Maritime Dynamic Resource Allocation and Risk Minimization Using Visual Analytics and Elitist Multi-Objective Optimization

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Abstract: Enhancing the safety of protected regions around Navy vessels is one of the most challenging research topics in maritime domains. Robust tactical resource allocation depends on understanding of how the placement, configurations, orientations of multiple assets affect both the area and intensity of coverage around the ships. Towards this end, we built a unique resource allocation problem where we apply a randomized genetic algorithm for searching through a space of 2^{144} possible parameters representing area coverage, orientation of 6 tactical assets. Our elitist genetic algorithm yielded a maximum fitness value of 90%, 98%, 100% within 50, 150 and 300 generations respectively. Moreover, we put forward a distinctive constrained dynamic resource allocation problem specific to USS Arleigh Burke Destroyer model (DDG-51), where the assets are defenses and coastal guards having binoculars. To solve this, we have used a cross-generational elitist selection based evolutionary algorithm (EA) where our objective is to maximize area of coverage and minimize risk simultaneously. It is a non-deterministic polynomial-time hard (NP-Hard) problem which required searching through a space of 2^{48} parameters and resulted in a fitness value of 98% within 35 generations. Furthermore, we present two novel visualization techniques addressing both types of resource allocations.

1 INTRODUCTION

In maritime domains, dealing with the wide range of possible threats to large ships requires a strategic placement of sensory and defensive resources (Benaskeur et al., 2007) . Large number of maritime surveillance tasks are focused towards effectively operating fixed and mobile surveillance assets which is also known as resource allocation (RA) (Dridi et al., 2012) . With dynamically evolving data about the presence of hostile ships, there is a ever increasing demand of intelligent systems to support in proactive decision making through multi-level resource allocation (Mishra et al., 2015) . Radar, sonar, infrared, and visual are some of the many sensors that are commonly present in Navy ships. Some of these assets come with spherical area of coverage, whereas, some assets have a conical area of coverage defined as a field of view (FOV). In case of tactical assets, the security level around a ship depends on both the area of coverage of the assets (how far it can cover) and the efficiency or strength of coverage at various locations (intensity of coverage). While some assets have almost the same coverage efficiency at any range or angle from a principal axis (for conical field of view), others have varying efficiency that decays with linear or angular distance from the principal axis. Identifying hostile vessels ahead of time (Carlson et al., 2019) can help ships plan their trajectory accordingly and allocate assets such that the level and range of protection around the vessel is increased. Moreover, visualizing target area around ships can help to conduct better surveillance by aiding prompt decision making (Davis et al., 2016) . For searching through a space of large number of solutions, evolutionary algorithms have proven to be one of the best optimization techniques where model performance is explainable and not a black box (Grefenstette, 1993). Elitist evolutionary algorithms are often preferred due to their tendency of converging faster by retaining copies of best individuals through radical recombination (Eshelman, 1991) .

Motivated by the potentials of area based intensity maximization in maritime security enhancement and the lack of similar research in this field, we propose the following:

- A generalized resource allocation (GRA) problem for multiple assets based on area of coverage

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where the linear range of coverage, angular coverage range and orientations are all dynamic. These are the parameters that are selected by our EA for optimization. We defined 6 locations to place the resources, any asset can be placed in any six locations provided that it maximizes area of coverage and that location is not already occupied by another asset. The set of resources and their specifications are flexible and can be changed according to any hypothetical or real ship model.

- A visualization technique using Pygame, for area based generalized resource allocation. Assets are represented with triangular shapes representing their area of coverage, and they can be placed in 6 different locations on the ship.
- A constrained dynamic resource allocation (DRA) problem for a DDG-51 ship model where the assets are 2 set of defenses with 2 different fixed locations and 4 different possible orientations per defense. Furthermore, the asset sets include 6 coastal guards having binoculars, who can be placed in 16 different locations on the ship and can have 8 different values for orientation placement.
- A technique for risk profile (intensity) and area based coverage visualization for multiple assets of DDG-51 Navy ship using OpenCV (Figure 2).

Our work focuses on finding optimum set of asset allocation parameters using elitist genetic algorithm and providing corresponding 2D visualization for navy ships.

