Defence Science Journal, Vol. 70, No. 4, July 2020, pp. 412-418, DOI : 10.14429/dsj.70.15066

A Heuristic Methodology for Optimal Deployment of Radar Systems in a Constrained Area of Operation

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ABSTRACT

In emerging network-centric warfare scenarios, the location of sensors in the sensor-grid plays a dominant role in determining the effectiveness of air defence against enemy air threats. Maximising the coverage area of sensors in the sensor-grid, considering operational performance parameters, terrain features and deployability is a challenging task for military operational planners and commanders. Such optimisation problems may not be amenable to classical operations research techniques, or may require enormous computational time to arrive at the results as the decision space grows non-linearly for large areas of operation. In this paper, a novel methodology that uses a heuristic technique (genetic algorithms) to compute the optimal or near-optimal deployment locations for a given set of sensors in a constrained area of operation is proposed. The proposed methodology is illustrated with a number of case studies and a decision support tool is developed as an aid to the military commanders.

Keywords: Network centric warfare; Sensor grid; Air defence; Optimal radar deployment; Heuristic optimisation; Genetic algorithms

1. INTRODUCTION

Network centric warfare is a military doctrine that seeks to translate a networked information advantage into enhanced mission effectiveness. It describes the combination of emerging tactics, techniques and procedures that a network force can employ to create a decisive warfighting advantage. The sensors grid, weapons grid, communications and information grid play a vital role in enabling information gathering about the enemy and effectively countering them. Sensor grid consists of radar systems which are electromagnetic sensors used for detection, location tracking, imaging and classification of targets such as aircraft, ships and ground moving entities. The role of radar systems becomes a critical factor in decision making and generating the commanders' battlefield awareness and thus their deployment in an area of operation (AoP) has always been a concern to operational planners. Identifying feasible sites for the deployment of radar systems in order to maximise the detection coverage area is an important optimisation problem in military systems analysis.

Deployment of a radar system at a site to provide sufficient early warning of incoming enemy air threats to the air defence (AD) commanders need to consider factors such as line of sight availability due to terrain features and other man-made obstacles. In addition, the planner must also consider the deployment site feasibility such as its ease of access to road and rail networks and absence of water bodies. However, mathematically this turns out to be an NP-hard problem where the decision space grows non-linearly for large areas of operation. Such optimisation problems may not be amenable to classical operations research (OR) techniques[1]. NP-hard problems are a combinatorial class of problems with inherent complexity that any technique of solving such problems to optimality requires computational effort that increases exponentially with the size of the problem. For solving such problems, heuristic or meta-heuristic optimisation techniques[2] are predominantly used. Such techniques do not guarantee finding the optimal solution, but can lead to a near-optimal solution in a computationally efficient manner.

Received : 11 September 2019, Revised : 27 March 2020
Accepted : 26 May 2020, Online published : 13 July 2020

2. RELATED WORKS

The problem of identifying the optimal deployment locations for radar systems that maximise the detection coverage is an area of interest to researchers and military operational planners. Two important problems of interest arise:

(i) given a set of *n* heterogeneous sensors, the planner needs to identify the locations that maximise the detection coverage;
(ii) given an AoP and the assurance levels of detection, the planner needs to know the *number* and *optimal mix* of sensors required.

Meguerdichian[3], *et al.* addressed the problem of evaluating the coverage area provided by a given placement of sensors and proposed a polynomial time optimal algorithm that uses graph theoretic and computational geometry constructs for solving best and worst case coverage. Chakrabarty[4], *et al.* formulated sensor placement for effective surveillance in distributed sensor networks as a combinatorial optimisation problem and solved it using integer linear programming (ILP) technique. However, computational complexity makes this approach infeasible for large terrains. Kasetkasem[5], *et al.* proposed an algorithm based on Bayesian and Neyman-Pearson formulations to determine the optimal communication structure for multi-sensor detection systems. Sakai[6], *et al.* proposed a framework to discover the optimal *k-coverage* deployment patterns that significantly reduce the number of sensors to be deployed. Howard[7], *et al.* proposed a potential field based approach to the deployment of a mobile sensor network in which the fields are constructed in such a manner that each node is repelled by both obstacles and by other nodes, thereby forcing the network to spread itself throughout the environment. Locatelli[8], *et al.* proposed an algorithm for solving the disk packing problem of scattering various points into the unit square in such a way that their minimum pair-wise distance is maximised. Zou[9], *et al.* proposed virtual force algorithm (VFA) combining the ideas of potential field and disk packing as a sensor deployment strategy to enhance the coverage. Li[10], *et al.* proposed an extended virtual force based approach to overcome the connectivity maintenance and nodes stacking problems in the traditional VFA. Wu[11], *et al.* proposed a deterministic strategy based on Delaunay Triangulation for planning the position of sensors in the environment with obstacles. Iyer[12], *et al.* proposed a GA based technique for identifying the optimal locations of acoustic sensors in under water sensor networks.

