

# Optimal Layout of Wireless Sensors Networks using Guided Hyperplane Evolutionary Algorithm

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**Abstract** — Wireless Sensors Networks are widely used to monitor the areas. In many WSN applications it is important to achieve a good coverage of the observed area while the energetic efficiency and the lifetime of the network are high. The task of placing the sensor nodes while addressing these objectives is known as WSN layout problem. As the optimal sensors network layout can be reformulated as a multiobjective optimization problem, the paper presents a possible use of GHEA technique for solving the considered problem.

**Keywords:** wireless sensors, multiobjective, optimization

## I. INTRODUCTION

WIRELESS Sensor Network is a network consisting of a high number of sensors deployed over a specific area, wirelessly communicating data to a central system. There are many applications based on wireless sensor networks for environmental monitoring: habitat monitoring, object tracking, fire detection, traffic monitoring, etc.

In many WSN applications the critical issue is the coverage of the monitoring area. Other applications demand an increased network lifetime. Generally, both criteria are fundamental and should be taken into consideration when the WSN is deployed. As the complexity of the problem is high, a metaheuristic option would be appropriate. Evolutionary algorithms are an interesting alternative for solving Optimal WSN layout problem. In [1] the problem is formulated as a bi-objective problem which involves the maximization of the network's lifetime, and the minimization of the number of sensor nodes, in order to reduce the network cost. The tool for solving the problem is a very popular algorithm Non-Dominated Sorting Genetic Algorithm (NSGAI). Another work presented in [2] considered the coverage and lifetime of the network as the objectives of the optimization problem and the solutions are obtained by a popular evolutionary technique for multiobjective optimization: MOGA. Other interesting problems related to the wireless

sensor network's issues have been successfully approached by evolutionary techniques: for example, the optimization of the coverage in a WSN [3], cluster formation and management in WSN, data aggregation trees in wireless sensor networks [4], energy-efficient coverage with distributed particle swarm optimization [5].

Recently, our work focuses on solving the optimal layout of the sensors using an original evolutionary technique called Guiding Hyperplane Evolutionary Algorithm [6]. The approach proves itself suitable for the considered problem. Next, we extend our work in a more general case, where the sensing and communication radius of the sensors differs.

## II. OPTIMAL WSN LAYOUT PROBLEM

Optimal sensors network layout can be reformulated as a multiobjective optimization problem. The involved criteria are several to be considered: lifetime of the network, communication's efficiency, degree of the connectivity, coverage of the network, and so on. In this paper, we formulate the problem of optimal placement of sensors as a bi-criteria optimization problem, emphasizing the two major objectives which derive from the main functions of the sensors: communication and sensing.

Sensor networks represent dense wireless networks of small, low-cost sensors, which collect and disseminate environmental data. Each unit of the network is attached by a battery that provides a limited amount of energy. The purpose of a sensor is to sense or react smartly at a possible event in its neighborhood and to transmit the proper information to the High Energy Communication Node (HECN) of the network. Given the sensing radius, a sensor is able to gather the right information from its vicinity and further transmit it to the HECN. Data transmission to the special node is done directly or via hops, using nearby sensors. Therefore, each sensor also behaves as a communication relay. The communication between two sensors is possible if they are within a fixed distance. Given the communication radius, two sensors are allowed to communicate if the distance between them is less than communication radius.

The lifetime of the entire network is measured by the elapsed time until the first sensor spends the initial allocated energy (Time to First Failure). Beyond other tasks, each data transmission accomplished by a sensor

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decreases its energy, and consequently, the lifetime of entire network. Therefore, the lifetime of the network depends by the maximum number of communication tasks of its nodes. In optimal sensors placement problem, we focus on finding a configuration which does not comprise nodes engaged in too many transmission activities.

The coverage of the network represents the other major criteria in optimal placement of the sensors. The coverage of a specific network is given by the ratio between the area of the union of the disks centered at the sensors' positions, of sensing radius and the total area of the region in which the sensors are placed. Better coverage affects in a positive way the quality of the network. Therefore, this objective is maximized.

Another criterion in finding the optimal position of the sensors arises from the connectivity degree of the network. This objective of our problem can be simply reformulated as a penalization of the other two major criteria.

