Optimal Placement of Weather Radars Network as a Multi-objectives Problem

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Abstract This work proposes an approach to the optimal placement of a weather radar network based on solutions to a multi-objective optimization problem. Given a finite number of weather radars, a network is produced by taking into account the maximization of network coverage area and the minimization of network general cost. Several constraints on the solutions are considered such as terrain blockage, radar beam elevation and distance from power grid and roads. By transforming the search space into a gridded system, a reduction in the number of possible combinations of radar networks is achieved making the problem manageable in size. The multiobjective optimization problem is solved by four different evolutionary algorithms and the obtained results are analysed using different performance metrics. The proposed approach can serve as an analysis tool for a decision support system by providing meteorologists a set of Pareto-optimal solutions to assist in the selection of future prime sites for the installation of weather radars.

1 Introduction

Weather Radar Networks (WRN) have been initially used by meteorologists in studying severe weather phenomenons and the issuing of important and essential weather bulletins and information to all major agencies such as civil and military aviation, oil and gas companies, and civil defence. WRN have been commonly used in both the prevision and research of weather systems. The Next Generation Weather Radar (NEXRAD) system [9] for example has been efficiently used in the prediction, study and research of severe weather systems such as supercells, mesocyclones, tornado vortices, and various types of precipitation.

A difficult task in constructing these networks is determining adequate sitting sites of radars in order to meet certain conditions. A clear propagation of the radar beam for an altitude below one kilometre without being obstructed by terrain features is

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of extreme importance as the core of heavier precipitation lies within a hight above ground of 1000 m as pointed out by [10].

A mathematical model of the problem was achieved by [5] by establishing a well defined optimization problem. A recent work in determining the placement of WRs is investigated by [4]. Through the utilization of a genetic algorithm (GA) a maximization of the coverage area within a set of physical boundary condition is achieved.

2 Multiobjective Evolutionary Algorithms

Multiobjective Evolutionary Algorithms (MOEAs) are methods which approximate the Pareto Front (PF) by mimicking processes found in biological evolution. Hence, their aim is to find solutions that converge as close as possible to the true optimal solutions obtained so far during optimization. In the following paragraph, we mention some details about the MOEAs selected for the resolution of our below-mentioned problem. MOPSO algorithm [1] starts by generating a swarm with N random particles along with a set of leaders representing the nondominated particles. Position and velocity of each particle in the swarm is initialized and the fitness of each particle is evaluated. NSGA-II [2] computes a crowding distance for each individual by measuring the distance to its neighbouring individuals along each objective function dimension. The obtained crowding distance is then used to modify the fitness of each individual. The algorithm SPEA2 [12] uses an external archive A containing the nondominated solutions found so far. A strength value is assigned to both individuals in the archive and in the population. The MOGWO is an algorithm proposed by [6] in which the social and hunting technique of grey wolves are mimicked.

2.1 Performance Metrics

As a Pareto noncompliant metric, the Nondominated Vector Generation (ONVG) [8] measures the number of elements in a nondominated solutions set obtained by MOEA generation. Hence, a solution set with a large *ONVG* is preferred. The spacing (S) [7] is Pareto noncompliant metric which measures the minimum value of the sum of distances between consecutive solutions in a nondominated set. Zitzler and Thiele [11] proposed the performance metric *dominated hypervolume* (HV) as the union of hypercubes constructed using a reference point R, which can be taken as the vector of worst objective function values and a solution i of PF_{known} as the diagonal corners of the hypercube.

3 Problem Formulation

The latitudinal and longitudinal co-ordinates of the radars $(\phi_1, \lambda_1), (\phi_2, \lambda_2), \ldots$ are considered as design variables which are to be optimized. The following two objectives are considered.