There are several heuristic and meta-heuristic deployment strategies available in literature. Musman[13], *et al.* proposed a sensor deployment and planning framework for elusive targets based on heuristic search procedures and decision theoretic techniques with probabilistic reasoning. Sweidan[14], *et al.* examined several evolutionary computation techniques in search for an optimal solution in a terrain aware wireless sensor network. Mingnan[15], *et al.* proposed a deployment strategy to improve the detection capability of a sensor network in the multi-dimensional space using improved particle swarm optimisation (PSO) technique. Wu[16], *et al.* proposed an approximate solution to deploy sensors on a planar grid using two-dimensional genetic algorithm (GA). Unaldi[17], *et al.* proposed a guided wavelet transform and GA based deployment strategy on 3D terrains to maximise the coverage quality. Longpo[18], *et al.* proposed a decision making model of optimal deployment for radar netting using GA.

3. MATHEMATICAL APPROACHES

Several mathematical formulations have been proposed in literature for identifying optimal deployment locations of sensors to maximise the coverage area. These approaches can broadly be classified into OR techniques and heuristic optimisation techniques.

Linear programming is used to solve optimisation problems in which the objective function and the constraints can be defined using linear functions. It has been widely used in the military operations research to solve variety of optimisation problems. However, it may not always be practically feasible to translate real world constraints into linear mathematical constraints.

Dynamic programming explores the entire search space and then finds out the best solution. However, it is applicable to problems having properties of optimal substructure and overlapping subproblems.

Rao[19], *et al.* proposed a static, physics-based methodology based on an iterative algorithm to deploy radar systems to maximise the coverage under various terrain conditions. In this work, the effectiveness of the deployments was evaluated using game theory and simulation techniques. However, a major drawback of the algorithm is its iterative nature which leads to very large computational time for practical areas of operation.

In VFA, each sensor acts as a source of force for all other sensors. This force can either be *attractive* or *repulsive* depending on the distance between them. In addition to the attractive and repulsive forces, a sensor is also subjected to forces exerted by the obstacles and the areas of preferential coverage such as those having a high elevation. The total force $\vec{F}_i$ on sensor S_i is expressed as:

$$\vec{F}_i = \sum_{j=1, j\neq i}^{k} (\vec{F}_{ij} + \vec{F}_{iR} + \vec{F}_{iA}) \tag{1}$$

$$\vec{F}_{ij} = \begin{cases} (W_a(d_{ij} - d_{th}), \alpha_{ij} & if \quad d_{ij} > d_{th} \\ 0 & if \quad d_{ij} = d_{th} \\ \left(\dfrac{W_r}{d_{ij}}, \alpha_{ij} + \Pi\right) & if \ otherwise \end{cases} \tag{2}$$

where k is the number of sensors, $\vec{F}_{ij}$ is the force exerted on sensor S_i by another sensor S_j, $\vec{F}_{iR}$ is the total repulsive force on sensor S_i due to obstacles and $\vec{F}_{iA}$ is the total attractive force on sensor S_i due to preferential coverage areas, d_{ij} is the Euclidean distance between sensors S_i and S_j, d_{th} is the threshold on the distance between S_i and S_j, α_{ij} is the orientation of a line segment from S_i to S_j and W_a (W_r) is a measure of the attractive (repulsive) force.

While VFA has been extensively used for deploying wireless sensor networks, its applicability to deploy long range sensors (such as radars), whose performance is largely dependent on terrain and environmental characteristics, becomes limited.