According to the two main functions of a sensor: sensing and communication, two major objectives arise: the first refers to the lifetime of the network and the second one measures the coverage of the net.

### III. GHEA TECHNIQUE

A new evolutionary technique for multicriterial optimization called Guided Hyperplane Evolutionary Algorithm (GHEA) has been recently proposed in [6]. GHEA introduces a new non Pareto fitness assignment procedure based on guiding hyperplanes providing an intuitive form of guidance towards the desired front for the population. The techniques proved to be efficient in many static and dynamic multicriteria optimization problems.

Consider a multicriteria optimization problem with  $n$  objectives. The Pareto front is a hyper-surface (compact or not, convex or concave, etc) of  $n$  order. The use of a hyper plane to guide the search in the objective space is suggested. This hyper plane is updated every generation according to the configuration of the current population. The following criteria are used to construct the hyper plane:

- It should not intersect the area covered by individuals in the current population;
- Each point belonging to the hyper plane is better in terms of performance function than any individual of the current population.

Such a hyperplane would guide the population towards promising areas of the search space. The population dynamics towards the guiding hyper plane can be viewed as convergence towards the Pareto front. The guiding hyper-plane which is built for each generation is called the target of the current generation.

Individuals in the current population are not evaluated through a performance function in relation to the problem's objectives but through how close they are to the guiding hyper plane. Each generation the evolution of the current population towards the corresponding target hyper plane is pursued by focusing on the production of offspring closer to the target and not necessarily on the convergence to the Pareto front. However, the manner of building the

target hyper plane for the current population leads to convergence to the Pareto front without using a performance function based explicitly on the Pareto dominance concept.

Regarding the diversity preservation, the target hyper plane can also be used to estimate a diversity degree of the current population. Thus, projecting the individuals of the present population on the target hyper plane could provide an image of the population's distribution. In order to maintain a good distribution during the search process GHEA is supplemented with a mechanism that favors increased search in the areas poor in individuals of the search space.

Two measures are associated to each individual of the current population: the first one refers to the proximity degree to the target and the second refers to the agglomeration degree of its projection in the guiding hyperplane. Both measures are used to set the balance between exploring and exploiting, which is so necessary for a good dynamics of the population.

The mechanism of replacing parents with offspring must be designed in such a way to accelerate the convergence of the population, namely to favor the survival of the best solutions found. A form of elitism is used in order to accomplish this aim.

The basis of Guiding Hyperplane techniques resides in creating an ideal hyperplane and to evaluate the individuals regarding the target.

Consider the following minimization problem with  $n$  objectives:

$$\begin{cases} \text{minimize } F(c) = (f_1(c), \dots, f_n(c)) \\ c \in D \end{cases} \quad (1)$$

where  $F : D \rightarrow R^n$ .

The current population may be considered as a cluster of  $n$ -dimensional points in the objective space. The current cluster population in the objective  $n$ -dimensional space can be described in a similar manner with the principal components analysis used in classification theory.

The current population can be viewed as a cluster of  $n$ -dimensional points in the objective space. The use of a hyperplane to guide the search in the objective space is suggested. The guiding hyperplane represents an "ideal" of the current population and its role is to lead the individuals to the multiple solutions of the considered problem.

Two characteristics of the current population are used to construct the hyperplane: an ideal vector in the objective space that is better with regard to every component than all individuals in the current population; the most important direction along which the population is spread out in the objective space.

Each individual of the current population is mostly evaluated by using the distance measure to the target hyperplane.

The objective function values corresponding to the current population may be considered as a cluster of  $n$ -dimensional points. This cluster in objective space ( $n$ -dimensional) may be described by means of principal components analysis.

Let  $A = (\alpha^1, \alpha^2, \dots, \alpha^d)$  be the current population forming a cluster in  $\mathbb{R}^n$ . Each individual of the set  $A$  corresponds to an  $n$ -dimensional vector.

Let  $m$  be the mean vector (the centroid) of set  $A$ . The most important directions along which cluster  $A$  is spread out are given by the eigenvectors of the scatter matrix  $S$ , given by

$$S = \sum_{i=1}^d (\alpha^i - m)(\alpha^i - m)^T \quad (2)$$

Eigenvectors of the matrix  $S$  are called the principal directions of the cluster  $A$ . The eigenvector  $u$  corresponding to the largest eigenvalue gives the most important direction along which the cluster is spread out.