2 RELATED WORK

With growing complexity of maritime threats, allocation of navy resources (sensors/defenses) is of key interest and has many relevant applications. Some include RA for maritime search and rescue (SAR) (Ai et al., 2019), (Guo et al., 2019), emergency people evacuation (Zhang et al., 2017), power allocation of multi-satellites for maritime mobile 6G communication (Hassan et al., 2023), straddle carrier scheduling in maritime container terminal at import (Dkhil et al., 2018), beam scheduling problem for multifunctional radar (Jeong et al., 2023), threat evaluation and weapon allocation (TEWA) (Paradis et al., 2005), weapon-target assignment (WTA) (Zhang et al., 2023), risk assessment (Malik et al., 2014) and many more (Cao et al., 2022; Dridi et al., 2012; Qian et al., 2022; Hattaway, 2008).

Recently, a rapid growth of visual analytics tools has taken place (Stasko et al., 2007; Willems et al.,

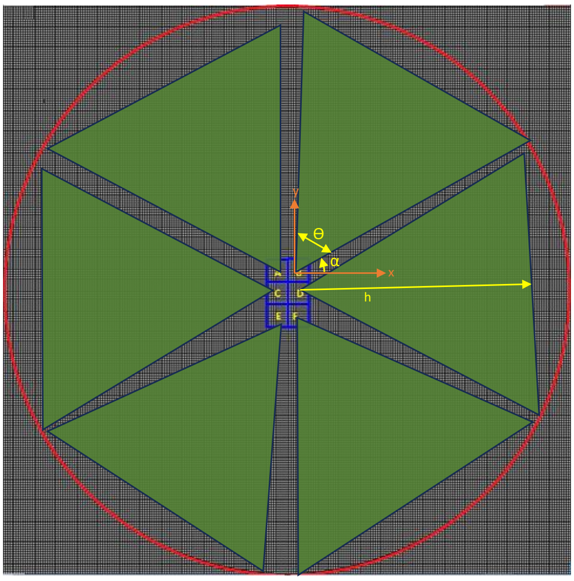


Figure 1: An example of generalized RA using visualization interface of Pygame where A-F are locations for asset placement.

2009) . Mostly, such tools offer graph visualization (Cleveland and McGill, 1988) and coordinate plots (Inselberg, 2009). Although these allow us to derive better understanding of the data and aid decision making process, it is only very recent that researchers have started incorporating output from visualization techniques in risk assessment (Malik et al., 2014).

Integration of visual analytics in maritime domain can provide deeper insights into many problems such as risk assessment, threat evaluation, intent recognition (Carlson et al., 2019) and resource allocation. Although we see the use of visual data in various RA problems targeted towards SAR applications (Malik et al., 2014), there are rarely any available systems for visualization of tactical resources (mainly sensors and defenses) . Visualization of the level of protection provided by various sensors and defenses following any allocation pattern can lead to better threat evaluation and enhanced understanding of point and area defense. Having data related to location of various red ships near a blue ship can only be of little significance in real time scenarios, where prompt decision making is crucial. Algorithmic approach towards modeling RA for tactical resources of navy ships can yield better outcome due to maximum utilization of limited resources and enhanced security. RA along with available visualization technique can lead to better anticipation of risk and threat level associated with complex maritime scenarios. With this idea, we have defined and solved two different RA problems for navy ships utilizing evolutionary algorithms and visual analytics.

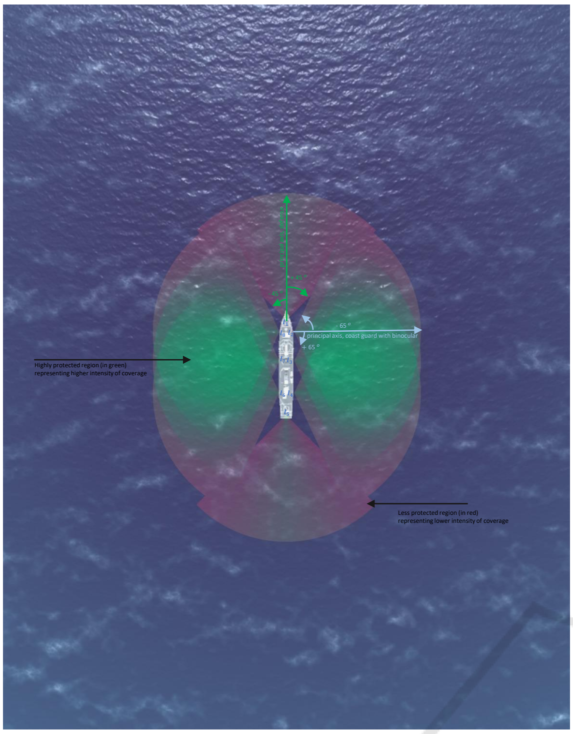


Figure 2: Tactical Asset Intensity Visualization for Risk Minimization using OpenCV.