Terrain Coverage In our work, a modified explicit enumeration method is used similar to the one used in [4]. The selected geographical region is discretized into a grid with a resolution of approximatively 0.09° (1 km) M latitudinal and N longitudinal spacing stored in a matrix $\mathbf{A}_{M \times N}$. We incorporate a new factor to our model using global digital elevation data at a resolution of 30 arc seconds (≈1 km) provided by the United States Geological Survey. The radar propagated beam is checked for terrain blockage at each grid point that either represent a potential radar site or is included inside the theoretical coverage layer of a radar [3] through the 4/3 law:

$$h = \sqrt{r^2 + R_e^2 + 2rR_e \sin\theta_e} - R_e \tag{1}$$

where h is the height of beam in km, r is the range of beam in km, θ_e is the elevation angle, and R_e is the effective earth's radius in km (4/3 the earth's radius). Using a binary encoding, all grid points are set initially to zero. The radar site along with the points which hight are below the radar beam and their slant range from the radar site is less than the maximum beam range are all set to one. The coverage area of a radar is the sum of all values of the grid points,

$$C_r = \sum_{i=1}^{M} \sum_{j=1}^{N} a_{i,j} \tag{2}$$

The minimization problem is then formulated with respect to (2) as

$$f_1 = 1 - \frac{\sum\limits_{r=1}^{R} C_r}{T} \tag{3}$$

where R is the number of radars in the network and $T = \sum\limits_{i=1}^{M} \sum\limits_{j=1}^{N} 1$, is the total area of the studied region.

Network cost The economic and maintenance cost of installing a WR in R different sites is given by:

$$f_2 = \sum_{i=1}^{R} C_i x_i \tag{4}$$

where $C_i = q_1 EC_i + q_2 MC_i$ and $q_{1,2} \in [0, 1],\ q_1 + q_2 = 1$ are weighting parameters. The parameter EC_i is the minimum economic cost of installing a WR in site i which depends on the infrastructure and power availability. MC_i is the minimum maintenance cost parameter related to the distance of a site i to the nearest road accessible to truck traffic. Both EC_i and MC_i are obtained as the minimum *haversine* distance between the radar site and the nearest power line for the economic cost and road for the maintenance cost.

$$\Xi_i^k = \min_{\chi_j^k \in \Omega^k} \{2R_e \arcsin\left(\sqrt{\sin^2(\Delta\phi) + \cos(\phi_i)\cos(\phi_j)\ \sin^2(\Delta\lambda)}\right)\},\ k = a, b \tag{5}$$

where $\Delta\phi = \frac{\phi_i - \phi_j}{2}$, $\Delta\lambda = \frac{\lambda_i - \lambda_j}{2}$, (ϕ_i, λ_i) are the latitude and longitude coordinates of the radar site, and (ϕ_j, λ_j) are the latitude and longitude coordinates of a location $\chi_j^k \in \Omega^k$. The formula in (5) was used for both the economical cost, with $k = a$ and Ω^a being the power grid and for the maintenance cost with $k = b$ and Ω^b representing the road network.

4 Numerical Results and Discussion

The selected geographical region is the north of Algeria bounded by parallels 34° N and 36° N and meridians 3° E and 6° E with a total surface area of $6.076 \times 10^4 \text{km}^2$. The area is a mix of flat and complex surfaces supporting a diverse testing of the presented strategy. The analysis was conducted with a 1.1° radar beam elevation angle and the tower height of the radar is set to 15 m in order to reduce the effect of ground clutter. A theoretical coverage range of the radars is set to 45 km. For all the results presented in this section, the number of radars was limited to 5. Figure 1