Denote by the vector of components

$$x_i^0 = \min\{\alpha_i^k \mid k \in \{1, 2, \dots, d\}\}, i \in \{1, 2, \dots, n\} \quad (3)$$

Each component of vector is given by the minimum value of the components of the vectors. Thus  $x^0$  represents an ‘‘ideal’’ vector formed with the best components from the vectors of  $A$ .

The aim is to guide the search of population  $A$  toward what could be called the most promising region provided by it. Thus the hyperplane  $H$  orthonormal to direction and passing through the sustaining point is constructed:

$$H : u^T (x - x^0) = 0 \quad (4)$$

Hyperplane  $H$  characterizes the set  $A$  and it will be considered the target of the current population in the objective space. Hyperplane  $H$  will be further used to evaluate individuals. The hyperplane is updated at each  $k$  generations according to the new configuration of the current population. Such a hyperplane would guide the population towards promising areas of the search space and the population ultimately attains the Pareto frontier.

The GHEA algorithm uses selection operator and genetic operators. At each generation, the individuals of the population are evaluated by using a fitness function accordingly to the closeness to the hyperplane. By each generation, the evolution of the current population towards the corresponding target hyper plane is pursued by focusing on the production of offspring closer to the hyperplane and not necessarily on the convergence to the Pareto front. However, the manner of building the guided hyperplane for the current population leads to convergence to the Pareto front without using a performance function based explicitly on the Pareto dominance concept.

#### IV. GHEA FOR OPTIMAL SENSOR NETWORK LAYOUT PROBLEM

In a previous article [7], GHEA technique was successfully applied on the optimal layout of the WSN problem. Then, the sensing and communication radius was set to be equal. Further, we reconsider the problem, taking into account different values for those two parameters of the sensors.

In optimal sensor network placement, a solution is given by any configuration of sensors’ locations on the given map. For simplification we consider that the region where the sensors are placed is a 2-dimensional area, and each

sensor’s location is given by the pair of coordinates  $(x_i, y_i)$ . Therefore, a possible network of  $n$  sensors located on the map is represented by the vector: of  $n$  pairs of coordinates.

In our approach, we consider a homogenous network; each sensor has the same initial energy. One sensor will consume exactly one unit of energy per each transmission it makes. Therefore, if one sensor behaves as a communication relay, and the number of transmission tasks is higher, its lifetime decreases accordingly and further the lifetime of the network decreases. At one time, a particular network should send data from all sensors to the HECN in an optimal manner. Optimality in this context refers to the problem of finding the minimum paths from the HECN to each sensor. For completing this job, Dijkstra’s algorithm is applied. The network is seen as an oriented graph and it is represented by the cost adjacency matrix, where the cost is given by the Euclidian distance of each pair of nodes, if they communicate, or  $+\infty$  if they do not communicate. After the minimum paths are found, the number of transmission tasks per sensor is computed. The number of transmission tasks per sensor is measured by the total number of inputs and outputs a sensor has to assure. The standard deviance of these values offers an appropriate measure of the tasks distribution among the network. A smaller value of this metric is preferred, as it denotes the fact that transmissions tasks are uniformly distributed among the network and, therefore, very few sensors are extra loaded and suppressed by too many communications. Also, the connectivity degree of the network is an important issue for the formulation of the criteria. The connectivity can be measured by the number of sensors that are able to communicate to at least another sensor. If the connectivity is less than the total number of sensors, the overall quality of the network decreases.

The second criterion refers to the degree of coverage of the network. As finding the exact value of the area of union of the disks of sensing radius, centered in sensors’ locations  $(x, y)$  needs high computational costs, an approximation approach of the coverage is chosen. In our approach, we consider a grid which covers the entire map. Each center of the grid’s cell could be included or not into at least one disk corresponding to a sensor. If the center of a cell is covered by at least one sensor, we consider that the area corresponding to that cell is covered by the net. The ratio between the number of covered cells and the total number of cells give us a useful measure of the network’s coverage ratio. As the GHEA algorithms performs a minimization of the considered objectives of the problem, and the aim is to maximize the coverage and the lifetime of the network, the following functions are considered as objectives for GHEA implementation.

