Optimized Sink node Deployment in WSN Using Genetic Algorithms through Coverage and Cost Constraints

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1 Abstract

Wireless Sensor Networks (WSN) is the main infrastructure of a smart building. An optimal installation of a WSN is needed to ensure the best operating of the smart building. WSN suffer from a multitude of constraints, the major ones are: (1) optimal coverage (to ensure best QoS), (2) deployment cost (installation cost), and (3) network lifetime (network energy consumption). In order to ensure a WSN deployment that meets these three goals, we must formulate our problem as a multi-objective one, which can be solved by different methods. Find the optimal sensors positions in a deployment space can be considered as NP-hard problem [1]. If we consider a *(M)* deployment space and a set of (*N)* sensors to be deployed, the possible combination is equal to $\frac{M!}{(M-N)!}$ [2]. Until this day, there are no specific solutions to deal with such problems. To get approximation of an optimal solution, the use of meta-heuristic methods is needed. In this paper, we attempt to propose a proper modeling of the three principal WSN deployment objectives. The deployment space is considered as a building. To solve the problem and to get optimal sensors positions we use Multi-Objective Genetic Algorithms (MOGA).

2 Introduction

Generally, Wireless Sensor Networks (WSNs) consist of a set of N sensor nodes scattered in a region called Region of Interest (RoI). This technology is generally used in all applications with specific monitoring needs (environmental, telemedicine, smart buildings …). Sensor nodes collect data about a specific physical phenomenon (temperature, humidity …), and then relays this collected data to a specific node called sink. This later plays a role of a gateway between sensors and server. Therefore, we can say that a sink node is one of the critical components of WSN, because it collects all sensed data and transmit them to the server. Vu the huge number of data that transit by the sink, it drains its energy faster than other nodes. For this, the sink node must be placed in such manner that it guarantees an optimal coverage rate taking into account all energy consumption constraints.
In our works, we are interesting by the WSN used in smart buildings applications. Despite the diverse challenges in WSNs, research works have only focused on post-deployment problems such as: routing optimization, MAC efficiency, sensors localization, etc. However, these problems depend mainly on the deployment process [1]. An optimal placement of sink nodes considering all the needed constraints such as: (1) network coverage, (2) network lifetime (network energy consumption), and (3) deployment cost (sensors installation cost), can guarantee better QoS, and ensure more less maintenance cost. This deployment process consists on defining required sinks number and their optimal positions to meet the pre-defined constraints.
Unfortunately, such problems were not totally investigated by researchers. In addition, these works only focus on free-space deployment and didn't include in their model the building architecture (walls, doors, etc.) which can have considerable effects on network coverage and lifetime. Also, didn't consider sink nodes only sensors.

Considering works done, we propose in our paper a model for optimal sink nodes deployment in WSN. We propose three objective functions: (1) Installation Cost, (2) Over-coverage, (3) Network Coverage. Given that the deployment process is considered as an NP-hard problem we use in our model, Multi-Objective Genetic Algorithms (MOGA) to get optimal sinks positions.

3 Related works

We address in this paper the Sink node positioning problem in WSNs. Sink nodes must be placed in strategic positions due to their critical role in the network. Regarding the cost of sink node installation, we propose a new solution for sink node positioning for indoor applications with taking into account deployment cost constraint. In general, the complexity of such problems is assumed to be NP-hard [3] [4] [5]. For this, we use in our algorithm some meta-heuristic methods to solve it.

In [6], M. Esseghir & al. presented a heuristic to solve the sensor node placement problem. Authors take in consideration two main objectives which are: network coverage and lifetime. The proposed algorithm starts by dividing the deployment space into multiple identical hexagons (cells). The coverage surface of a sensor node is assumed to be similar to the hexagon area. The proposed heuristic compute the sensor needed number to cover all the area with energy constraint consideration. Konstantidinis & al. [7] proposed a Multi-Objective formulation of WSN deployment problem that can be solved by a meta-heuristic method. The authors proposed a new Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) and compare it with an existing method MOGA (Multi-Objective Genetic Algorithm). The result of the proposed algorithm MOEA/D outpaced those of MOGA method. Later, the same authors have applied the same method for DPAP (Deployment and Power Assignment Problem) in WSNs. The proposed algorithm decomposes the DPAP in a multitude of scalar sub-problems which can be solved by MOEA/D. Results presented in the paper shows that the performance of MOEA/D outpaces the NSGA II method. M. Le Berre & al. [8] [9], proposed a new modelization of the sensors deployment problem under three constraints (Coverage, Network Lifetime, deployment Cost). The modelization consists on decomposing the deployment area into a grid which contains a number $M \times N$ cell. Only one sensor can be placed in each cell. After the problem formulation with analytical model, the authors use Multi-Objective evolutionary algorithms: NSGA II, SPEA II and MOGA. Also authors consider the problem of sensor deployment as a K-coverage problem and use specific methods to solve it.