Therefore, when a given problem cannot be solved by traditional optimisation algorithms due to large computational time, heuristic optimisation techniques can be used to obtain approximate or near-optimal solutions in reasonable time. Heuristic techniques solve problems more quickly when traditional methods are too slow, or unable to find any exact solution. This is achieved by trading optimality for computational speed.

In this work, authors proposed a novel methodology that uses genetic algorithm, a heuristic technique, to solve the optimal sensor deployment problem.

4. OPTIMISATION USING GENETIC ALGORITHM

The genetic algorithm (GA)[20,21] is a search based heuristic optimisation technique used for solving both constrained and unconstrained optimisation problems based on the concepts of natural selection and genetics. It is often used to find optimal or near-optimal solutions for NP-hard problems in reasonable amount of time.

In general, GA starts with a set of individuals (‘*initialisation phase*’). Each individual is called a ‘chromosome’ and represents one of the feasible solutions to the problem under study. Each chromosome is assigned a fitness score based on the objective function. The chromosomes having better fitness scores are selected (‘*selection phase*’) for mating to produce offspring (‘*crossover phase*’). Once the offspring are produced, mutation is applied (‘*mutation phase*’) to them as a small random tweak. Mutation helps in maintaining and introducing diversity in the population. The offspring are then inserted into the population (‘*insertion phase*’). Over successive generations, the fitness of chromosomes in the population increases gradually and the best solution in the population approaches (near) optimal solution.

5. RADAR MODEL

Radar systems are sensors that continuously scan a specified volume of space for air borne threats. Once detection is established, the target information such as range, angular position, and possibly velocity are extracted by the radar signal and data processors. The standard radar range equation[22] is used to compute the maximum range (R_{max}) provided by a radar system. When deployed on a terrain, the scanning radar beam can be partially or completely blocked due to the non-availability of line of sight thereby reducing the effective coverage is shown in Fig. 2 as compared to the maximum coverage is shown in Fig. 1. The radar model along with line of sight computation in every direction using digital terrain elevation data (DTED) is used to compute the effective coverage of a radar system in the grid location.

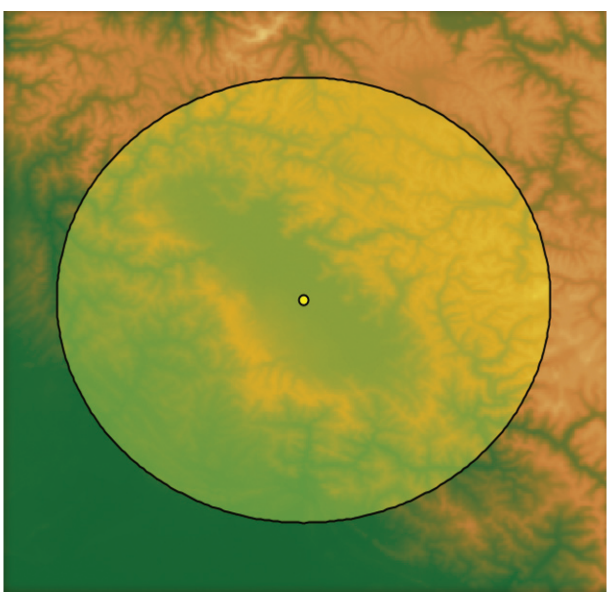

Figure 1. Radar coverage (instrumented range).

6. PROPOSED METHODOLOGY

The proposed methodology starts with mapping the given AoP to a grid matrix. The physical areas represented by the

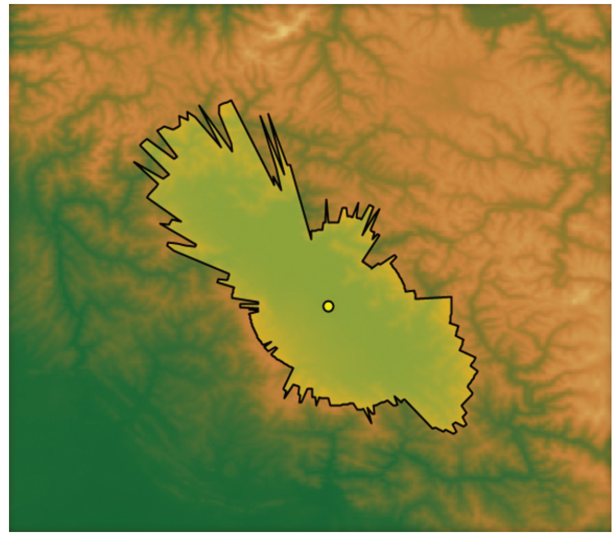

Figure 2. Radar coverage considering terrain features.

