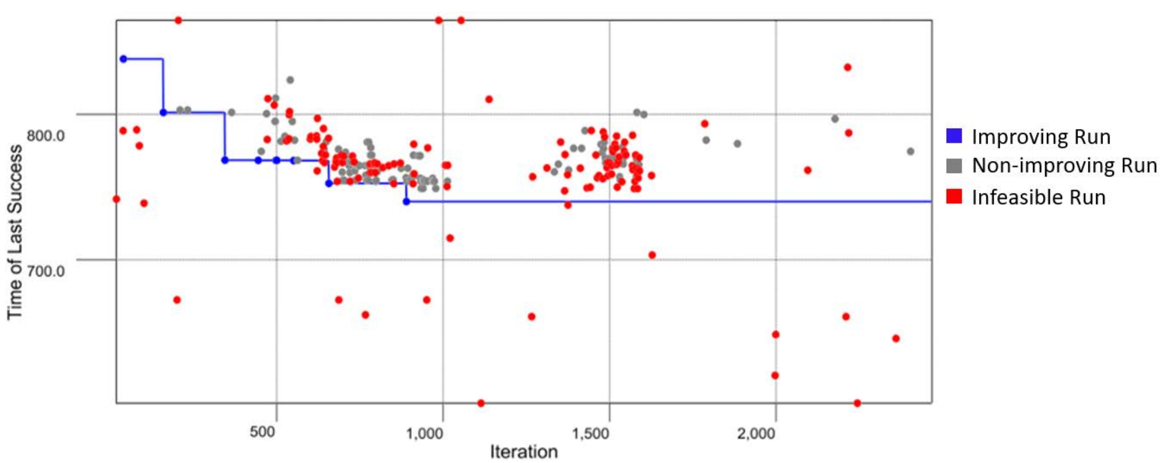

Figure 5: Case 2 optimization progress.

4.2.1 Results

Case 2 considers T_{LS} since a $P_{RA} = 1$ was achieved in Case 1. As stated previously, T_{LS} is a means to quantify risk by attempting to destroy the CMs as far from the ship as possible (when all CMs are destroyed). For this case, a high experienced crew and small sensor elevation tended to produce the best solutions when minimizing T_{LS} (e.g., the best 30 runs all had a high experienced crew and sensor elevation of 20°).

The variable sensitivity analysis for the optimization case showed that the sensor's elevation and maximum range, and the maximum range for the medium and short-range interceptors are the most influential variables to the results that successfully obtain a $P_{RA} = 1$ and minimize T_{LS}. Therefore, changing the optimization focus from maximizing P_{RA} to minimizing T_{LS} (while ensuring $P_{RA} = 1$) also changed the most influential inputs. This demonstrates the valuable insights that can be gained by analyzing different optimization cases.

Correlation analysis showed positive correlations of 0.67 and 0.65 with the sensor's elevation and maximum range, respectively (i.e., T_{LS} increases as the sensor's elevation and maximum range increase) and negative correlations of -0.63 and -0.53 with the maximum range for the medium and short-range interceptors, respectively (i.e., T_{LS} decreases as the maximum range for the medium and short-range interceptors increases).

As sensor elevation has a positive correlation, this indicates that having a larger vertical FOV is correlated with an increase in T_{LS}. This positive linear correlation may seem counterintuitive, as the sensor's ability to see more should hypothetically improve the objective (i.e., decrease T_{LS}). However, one factor that explains this result is the dependency between sweep rate and elevation. An increase in elevation also increases the sweep rate, which denotes an increase in the number of seconds that it takes to scan the entire FOV of the sensor. If there is a precise elevation pointing angle, then a small elevation can greatly improve the results as this will also decrease the sweep rate. More frequent scans will allow for an earlier first detection, which consequently reduces T_{LS}.

The sensor's maximum range also has a positive correlation with T_{LS}, when it seems the opposite should be true. Increasing the sensor's maximum range should decrease T_{LS}, as increasing the range of the sensor should never worsen the objective. Further analysis revealed the simulation runs that had a sizeable value for both the sensor's maximum range and T_{LS} also have a low quantity of medium-range interceptors. Having a low quantity of medium-range interceptors makes the sensor's maximum range irrelevant, as a majority of CMs will have to come into the range of the short-range interceptors. Since this occurs later in the simulation, this increases T_{LS} for these simulation runs. Therefore, the positive correlation seen by the sensor's maximum range on T_{LS} is in fact caused by the simulation runs with a low medium-range quantity.

Finally, the maximum ranges of the medium-range and short-range interceptors both have a negative correlation with T_{LS}. This is intuitive since the ability to engage CMs further out (i.e., with an increase in the maximum range of the interceptors) should decrease T_{LS}.