K. E. Lee [10], proposed in there proposal a meta-heuristic method for WSN coverage optimization. Authors used the PSO (Particle Swarm Optimization) to ensure maximal network coverage. Nodes are firstly scattered with a random manner. Next, every node computes its number of adjacent nodes. If this number of adjacent nodes is smaller than a predefined threshold; the node stays in its position. Otherwise, the node moves with a predefined strategy to a better place. Finally, in this algorithm, nodes who were randomly deployed in an area will occupy the maximum of its surface. Results present in this paper shows that with this algorithm we can have 80.45% covered area which still very lack. An improved PSO algorithm was proposed by S. M. A Salehizadeh et al. [11] which was called IPO (Individual Particle Optimization). Unlike PSO, which use a set of swarm particle called initial population, this algorithm consider one particle. This minimization of the individual present in the initial population aims to minimize the computational time. The algorithm proceeds sensor by sensor. It models each sensor by the particle and optimize it position using the generalities of the PSO method. Then, when a sensor is placed the algorithm reset the particle and affects it to another sensor.

X. Xu & al. [12], proposed a new algorithm to solve the node placement problem in sensor network. The algorithm treats only the sink node placement. The Sink node plays the role of a relay between sensors and server. In their paper, authors show that the Sink node drains its energy faster than sensors due to the huge number of messages that they relay. Also, they demonstrate that if a Sink node is turned off all data generated by sensors connected to it will be lost (network failure). For this a heuristic which deal with sink placement in WSN was presented and evaluated in this paper.

From these related works we can say that the most popular solutions to deal with WSNs deployment problem are the Evolutionary Algorithms (EA) (MOGA, NSGA II, SPEA II, …), or other meta-heuristics (ACO, PSO, …). Also, we find that there is a lack of research works that deal with indoor applications (buildings). We must consider in such applications the radio propagation constraints i.e.: signal attenuation, walls, and doors. These constraints can have a great effect on energy consumption and network coverage [13] [14]. For this, we propose in this paper a proper modelization of an indoor WSN deployment problem with taking into account all the radio propagation constraints. We also use EA to solve this problem.

4 PROBLEM FORMULATION

Coverage rate of sink nodes

Let A (m^2) be the WSN deployment surface, supposing that all sink nodes have the same electrical and cost properties (electrical circuits, coverage range…) and due to the need of the application (smart building, indoor application); we adopt the Multi-Wall propagation Model (MWM). This model computes the attenuation of a node transmitted power according to (1) [13] [14].

$$P_R = P_T - PL(d_0) - 10n\log(d) - \sum L_w \tag{1}$$

Where P_R, P_T, are reception and transmission power respectively, PL denotes the path loss at a distance d, d_0 is a reference distance equal to 1 m, n is the path loss exponent, and L_w is attenuation of a wall w.
We add to (1) a random variable μ which describe signal attenuation effects like: shadowing and multipath effects (2), to get a realistic propagation model for in-building applications. The random variable is assumed to follows a log-normal distribution function as presented in [15] (Fig. 1).

$$P_R = P_T - PL(d_0) - 10n\log(d) - \sum L_w - \mu d \,\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \tag{2}$$

If we consider that the area can be digitized into $M \times N$ cells. From (2), we assume that a cell can be covered, if the reception power in this cell P_R is acceptable (greater than a predefined threshold). From (1) and (2), we can say that the reception power is a log-distance based function. Therefore, a cell in the area A can be covered by a sensor s_i, if it is in its sensing range. A cell is considered as in the sensing range of a sensor, if the distance between this cell and the sensor is less than its sensing range R_s (3).

$$couv(s_i, p) = \begin{cases} 1 & dist(s_i, p) \le R_s \\ 0 & dist(s_i, p) \;\; R_s \end{cases} \tag{3}$$

$$dist(s_i, p) = \sqrt{(s_x - p_x)^2 + (s_y - p_y)^2} \tag{4}$$

Where:

- *Couv* (s_i, p): is the coverage function of a cell p with a sensor si.
- *Dist* (s_i, p): is the distance between the sensor si and the position p.
- $S_{x,y}$, $P_{x,y}$: are the coordinates of the sink and the cell respectively.