grids are then assessed for their deployability and filtered to generate the feasible solution space. These feasible grids are then used in the initialisation phase and mutation phase of the genetic algorithm to generate (near) optimal deployment solutions.

6.1 Pre-Processing Stage

During this stage, the area of operation is mapped to a grid matrix of dimensions $m \times n$, where each grid in the matrix represents a possible deployment site for the given radar systems. Grid size is selected on the basis of minimum physical area required on the ground for the radar deployment. These grids are then assessed for their deployment feasibility. A grid is considered to be fit for deployment, if it meets the following constraints:

(i) *Road network constraint*: Road network must exist within a specified distance (*dist_road*) from the grid to ensure that the deployment site is reachable through the road network.

(ii) *Rail network constraint*: Rail network must exist within a specified distance (*dist_rail*) from the grid to ensure that the deployment site is also reachable through the rail network.

(iii) *Water body constraint*: The selected grid should not contain a water body.

A feasible deployment grid matrix (*FM*) of dimensions $m \times n$ is generated for every constraint. Grids fit for the deployment after feasibility analyses are marked as 1 and rest as 0 in the corresponding feasible deployment matrices. Following matrices are generated:

(i) *Feasible road matrix:*

$$FM_{ro} = \begin{cases} 1, \text{ if road constraint is met} \\ 0, \text{ otherwise} \end{cases}$$

(ii) *Feasible rail matrix:*

$$FM_{ra} = \begin{cases} 1, \text{ if rail constraint is met} \\ 0, \text{ otherwise} \end{cases}$$

(iii) Feasible water body matrix:

$$FM_{wb} = \begin{cases} 1, \textit{ if water body constraint is met} \\ 0, \textit{ otherwise} \end{cases}$$

Finally, a feasible deployment matrix (FM_{dc}) which meets all the deployment site constraints is computed from FM_{ro}, FM_{ra} and FM_{wb} as:

$$FM_{dc} = FM_{ro} \cap FM_{ra} \cap FM_{wb} \tag{3}$$

Grids having value 1 in FM_{dc} represent feasible solution space and are considered in the subsequent phases of the proposed methodology.

6.2 Initialisation Phase

Consider the number of available radar systems to be deployed in an AoP is denoted by N_r. A *chromosome* is constructed from N_r grids to represent a feasible deployment solution. Each grid in the chromosome is called a *gene* and represents a feasible deployment site (specified by its latitude and longitude). Let the number of chromosomes in the initial population be denoted by N_p. The initial population (I_p) is selected randomly from the set of feasible grids (FM_{dc}) as:

$$I_p = \{C_1, C_2, C_3, C_4 \ldots C_{NP}\} \tag{4}$$

For example, an initial population of three chromosomes $\{C_1, C_2, C_3\}$ is shown in Fig. 3, where each chromosome is depicted by a set of four feasible deployment sites $\{R_1, R_2, R_3, R_4\}$ selected randomly.

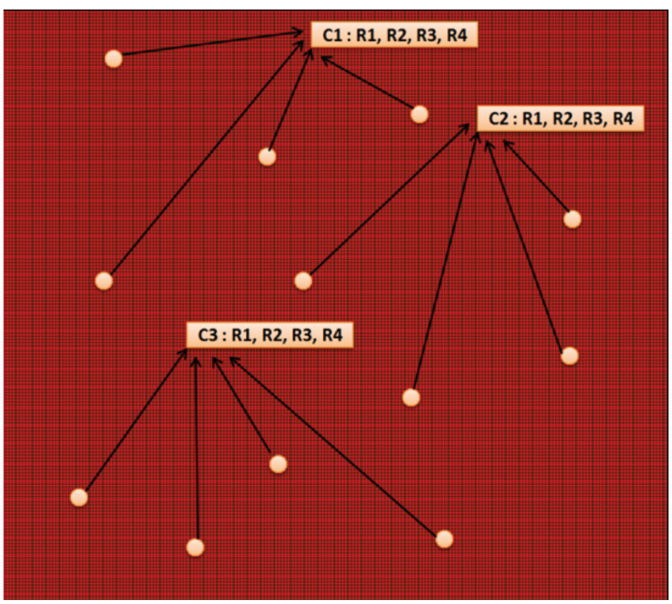

Figure 3. Initial population of deployment locations.