h1	h2	h3	h4	h5	h6	α_1	α_2	α_3	α_4	α_5	α_6	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6

(a)

o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8	l_1	l_2	l_3	l_4	l_5	l_6

(b)

Figure 3: Structure of chromosome for generalized Resource Allocation and Multi-objective Resource Allocation specific to DDG-51 shown in (a) and (b) respectively.

3 METHODOLOGY

In this section, we will discuss our algorithm framework and its specification for GRA and MOEA for DDG-51.

3.1 CHC Selection Based Genetic Algorithm

Genetic algorithms (GA) differ from other search algorithms due to their ability to overcome local maxima by starting search from a random set of solutions (Goldberg, 1987). Instead of providing one single solution, GAs provide a set of solutions to a given problem (Louis and Zhao, 1995). Each of these solutions contain the search parameters and these solutions are called chromosomes (also known as individual). A set of chromosomes is known as a population. Different sets of chromosomes create different set of populations over different generations. GAs select superior individuals from parent population through a selection procedure and retain superior individuals while introducing diversity through crossover and mutation processes. GAs can be of various type depending on the method of selection, crossover and mutation. Cross-generational elitist selection (CHC) is a non traditional GA (Whitley and Sutton, 2012), which combines parent and child population and keeps half of the chromosomes with best fitness values. This strategy retains the best individuals from one generation to another. In this way, CHC based GAs can find solutions of very complex search space within a few generations.

3.2 Generalized Area Coverage Based Resource Allocation and Visualization

We have defined the GRA as a set up where 6 assets can be placed in 6 fixed locations (namely *A, B, C, D, E, F*) of a rectangular region representing a ship (see Figure 1). The objective to find which dynamic asset configuration is the best fit for each of the 6 pre-defined locations provided that we are placing the assets sequentially and one location cannot be occupied by more than one asset. By best fit we refer to the amount of area an asset covers based upon various parameters such as linear coverage (h), angular coverage(θ) and orientation. Therefore, the asset type is not fixed. The assets can be anything such as defense, sensors, coast guards, etc. All the assets have a FOV ranging between +60°\-60°, i.e., 120° is the maximum possible angular coverage for each asset. The linear coverage range of the assets can be from 1 km to 256 km. We chose this linear range to increase the complexity of search space. By orientation (α) in GRA problem, we refer to the angle by which an asset can rotate anticlockwise from the x axis of its coordinate system. At first, we make all calculations required for height, angle and orientation (h, θ *and* α) considering the center of the Pygame interface as the origin. Therefore, there is a single coordinate system for all assets with the center of the Pygame window as origin. Later, all calculations are performed on the transformed coordinate system specific to each asset. For instance, we can see the x and y axes for asset placed in location B in Figure 1. In this case, the orientation values range from 1° to 360°. Here, the location (l) of the assets are static parameters. We use triangular shapes to represent assets having sector-like field of view. The heights of the triangles representing the assets, namely *h1-h6*, indicate the linear coverage of assets. The FOV angles and orientations are represented by parameters named (θ_1 - θ_6) and (α_1-α_6) respectively (see Figure 1). Therefore, the parameter sets of (h, θ, α) values are defined by the search space. For this problem we are using a chromosome of length 144, where there are 6 height values, 6 corresponding angle values and 6 different values for orientations from transformed positive x axis. Our chromosome structure is visualized in Figure 3a. The height, angle and orientation values have a binary encoding, comprising of 8, 7 and 9 bits respectively. Here, all the parameters (h, θ, α) are dynamic, thus resulting in a huge search space. This approach makes this GA flexible to be tuned according to any model of navy ships with unique set of assets.