The *PNC* value (Percentage of Network Coverage) of a set of sink nodes $S = \{s_1, s_2 \ldots s_N\}$, represents the number of cells covered by S over the total number of cells (area of A):

$$PNC(S) = \frac{\sum_{n=1}^{n=N} couv(s_n, p)}{N \times M} \times 100 \tag{5}$$

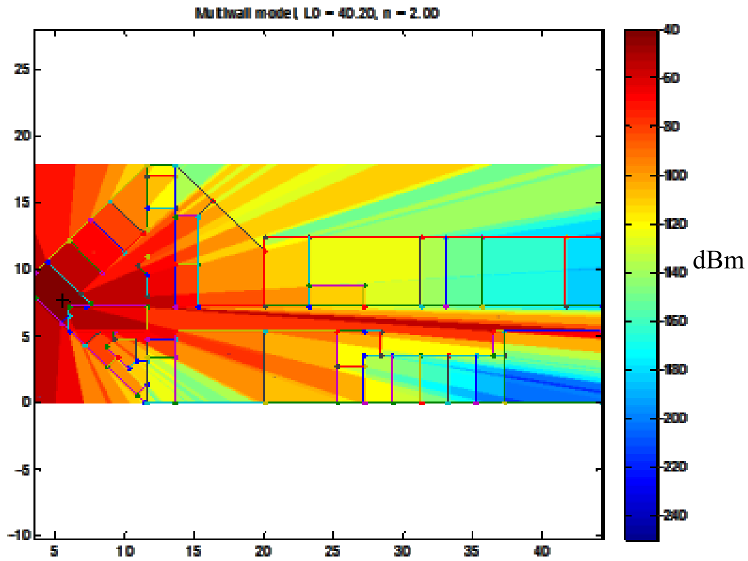

Fig.1 Radio wave propagation in a building

Deployment Cost

Let $S = \{s_1 \dots s_n\}$ be the set of deployed nodes, . The deployment cost is computed by the following equation:

$$Cost(S) = \sum_{i=1}^{N} s_i \times c_i \tag{6}$$

Where c_i is the price of sink i.

5 Implementation of evolutionary algorithm for sink node placement optimization

The sink node placement algorithm follows the organigram represented in Fig. 2.

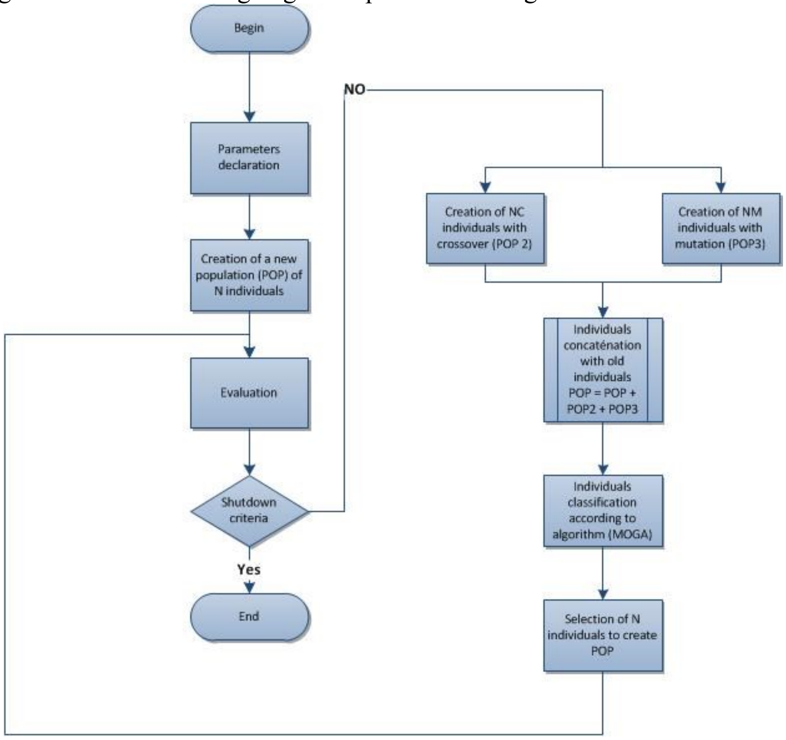

Fig. 2 Deployment Algorithms steps

Chromosome Codification

To determine required sinks number to be deployed, we propose to model the deployment space as a grid. Each cell of this grid represents a candidate placement of a sink s_i. This grid generates a matrix $M\,(i, j)$, each variable of this matrix can be set to 0 or 1 (9).