6.3 Fitness Function

Fitness function is modeled to evaluate the effectiveness of a chromosome (a feasible deployment solution) in terms of the coverage area i.e. how effectively it is covering the AoP. A grid is considered to be covered, if it is within the effective coverage of any radar system. A coverage matrix (CM) of same dimensions as that of grid matrix is generated for every chromosome (1 to N_p) in the population in which the grids which are covered by the deployment solution are marked as 1 and others as 0. The fitness function for each chromosome is expressed as follows:

$$F = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} CM(i,j) \tag{5}$$

6.4 Selection Phase

The roulette wheel selection method is used for selecting the parent chromosomes. In this method, all chromosomes in the current population are placed on the roulette wheel according to their fitness scores. Then, the roulette wheel is spinned and the chromosome corresponding to the segment on which the roulette wheel stops is selected. In this approach of selection, the chromosomes with higher fitness scores will have higher probability of selection.

6.5 Crossover Phase

Once the parents are selected using roulette wheel selection method, crossover takes place between them to produce offspring. A single point crossover method (Fig. 4) is used in which a crossover index between $[1, N_r]$ is randomly selected. This index represents the point of crossover of the selected parents. To allow some chromosomes in the population to survive to the next generation a crossover probability (P_c) is used.

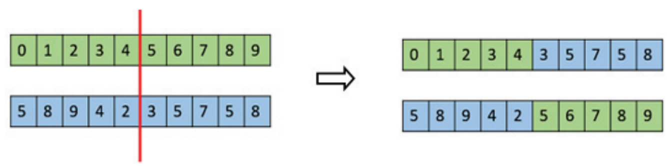

Figure 4. Single point crossover.

6.6 Mutation Phase

Mutation is applied with a very low probability to the offspring produced. Every gene in a chromosome of the offspring is given a chance for mutation by generating a random number. If the random number is less than or equal to the mutation probability (P_m), then the corresponding gene (deployment grid) is replaced with a new grid (not part of initial population) selected randomly from the set of feasible grids (FM_{dc}). Once mutation is applied, the offspring are then injected into the population (insertion phase) replacing chromosomes of poor fitness scores.

6.7 Termination Phase

With the completion of selection, crossover, mutation and insertion phases for the initial population, the updated population is again subjected to these phases and this procedure is repeated for

(i) predefined number of generations (N_g), or
(ii) there has been no further improvement in the population for a predefined number of iterations, or
(iii) the objective function has reached a predefined coverage value.

The chromosome with highest fitness score in the final population represents (near) optimal deployment solution. A decision support tool based on the proposed methodology is developed as a planning tool for military commanders.

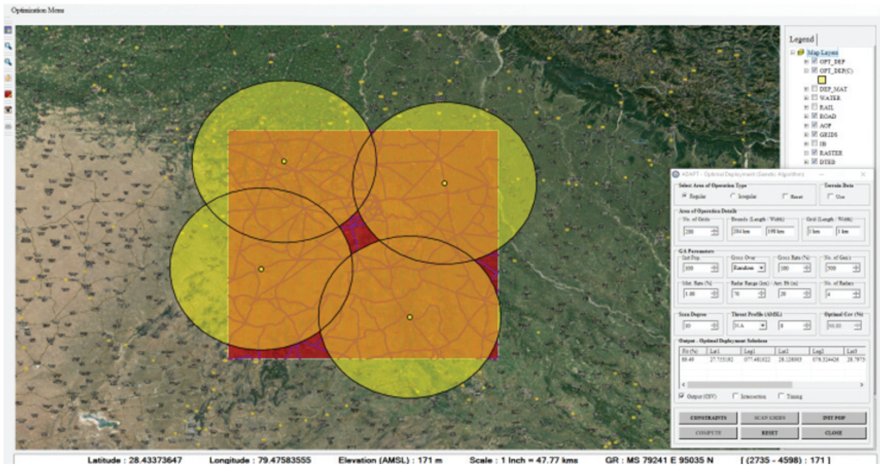

Figure 5. Decision support tool (ADAPT).