*First objective:* Considering  $n$  – the number of sensors,  $\chi$  – the number of connected sensors (connectivity degree) and  $\sigma$  – standard deviation of the numbers of transmission tasks  $t_i$  of the  $i^{\text{th}}$  sensor: the first objective is formulated as follows:

$$F_1 = \sigma / \sqrt{n} + n - \chi \quad (5)$$

*Second objective:* Considering the grid with  $m$  rows and

$p$  columns and  $g$  - the number of covered cells of the grid, the second objective function is formulated as follows:

$$F_2 = (m \cdot p - g) / (m \cdot p) + n - \chi \quad (6)$$

## V. EXPERIMENTS

In our simulation experiments, we tried several scenarios which involve different number of sensors of communication radius  $R_C$  and sensing radius  $R_S$ . We considered that sensing and communication radiuses are not equal. In our experiment sensing radius is less than communication radius. Regarding the two parameters lifetime and coverage are computed. Therefore, coverage measure takes into account the sensing radius and lifetime is computed accordingly to the communication radius.

The area of 500x500 units has to be covered with the given number of sensors in an optimal manner. The High Energy Communication Node (HECN) represents the gateway for external access to the network and it is located in the center of the area. Several scenarios have been taken into consideration. The GHEA algorithm runs for variable number of sensors, with different sensing radius and communication radius. The size of the population is set to 50 individuals and the maximum number of generations is 100.

Figure 1 shows one of the compromise solutions found among the final Pareto frontier. The solution is the best one considering the only the coverage function. Pareto front is presented in figure 2. *The diversity among the solutions is considerable; therefore, the decision maker has a large range of choices.* The black dots represents the final solutions of the problem; X-axis correspond to the first objective (increased coverage) and the y-axis corresponds to the second criterion (high lifetime).

In the next experiment described in the figures 3 and 4, the number of sensors is 40, and also the radiuses  $R_C$  and  $R_S$  are established accordingly. Also, for an increased number of sensors, the algorithm succeeds to find a well distributed Pareto front in a small number of generations with a population of only 50 individuals.

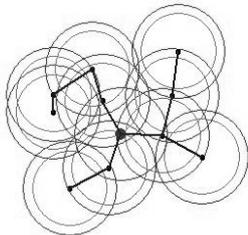


Fig. 1. Sensors placement regarding the coverage

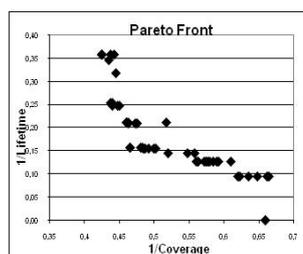


Fig. 2. Pareto front after 100 generation, 10 sensors with 90 units RC and 72 units RS

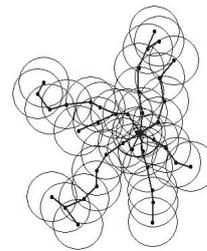


Fig. 3. Sensors placement regarding the coverage

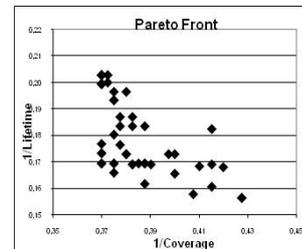


Fig. 4. Pareto front after 100 generation, 50 population size, 40 sensors with 45 units RC and 36 units RS

## VI. CONCLUSION

Using an ideal hyperplane to guide the population of solutions toward the Pareto front of the considered optimization problem, GHEA offers in many situations better results than the state-of-the-art evolutionary algorithms [4]. The WSN layout problem is formulated as a multiobjective optimization problem, emphasizing two criteria: attaining the maximum area coverage and a maximum lifetime of the network. For the simplified model of 2-dimensional map, having a pre-estimated fixed number of homogenous sensors, GHEA provides the Pareto optimal solutions of the bi-objective problem. The results show that GHEA technique is suitable for optimal WSN layout problem; in all experiments, GHEA offers a good approximation of the Pareto front.

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