$$M(i,j) = \begin{cases} 1 & \text{if there is sink placed in cell}(i,j) \\ 0 & \text{else} \end{cases} \tag{7}$$

With this definition the chromosome used in genetic algorithms will be modeled as a bit string with a size equal to $L \times W$ (L, W, represents the length "M cells" and width "N cells" of the deployment area respectively) (Fig. 3).

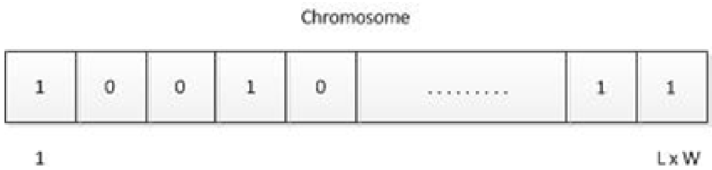

Fig. 3 Chromosome representation

Fitness Functions

Each individual is evaluated according to three fitness functions which are:

- $f_1(S) = 1/PNC(S)$
- $f_2(S) = Cost(S)$
- $f_2(S) = Cost(S)$

Where *PNC (S)* is the network coverage percentage, *Cost (S)* is the deployment cost, and *Ov-Cov (S)* is the over-coverage of the area by the set of deployed sinks *S*. *Ov-Cov(S)* can be obtained by computing the number of sink nodes that cover the same cell. The evolutionary algorithms used will minimize these three functions (*f1, f2, f3*).

Used MOGA Operators

The selection of individuals is done according to the binary tournament process. The principle of this selection method consist on choosing a random number of individuals in the population and then select the best individual in this group according to its fitness function. This type of selection is used before any operation (crossover, mutation) to choose individuals which participate to it.

The modelization of the sink node disposition in a chromosome is a trivial task. Let *S* be the set of sink nodes deployed in the area *A*, the corresponding chromosome is a bit string where every component of this string can be set to 0 or 1 (9).The chromosome is the concatenation of the different matrix (M) rows (Fig. 4). To minimize the computing time we use in our model a single point crossover (Fig. 5).

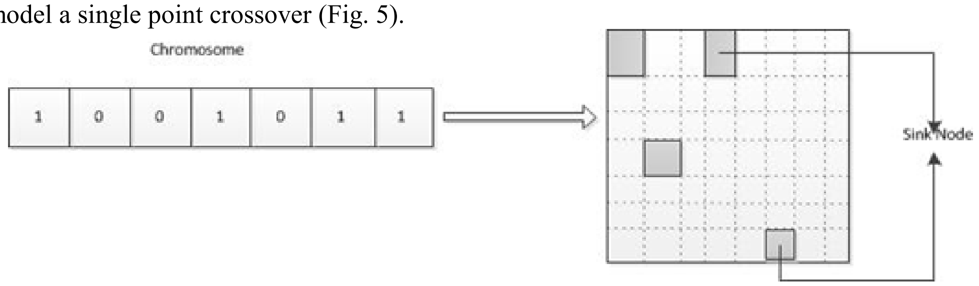

Fig. 4 Chromosome translation to deployment area

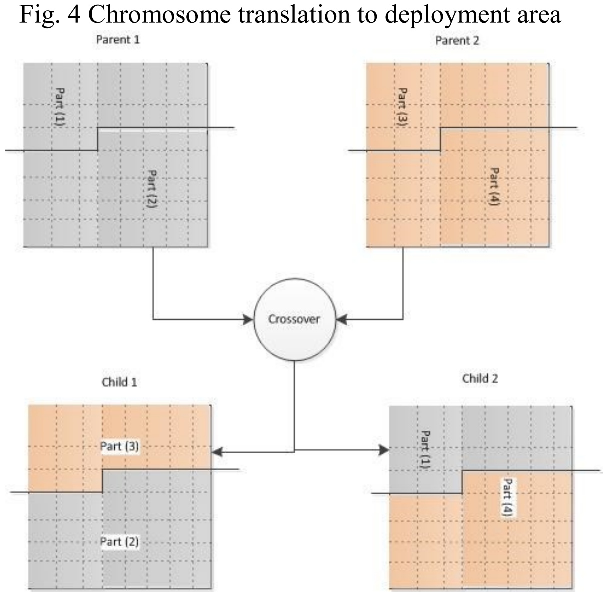

Fig. 5 Crossover process

The mutation process is carried in a random manner. For each individual chosen by selection the algorithm generates a random number (*id*) between 1 and N×M (N×M represents the chromosome size). After that the idth component of the individual is mutated (set to 1 if it was 0 and vice-versa) (Fig. 6).