Area of Coverage Based Fitness Function. For fitness function calculation, we considered the percentage of area covered inside a circle. For this we used the Pygame library to create a gray color display of size 970 x 970, where 1 pixel represents 0.5 km in real space. We drew a 512 x 512 grid to make calculations easier. Hence, there are total 940,900 pixels in the Pygame display interface and the whole window represents an area of 262,144 square km. Then we drew a circle having radius of 128 grid units where each grid unit is equivalent to 3.78 pixels. Finally, we placed triangles (resources) from a starting location of positive x axis in anti-clockwise direction of each of our six coordinates in our Pygame screen which can be seen in Figure 1. We are considering all the triangles to be isosceles triangle, since in case of ships, any asset's field of view is equally distributed from principal axis of rotation. Every triangle starts from an angle α (in Figure 3a) from the positive x axis in anti-clockwise direction where α can have values from 1° to 360°. Each isosceles triangle can have an adjacent angle (θ) value from 1° to 120° and height values (named *h1-h6*) ranging from 1 to 256 units (see Figure 3a). For drawing the triangles using Pygame, the library requires 3 coordinate points of a triangle: 2 adjacent sides of isosceles triangle have one point in common, which give us one of the three coordinates. We calculated the remaining coordinates of end points of each of 3 sides of triangles by solving 3 trigonometric equations for each side. We considered the trigonometric equation of a line whose perpendicular makes an angle p from the positive x axis and that line is q angle away from positive x axis (Algorithm 1). We did this calculation to determine the orientation values and place the triangles (asset covered area) in the Pygame visualization window using the θ and α values which can be seen in Figure 4 and Figure 5. In this way we do similar calculation for each triangles with respect to each given location point on a transformed coordinate system (see Algorithm 1). The transformation is done respect to the origin of the circle whose pixel location in the Pygame window and our original coordinate system is (485, 485) (see Algorithm 2). Once the coordinates of each sides end point are found, we draw green color filled triangles using Pygame's gfxdraw library's drawFilledTrigon() function. Our algorithm is designed to deal with overlap of coverage of area from multiple assets using visual analytics. Since we are considering the intensity of coverage to have the same value for each pixel irrespective of the number of assets that cover that area, we used pixel-wise visual cue for calculating covered area around ship. Once the assets are placed and visualized, our algorithm takes input from Pygame's visual grid and counts the number of pixels having green color within the circular region to calculate the effective covered area in target region (circular region). When a pixel has green color RGB value then it is considered as covered, provided that it is within the circumference of the circular region. This is in order to compute the area that our asset placement has covered within a certain circular boundary.

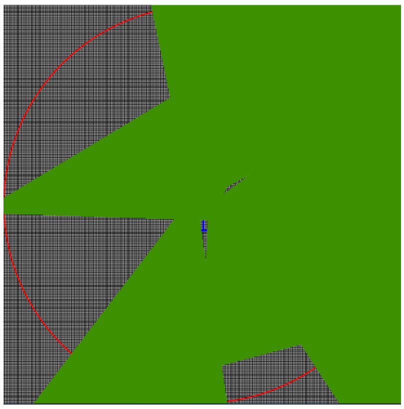


Figure 4: A sample of GRA based on solution generated by our algorithm where height values are = [139, 178, 177, 225, 123, 217] and θ values are = [96, 115, 43, 70, 51, 2],α values are =[235, 114, 236, 56, 346] where population size = 50 and Generation number = 70, Area covered (inside circle) = 75 percent.

Once the coordinates of each sides end point is found we draw green color filled triangles using Pygame's gfxdraw library's drawFilledTrigon() function.

Area Covered Calculation. For area coverage calculation, we calculate the number of green pixels inside the boundary of the circle and multiply it with pixel size (see Equation 2). The area of circle is calcu-

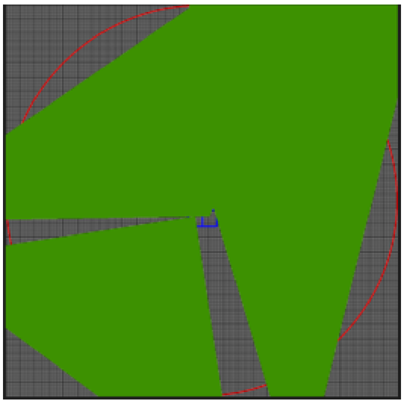


Figure 5: height1-height6 = [221, 199, 255, 130, 31, 127] and θ1-θ6 =[37, 84, 63, 40, 73, 28], α1-α6 =[97, 239, 220, 195, 286, 215] where population size = 100 and Generation number = 103, Area covered (inside circle) = 82 percent.