7. AD ASSETS PLANNING TOOL

AD assets planning tool (ADAPT) is developed based on the proposed methodology as a decision support tool to aid the military commanders for planning the optimal deployment of AD resources in an AoP (Fig. 5). An OGC compliant Open Source Geographic Information System (GIS) is provided that helps the planners to load high resolution raster and terrain maps, select an AoP, and specify the constraints (vector data in the form of shape files). The planner also selects the type and number of radar systems along with their parameters. GA parameters (size of initial population, number of generations, crossover and mutation probabilities) are then selected to obtain the system generated (near) optimal deployment solution (Fig. 6). The system generates a set of deployment solutions and their effective coverage from which the planner can select a deployment solution using his/her operational experience.

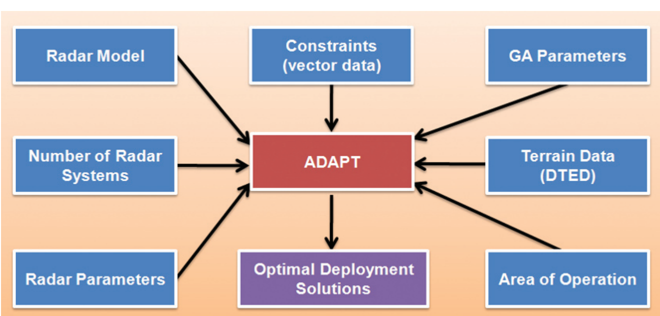

Figure 6. Block diagram of ADAPT.

8. RESULTS

In this work, we consider the following cases (Table 1). Case (i) considers optimal deployment of four radar systems each having an instrumented range of 80 km on a flat terrain. Case (ii) depicts their optimal deployment considering terrain features in the same AoP. The input parameters for AoP and constraints considered (Table 2) for cases (i) and (ii) are size of the selected AoP, number of grids and minimum distance to road and rail networks. GA parameters considered (Table 3) for cases (i) and (ii) are number of generations, size of initial population, crossover and mutation probabilities.

Feasible deployment matrices for road (FM_{ro}), rail (FM_{ra}) and water body (FM_{wb}) generated from the vector data of the constraints are shown in Figs. 7, 8, 9. Grids fit for deployment in the corresponding matrices are highlighted in blue color. Feasible deployment matrix (FM_{dc}) which meets all the deployment site constraints is shown in Fig. 10. Grids highlighted in blue color in FM_{dc} are the only sites fit for deployment and represent the feasible solution space. System generated (near) optimal deployment solutions on the application of the proposed methodology are shown in Figs. 11-12.

Table 1. Case study and analysis

Parameter	Description	Case I	Case II
N_r	Number of radar systems to be deployed	4	4
$R_{\max}$	Maximum range of the radar system (km)	80	80
Terrain	Terrain features : DTED 90m resolution	No	Yes

Table 2. AoP and Constraints

Parameter	Description	Value
AoP	Area of operation	200 km^2
m, n	Number of grids	200 x 200
	Size of each grid	1 km^2
dist_road	Minimum distance to road network (km)	1
dist_rail	Minimum distance to rail network (km)	1

Table 3. GA Parameters

N_p	Size of initial population	200
P_c	Crossover probability	0.9
P_m	Mutation probability	0.1
N_g	Number of generations	500