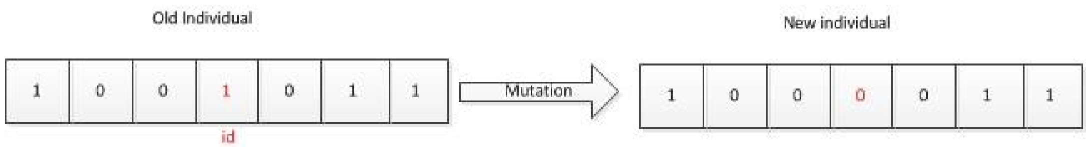

Fig. 6 Mutation process

6 Results and discussion

The objective of this work is to have an optimal implementation of a WSN considering coverage, and network installation cost. We consider in the simulation a 10 meter square area. Each cell is set to $1{\times}1m^2$. The area is composed of two separate rooms in which we want to deploy a number of sink nodes [13] [14]. The disposition of these sink nodes must guarantee a 100% coverage and there number must be minimal.

Tab.I summarizes the parameters used in the implementation of MOGA. These parameters were obtained empirically after several experiences.

Tab. I Used MOGA parameters

Parameter	Value
Size of population	300
Chromosome size (*N*×*M*)	100
Crossover probability	0.9
Mutation probability	0.1

The MOGA algorithm was implemented using Matlab© software. It ensures the convergence with deferent performances regarding the three proposed criteria. The following paragraphs present the obtained results using MOGA method.

The results of the Multi-Objective Genetic Algorithm (MOGA) are expressed by the pareto-front of the generation number 210 as presented by Fig.7 (a). One of the pareto-front solutions is presented in Fig. 7 (b). The solution presented in Fig. 7 (b) was chosen according to our preferences (100% coverage rate and minimum of sensors with minimal over-coverage (+ 38%)).