Algorithm 1: Calculates the 3 corner coordinates of each triangle with respect to transformed coordinate system.

Input: List of heights, FOV angles and orientation angles(q) from positive x axis in transformed coordinate system, p angles (the angles made by perpendiculars of each side of triangles with positive x axis)
Result: 3 corner coordinates of a triangle in transformed coordinate system($x, ycoordinatevalues$);
a1 = 270 + q;
a2 = q + p/2;
a3 = 270 + q + p;
foreach *p in angles (where p[i] > 0* **do**
  xcos(a1) + ysin(a1) = 0;
  xcos(a2) + ysin(a2) = height;
  xcos(a3) + ysin(a3) = 0;
end

Algorithm 2: Calculates the 3 corner coordinates of each triangle with respect to original coordinate system.

Input: List of 3 corner coordinates of a triangle in transformed coordinate system, i.e. list of 3 (x,y) coordinate values and coordinate of a given pixel location on ship's rectangular area
Result: 3 corner coordinates of a triangle in original coordinate system (x,y) coordinate values;
foreach *index in range len(coordinate_solutions)* **do**
  coordinate_solutions[index][0] = coordinate_solutions[index[0] + location_point[0];
  coordinate_solutions[index][1] = coordinate_solutions[index][1] + location_point[1];
end

Algorithm 3: Calculates the fitness value for each member of chromosome.

Input : List principal axis and locations in form of pixel coordinates of all 8 assets, FOV_angle
Result: combined fitness value of a pixel resulting from all the allocated assets;
asset_coverage = 0
for $i = 0$ *to* 6 **do**
  binocular = b_coordinate.append(b_location[i])
  for *i in range width* **do**
    for *j in range height* **do**
      angular_distance = Calculate β from each principal axis;
      if *angular_distance <= FOV_angle* **then**
        asset_coverage + = Intensity(eDistance, minDist, maxDist, angular_coverage, β, maximum_angularRange, mapping, intensity_distribution_pattern, c);
      else
        return 0.0;
return asset_coverage;

lated using Equation 1, where the radius of the circle represents 256 km according to the maximum linear coverage range of each assets for this problem. For calculation of area covered inside circle by triangles, we used the Equation 2. Here, trianglePixelCount is the number of pixels whose RGB pixel value is green and are inside circular boundary. Pygame window size here is 512 x 512 pixels, therefore the pixel size is 0.73 μm. Finally, for calculation of percentage of area covered, we use Equation 3. We can see how our display looks with various height, theta, alpha values in Figure 4.

$$CircularArea = 3.146 * (radius)^2 \quad (1)$$

$$AreaCovered = pixelSize * trianglePixelCount \quad (2)$$

$$Fitness = (AreaCovered/CircularArea) * 100 \quad (3)$$

3.3 Intensity and Area of Coverage Based Resource Allocation

This RA approach is based on constraints imposed by the assets of DDG-51 where we are considering allocation of 2 defenses having a maximum linear coverage range of 14 km and 6 coastal guards having binoculars represented with visual sensors having a maximum linear coverage range of 20 km. For the defenses, one pixel represents 1 km and for visual sensors each pixel represents 1.5 km. The locations for defenses are fixed and each of them can have 4 predefined different orientations. The locations of the visual sensors are dynamic and 16 different locations have been defined along the borders of the ship model. The coastal guards can be placed at any of these 16 locations and each of these mobile assets can have 8 different orientations. Here we have manually defined 8 possible orientations values that each of these coastal guards can have in order to reduce the complexity of search space. The GA searches through each of these 8 different possible orientations for coastal guard assets. Our chromosome has all binary values. It contains 8 different orientation values where the first two are for defenses (2 bits each), the next 6 values are for orientation of visual sensors (3 bits each), and the succeeding 6 values (4 bits each) represent the location of the visual sensors. In this case there are fewer parameters compared to the generalized GA for area based RA, since specific model of ships have particular range of orientations and distance coverage, which results in reduced search space.