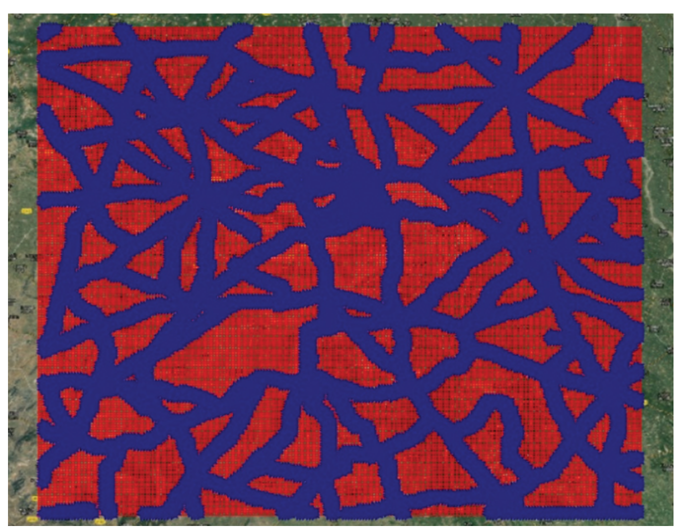

Figure 7. Feasible road matrix (FM_{ro}).

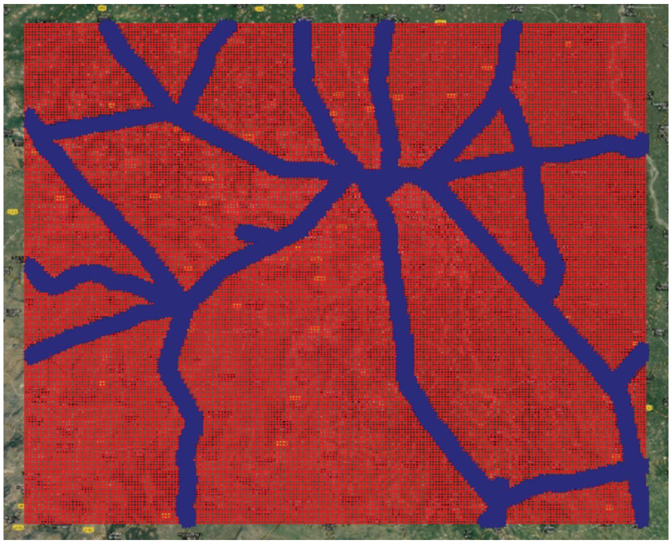

Figure 8. Feasible rail matrix (FM_{ra}).

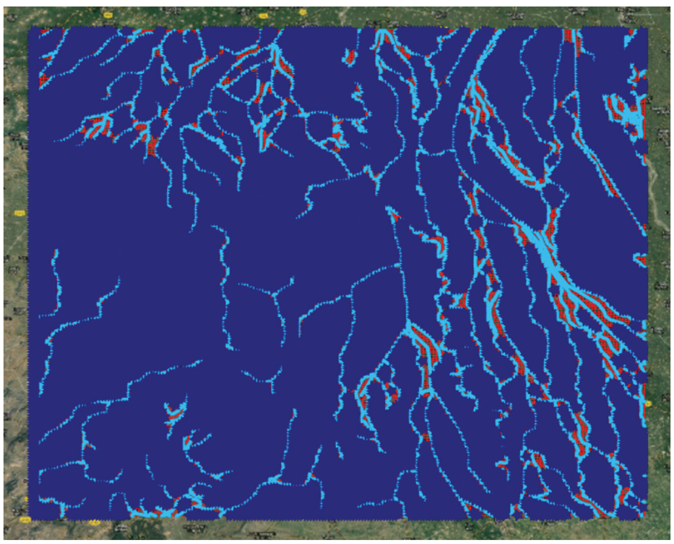

Figure 9. Feasible water body matrix (FM_{wb}).

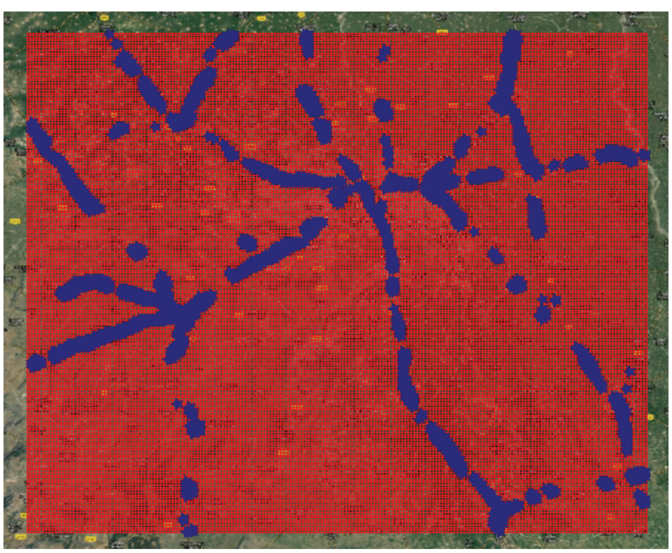

Figure 10. Feasible deployment matrix (FM_{dc}).