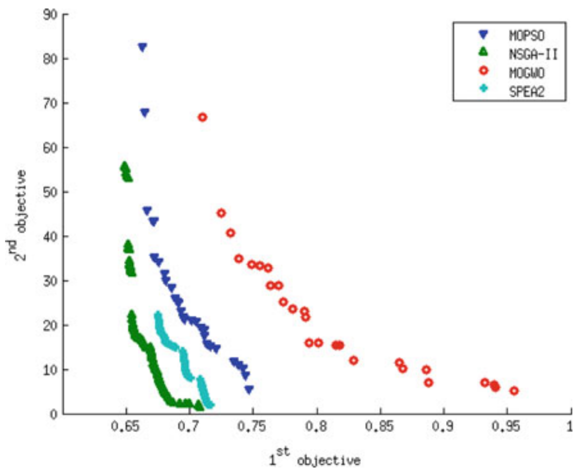
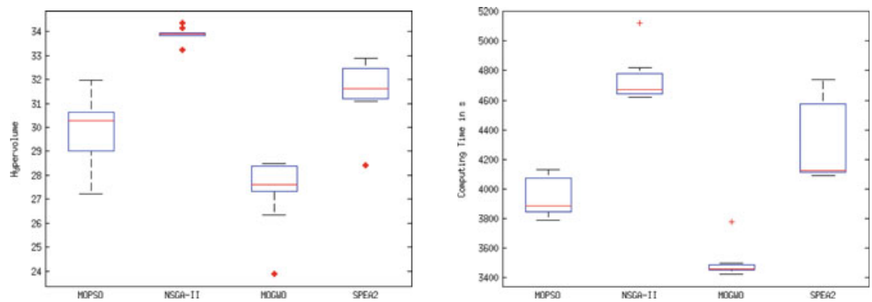
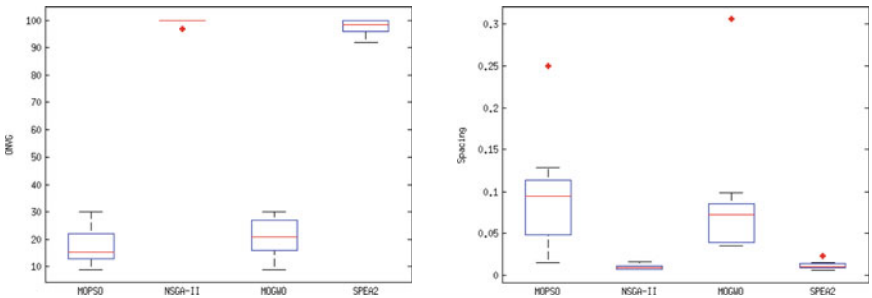


Fig. 1 Pareto front of *MOPSO*, *NSGA* − *II*, *MOGWO*, and *SPEA*2 obtained after 500 iterations for a population of 100 individuals



(a) Comparison of Hypervolume metric results

(b) Comparison of Execution time



(c) Comparison of ONVG metric results

(d) Comparison of Spacing metric results

Fig. 2 Comparison of the results obtained in 10 different runs by the four algorithms with a population of 100 individuals and after 500 generations

was produced by running each MOEA algorithm ten times with a population of 100 individuals and a maximum of 500 generations. From the figure we can see that the solution quality with respect to Pareto optimality obtained by MOGWO was quite low. MOPSO, NSGA-II, and SPEA2 produced a PF with similar patterns but different values. For this test, the NSGA-II algorithm had a better convergence. Starting with a comparison of the hypervolume metric, it becomes clear that the NSGA-II PF score comes first, followed by SPEA2, MOPSO, and finally MOGWO as shown in Fig. 2a. A similar order is also obtained with respect to ONVG and spacing metrics as indicated in Fig. 2c, d. As for computational time, the boxplot in Fig. 2b clearly indicates that MOGWO outperformed all algorithms while NSGA-II scored last.

5 Conclusion

The multioptimization method developed in this study can provide an efficient strategy for the radars optimal placement problem, resulting in network configurations at a relatively short time and with sufficient accuracy. For our study region, the proposed strategy gave results that were relatively insensitive to the number of individuals in the population of MOEA involved in the selection of a single best network. The radar coverage and cost objective functions selected for this study appear to be suitable for guiding network selection in support for a better weather observation. This tool could reduce valuable time and cost through the reduction of suitable sites that are evaluated on field by experts.

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