Multi-Objective GA Fitness Function for DDG-51. We have taken into consideration the fact that the intensity of coverage from each assets is not of equal magnitude in every location around the ship. Intensity values degrade with distance and angle from the direction where it is pointed (also known as principal axis). In order to model the distribution of intensity based on linear distance, orientation and area of coverage, we built a visual analytic algorithm, based on OpenCV, and we designed a set of intensity deterioration functions to achieve this effect (see Algorithm 4). This enables us to know the combined effect of orientations and allocations of multiple static and mobile assets at any point of time and can be used in fitness function for our GA since it can easily tell which area is comparatively less covered by the current set of asset allocations (see Algorithm 3). In Algorithms 3 and 4, the variable *eDistance* refers to the euclidean distance of a pixel from a principal axis (PA) of an asset, *minDist* refers to the minimum coverage range of an asset, *maxDist* refers to the maximum coverage range of asset, β refers to the angular distance of a pixel from PA of an asset, *mapping* refers to the scaling parameter, and *b_coordinate* refers to the location of coast guards with binoculars.

In our fitness function, we have two main objectives:

- Maximize the area covered by assets around Navy ships and
- Maximize the strength of coverage, which implies reduced risk in the protected zone.

The summation of pixel values having combined intensity values from multiple assets help us meet both of our objectives simultaneously, i.e., higher intensity value of the entire image represents more area being covered along with higher strength of coverage. Both pixel intensity values and number of pixels having an intensity of coverage value greater than zero contribute in overall fitness value calculation of each image generated by our visualization.

The way we achieve this effect, is by searching through each pixel of image generated by our visualization technique and assigning an intensity value to it from every asset. We add intensity values of all pixels in the image and assign that value and a fitness value for a particular set of allocation parameters generated by our multi-objective evolutionary algorithm (see Algorithm 3).

In order to further optimize the calculations in fitness function, for every pixel of the image generated by our visual analytic algorithm we check its angular distance from principal axis of each asset and calculate fitness value for it only if it falls within the range of coverage specific to each asset (see Algorithm 3). In our visual analytic helper functions we are using inverse normalization to model the change of intensity value with respect to distance for visual sensors of binocular and piece-wise function for the same in case of defenses. We refer to this as intensity_distribution_pattern in Algorithm 3 and Algorithm 4. Variable *c* is a hyper parameter with values within a range of .01 to 1. The *FOV_angle* variable represents the maximum field of view a specific asset can have, for example: for coastal guards the *FOV_angle* is 130° (+65°\-65°) and for defenses the *FOV_angle* is 90° (+45°\-45°).

Additionally, we also have built functions to model the intensity of coverage for other possible assets such as radar, sonar sensors with spherical or circular area of coverage (see Algorithm 4). Although we only display visualization from defenses and conical FOV assets, spherical assets can also be represented using our Algorithm 4. Radar and Sonar sensors differ at the rate at which their intensities decays with linear and angular distance, due to which the *intensity_distribution_pattern* variable is set to two different types, "radar_exponent" and "sonar_exponent" respectively.

We calculate the final intensity of coverage of a pixel by combining the value of linear intensity (based on euclidean distance from principal axis) and angular intensity (using Equation 4). We calculate the intensity of coverage value of a pixel only when β (the angular distance from principal axis of an asset) falls within the maximum angular coverage region which is unique to each asset. To compute β we use vector dot product and calculate the cosine of the angle by dividing the dot product of two vectors representing line segments by the product of their magnitudes (see Equation 4).

$$Sector\_Intensity = 1 - (2 * \beta / (max\_coverage) \quad (4)$$

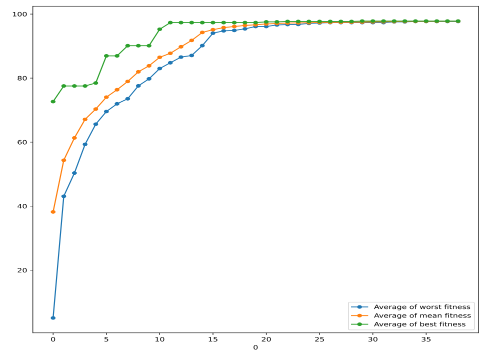
When a pixel falls within β range, then for calculation of intensity we follow Algorithm 4: this returns an intensity value corresponding to each pixel, which in turn is used by Algorithm 3 to iterate through all pixels of a visualization and calculate a fitness value for a chromosome.