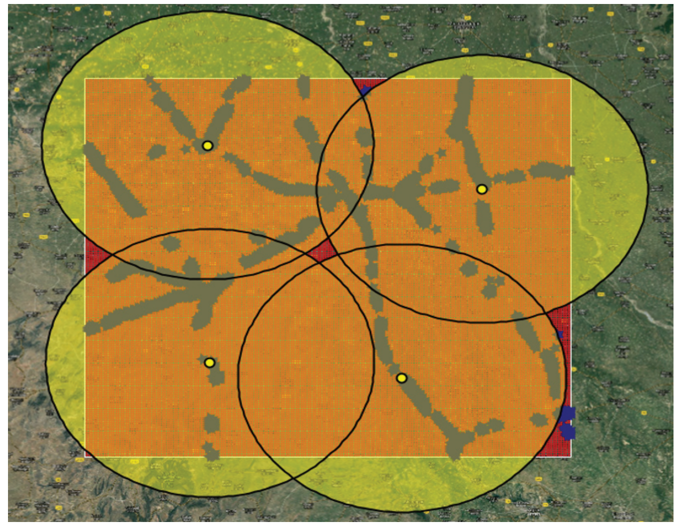

Figure 11. ADAPT generated deployment - Case (i).

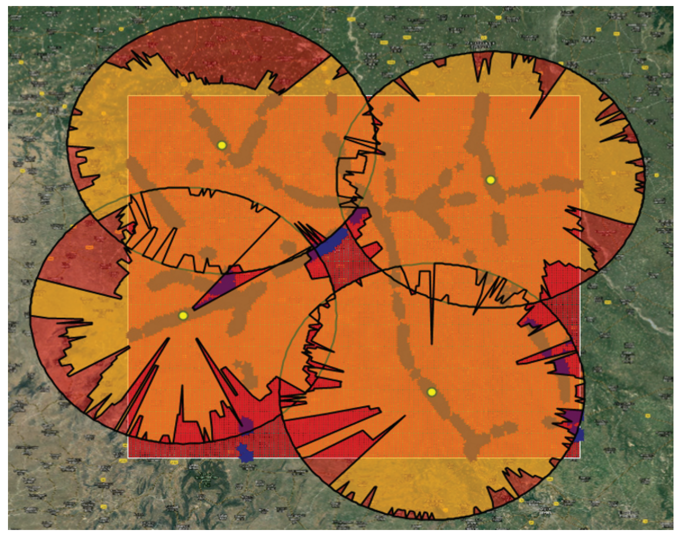

Figure 12. ADAPT generated deployment - Case (ii).

9. CONCLUSIONS

In this paper, a novel heuristic methodology that uses genetic algorithms to obtain (near) optimal deployment solution for a given set of radar systems in a theatre-level area of operation, considering real world deployment site constraints, terrain features, radar performance and effective coverage is proposed. AD Assets Planning Tool (ADAPT) is developed based on the proposed methodology as a decision support tool to aid the military planners. This tool is an important contribution to the field of military systems analysis that helps in answering the two important questions:

(i) given a set of n heterogeneous sensors, the planner needs to identify the locations that maximise the detection coverage;

(ii) given an AoP and the assurance levels of detection, the planner needs to know the number and optimal mix of sensors required.

The proposed methodology and decision support tool helps the planners in *scenario-based what-if* analysis in joint theatre based operations and service agnostic integrated air defence commands.

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In the current study, he is involved in designing and implementing the customised GA technique for the radar deployment problem, and design & development of ADAPT.

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In the current study, he is involved in the formulation and conceptualisation of the problem and suggesting the application of heuristic techniques to solve the radar deployment problem.