4.3 Case 3 (Minimize T_{LS} and WE)

Case 3 minimizes both the time of the last success (T_{LS}) and the number of weapons expended (WE) subject to the constraint that $P_{RA} = 1$. In this case, both objective functions are of equal importance (i.e., no weighting or strict preference is given). Moreover, these are competing objective functions by nature, as decreasing T_{LS} is expected to come at the cost of increasing WE. In order to decrease T_{LS}, the raids must be intercepted further from the ship necessitating the use of more medium-range interceptors. Furthermore, the medium-range interceptors also have a lower P_k than short-range in this scenario, which means even more medium-range interceptors would need to be expended to defeat the CM raids. For this case, the optimization program executed a total of 3500 simulation runs; however, there is no longer a clear best solution as defined by a single objective value. Figure 6 depicts the tradeoff between T_{LS} and WE with the blue line estimating the Pareto frontier. In other words, moving from one point to another on the blue line will invariably make one of the objectives better at the cost of worsening the other objective. For example, the furthest left point in Figure 6 has a T_{LS} of 805.65 seconds and a WE of 34.26 (these values are averaged over 30 MC replications). The next point to the right has a T_{LS} of 780 seconds and a WE of 34.4, which is better in terms of T_{LS} but worse in terms of WE, thus a tradeoff between the two objective functions.

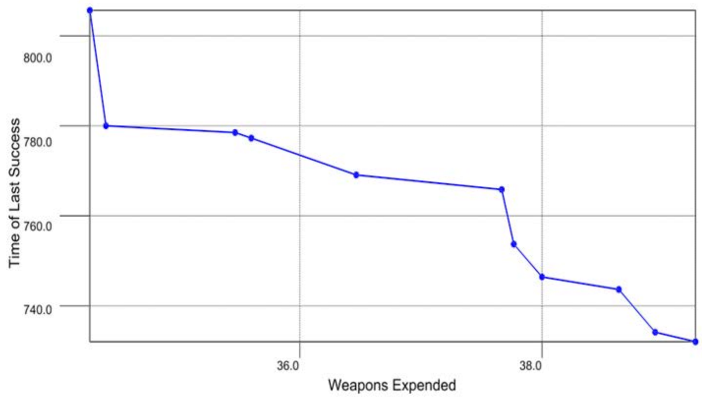

Figure 6: Case 3 pareto frontier.

4.3.1 Results

For this multi-objective optimization problem, correlation analysis showed the medium-range and short-range quantities are the most significant inputs for both T_{LS} and *WE*. However, these two inputs have opposing impacts upon the different objectives, as the sign on the correlation flips when looking at the correlation values with T_{LS} versus the correlation values with *WE* for each input variable. Specifically, medium-range quantity had a -0.734 correlation on T_{LS} and a 0.841 correlation on *WE*, whereas short-range quantity had a 0.734 correlation on T_{LS} and a -0.841 correlation on *WE*.

As the short-range interceptors have a significantly higher P_k, increasing the short-range quantity will decrease the number of weapons expended as it will use less weapons to achieve a success. However, increasing the quantity of medium-range interceptors positively affects the time of the last success, as medium-range interceptors can intercept the targets at an earlier point in time within the simulation. Therefore, the optimal ratio of interceptor quantities depends on which objective is prioritized. A greater number of short-range interceptors will produce better results in terms of *WE*; however, a greater number of medium-range interceptors will produce better results in terms of reducing T_{LS}. This demonstrates the utility of multi-objective optimization to evaluate the tradeoffs between different measures of significance.

5 CONCLUSION AND FUTURE WORK

The objective of this study was to develop a simulation optimization and analysis concept for future integration with US Navy modeling and simulation (M&S) tools. For a notional scenario, this study identified and defined key input categories to vary for a simulation of the ship's defensive system, outputs to collect for the maritime AAW scenario, measures to optimize, and three distinct optimization cases. This study also developed a simulation optimization and analysis approach for an operationally-meaningful maritime AAW scenario modeled in EADSIM and optimized using a metaheuristic optimization program. This approach effectively demonstrated the ability to determine specific sensor and weapon input values that maximized, within the EADSIM scenario, the ship's probability of raid annihilation while minimizing the number of intercept missiles used and the operational risk by destroying cruise missile threats as far away from the ship as possible. Furthermore, good sensor and weapon parameters were found using a relatively small number of simulation runs compared with a simple experimental design or full enumeration of the decision space.

Simulation optimization is a technically challenging endeavor especially for complex simulation environments. Certainly, the US Navy's M&S federation qualifies as such an environment. Going forward, the goal is to infuse this M&S federation with a robust and flexible optimization and analytics capability that will allow engineers, analysts, and planners to quickly evaluate and identify optimal system improvements to counter evolving ASCM threats thereby allowing the US Navy to test and field new capabilities at a pace that counters the advancing technology of adversaries. Ideally, this capability will provide the ability to quickly set up and configure common scenarios and make it possible to find and evaluate the best *blue* option(s) across a diverse range of possible *red* actions such as the number and types of threats and attack angles. These scenarios will be far more complex such as defending a fleet of ships.

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