Algorithm 4: Calculating the intensity of a pixel with respect to an asset.

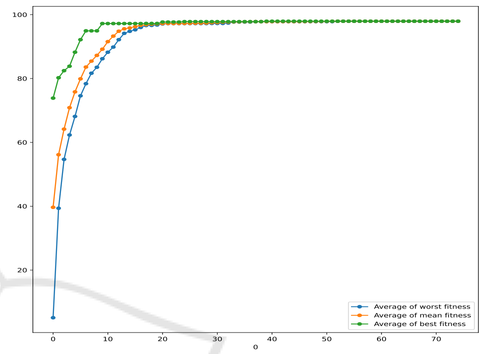
Input : eDistance, minDist, maxDist, angular_coverage, β, maximum_angularRange, mapping,intensity_distribution_pattern,c
Result: intensity value of a pixel resulting from one asset placed at a particular location;
if *eDistance < minDist or eDistance > maxDist* **then**
  return 0;
if *intensity_distribution_pattern = "piece_wise"* **then**
  if *eDistance > 0 and eDistance < 0.025 * maxDist* **then**
    retrun 0.9;
  else if *eDistance >= 0.025 * maxDist and eDistance < 0.045 * maxDist* **then**
    return 0.7;
  else if *eDistance >= 0.045 * maxDist and eDistance < 0.2 * maxDist* **then**
    retrun 0.2;
  else
    return 0.05;
else if *intensity_distribution_pattern = "inv_norm"* **then**
  return 1 - ((eDistance - minDist)/(maxDist-minDist);
else if *intensity_distribution_pattern = "radar_exponent"* **then**
  return $1/e^{(c*eDistance)/(maxDist-minDist)}$;
else if *intensity_distribution_pattern = "sonar_exponent"* **then**
  return $1/e^{(c*(eDistance-minDist))}$;
else
  return 0;

3.4 Common Parameters Used in both Approaches

Through experimentation we found that probability of mutation of 0.05 and probability of cross over of 0.9 works best for our generalized resource allocation and DDG-51 specific resource allocation problem. For the GAs used to address both problems we used CHC-based selection with μ value of 2, where μ refers to the number of parents selected by the GA at a time before crossover and mutation takes place. We used 30 different random seeds and we averaged the minimum, maximum and average fitness of our GA in every generation over these 30 random seeds. We did this in order to confirm that the result we obtained was not an outcome of random initial set of chromosomes that the GA started working with. This can be seen in Figures 6a, 6b and 6c.



(a)



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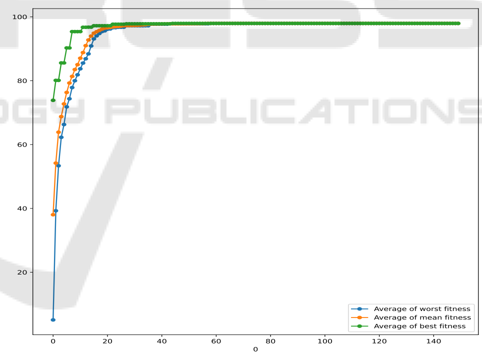

(c)

Figure 6: Average of best, mean and worst fitness curves for RA of DDG-51 ship for 35, 70 and 150 generations in (a), (b) and (c) respectively.

Table 1: Parameters and Maximum Fitness values (Area covered) for generalized RA having dynamic parameters.

Pop & Gen No.	Crossover and Mutation Rate	Static parameters	Dynamic parameters	Fitness (%)
50 , 37	0.9, 0.05	l	h,θ,α	69
50 , 70	0.9, 0.05	l	h,θ,α	75
100 , 103	0.9, 0.05	l	h,θ,α	82
100 , 150	0.9, 0.05	l	h,θ,α	98
200 , 300	0.9, 0.05	l	h,θ,α	100
300 , 450	0.9, 0.05	l	h,θ,α	100

Table 2: Parameters and Maximum Fitness values multi-objective RA.