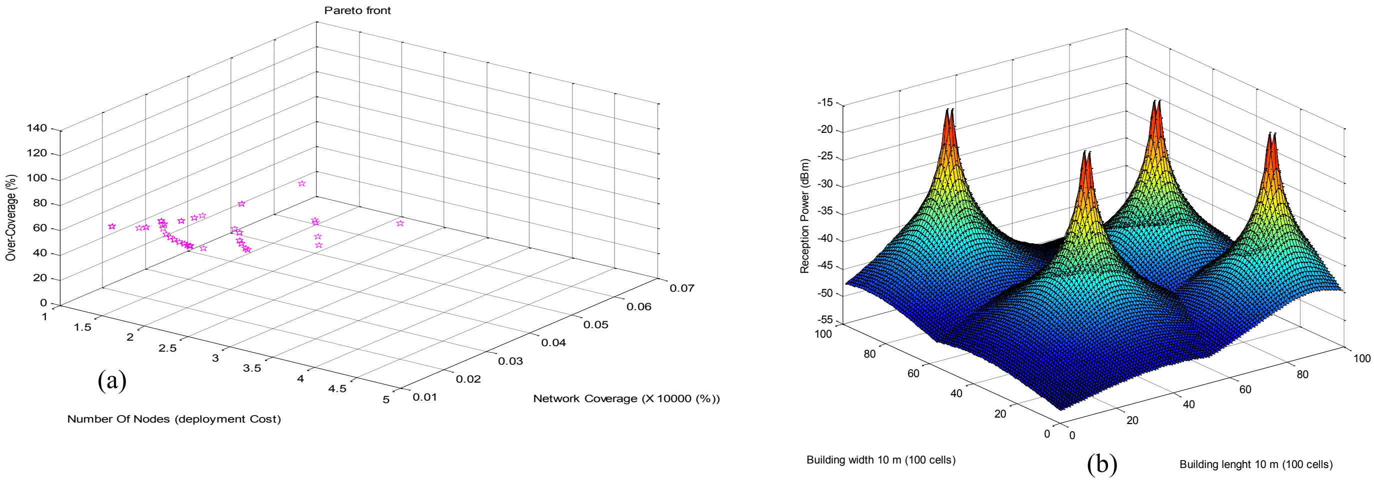

Fig. 7 (a) Pareto Front of MOGA (b) Sink nodes dispositions in area A

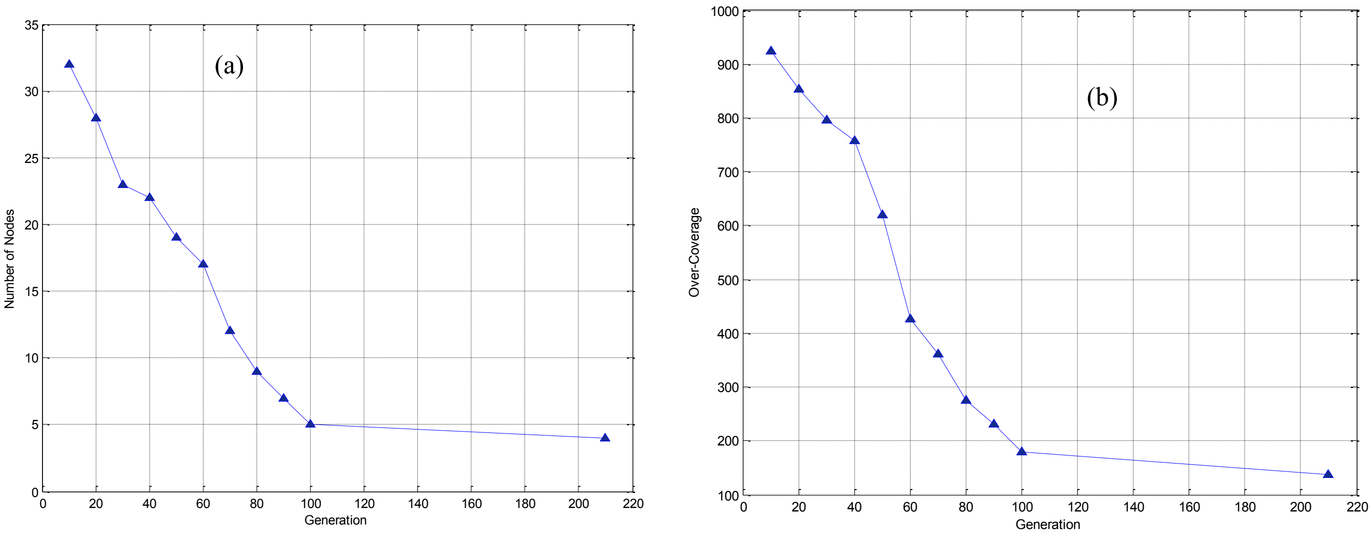

Fig. 8 (a) number of nodes vs. number of generations, (b) Over-Coverage rate vs. number of generations

We can see in Fig. 8(a) the evolution of nodes number over MOGA generations. The algorithm begin by generating a random number of sink nodes (example: 32 deployed nodes in 10^{th} generation), and then try to minimize it until it reaches the global optimum (example: 4 deployed nodes in 210^{th} generation). Also, the algorithm tries to find a compromise between the three objectives. We can say that at the 210^{th} generation the algorithm proposes a multitude of solutions represented by the Pareto front (c.f. Fig. 7(a)). The used method tries to minimize the objectives in parallel manner until it finds solutions that can satisfy these three goals. We can see in Fig. 8 (b) the evolution of the network over-coverage rate over MOGA generations, at the beginning (10^{th} generation) a cell of the area A is over-covered ten times (925% = 9.25 times). After several generations, this over-coverage constraint is minimized until we get an optimal solution (example: 210^{th} generations, 4 deployed sink nodes, 100% coverage and an over coverage about 0.38 (area covered at 138%)).

7 Conclusion

This paper has presented a new WSN optimized deployment model which, cost and coverage have been considered as the constraints. Furthermore a multi-Objective Genetic Algorithm (MOGA) has been applied to solve the sink node deployment problem.

The initial objective of the algorithm was to deploy the minimum number of sink nodes regarded to all the defined constraints.

Obtained results showed that the MOGA algorithm is able to generate an optimal network assuring maximal coverage of the deployment area with minimal cost.

Future work will be dedicated to consider another constraint that includes fault-tolerance (node failure probability) that NSGA II; can be used as an improved variant of MOGA algorithms to solve the complexity of the problem.

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