Pop & Gen No.	Crossover Rate	Mutation Rate	Static parameters	Dynamic parameters	Fitness(%)
26, 39	0.9	0.05	h,θ	α, l	97
50, 75	0.9	0.05	h,θ	α, l	97
100, 150	0.9	0.05	h,θ	α, l	98

4 EXPERIMENT

In this section, we evaluate the performance of our generalized RA and DDG-51 specific constrained RA by varying the hyper parameter values. We ran our evolutionary algorithm for various number of generations to see if it has an impact on the results (Table 1). For all the experiments we used a hybrid computer having Intel(R) Core(TM) i9-9900 KF processor, 32 GB RAM and NVDIA GeFORCE RTX 3060 GPU.

In Table 1, we show the population and generation number used by our GRA algorithm, along with the crossover-mutation rates, dynamic parameters, and best fitness value. We ran each of our GA iteration through 30 random seeds and average the best, minimum and average fitness value per iteration to ensure that GA results are not some random results influenced by the initial set of chromosomes. For each random seed we take the best fitness values and average them for each generation. In the best fitness column we indicate the maximum value of those averages from generation number 0 to generation number n.

Parameter l refers to the locations on the ship where asset can be placed. The dynamic parameters h, θ, α represents the linear coverage, field of view angles and orientations of assets respectively. From Table 1 it is evident that running the algorithm for higher number of generations yields better fitness values. Finally, for 300 generations with a population size of 200, leads towards finding set of parameters that give 100% of area coverage. We infer that finding a set of chromosomes that yield 100% fitness value within relatively small number of generations for such a large search space might have been possible due to the simplicity of constraints imposed upon the parameters. For instance, we represented the area of coverage of each resource to be simply triangular (which is not the case with real life assets), and the whole grid size was 512 x 512 pixels only. If we took a greater Pygame window size with more complex representation of sensor coverage then GA might have not found a set of solution resulting in 100% area of coverage within 300 generation only.

To explore the applicability of our approach for real life ships with dynamic location parameters, we also experiment with the MOEA that we built for DDG-51 that takes into account the specific linear, angular coverage ranges of its resources along with the constraints imposed upon it. From Table 2, we see that running our MOEA for greater number of generations with larger population size does not have a significant impact on our fitness value. This is due to the fact that in our second experiment we have built an algorithm that offers an enhanced representation of area of coverage in addition to intensity of coverage. Our elitist selection based GA searches through possible combinations of orientations and locations. Since DRA has constraints on each asset's linear and angular coverage ranges, these fall under the category of static parameter. Orientation and location are dynamic parameters in this case.

5 RESULTS

For the generalized RA, we used population sizes of 50 and 100 with varying numbers of generations (Table1). From Table 1 we can see that when we let the generalized RA run for more number of generations we obtained better results. Even for a generalized version of the problem with 2^{144} parameters, our elitist evolutionary algorithm was able to find good resource allocations parameters within 150 generations (Table1). For MOEA, upon using population size of 26, 50 and 100 for generation number 39, 75 and 150 respectively as hyper parameters for our MOEA (see Table 2), we found that within around 25 generations the fitness values converge to 98%. These sets of solutions can now be used for allocating resources on Arleigh Bruke Destroyer ship for maximization of area of coverage and risk minimization (meaning overall higher strength of coverage). We have calculated average of best, mean and and worst fitness across 30 random seeds for each generations and noticed that the mean fitness value starts from 40% fitness value and reaches a value of 80% within less than 10 generations and by 25 generations it finds the optimum set of solutions. Maximum fitness starts somewhere around 70% and reaches 96% fitness values within less than 10 generations.

6 CONCLUSION

We formulated two novel resource allocation (RA) problems for navy ships. The generalized version of RA focuses on maximization of area of coverage around ships and finds solutions having 98% area coverage within a given circular boundary. The second version of the RA problem was defined considering a DDG-51 ship's dimensions and ranges of its available resources. We found that our optimization approach was able to find solutions representing the location and orientation of the resources ensuring 98% risk minimization and area of coverage. Our novel visual analytic algorithm is capable of generating visualization of combined intensity of coverage also known as heatmaps around DDG-51 at any point of time. Moreover, tuning the GA for incorporating data based on location of multiple ships in real time, can lead to resource allocation in real time and parallel processing can help with generating faster outputs. This opens doors for future works related to integrating dynamic threatmaps with our multi-objective evolutionary algorithm to enhance the level of protection around ships in multi-agent scenarios (MAS).

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