Multi Objective Nodes placement Approach in WSN based on Nature Inspired Optimisation Algorithms

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***Abstract*—The enormous demand of Wireless Sensor Networks (WSNs) in various applications has intensified the concern about sensor nodes placement. The choice of sensor deployment strategy is mentioned among the most critical issues for the designer of such networks. Some objective functions, such as coverage, energy consumption and network connectivity, are a key challenge that should be satisfied while achieving optimal placement topologies. In this work, deployment issue has been modeled as a constrained multi-objective optimization (MOO) problem. The aim of this work was to find the optimal sensor nodes positions in the area of interest in terms of coverage, energy consumption and network connectivity. A new multi-objective optimization approach based on Flower Pollination Algorithm (FPA) was introduced. The simulation results show that the proposed approach improve both coverage and energy consumption compared with other multi objective approaches.**

Keywords- **WSN;** ***Deployment Problem; Multi Objective Optimization; Energy Consumption; FPA.***

I. INTRODUCTION

Over the last few decades, fields of microelectronics, micromechanics and wireless communication technologies have made a noticeable progress that allows the production of cost-effective components of a few cubic millimeters in volume. Therefore, wireless sensor networks(WSNs) have arisen as a new area of research to provide more economical solutions , an easy to deploy remote monitoring and processing of data in complex environments, . WSNs consist of a large number of nodes deployed in a region of interest (RoI) to collect and transmit environmental data to one or more collection points autonomously. These networks are of interest especially for military applications, environmental applications, home automation, medical and many of the applications related to the surveillance of critical infrastructure. These applications often require a high level of security and characteristics sharing because of the lack of infrastructure, limited energy and dynamic topology. Sensor nodes have limited resources, namely the energy resources and the calculation capabilities as well as the storage capacity. Thus, most studies and researches on WSN have dealt with resources optimization problems in order to enhance the performances and meet the quality of service (QoS) requirements.

The deployment of a sensor in the RoI is a crucial issue for any WSN designers especially with the limitations of sensor nodes. In fact, WSN performances are greatly influenced by the placement strategies since they directly affect QoS metrics, such as energy consumption, sensor lifetime and sensing coverage equally [1]. Hence, a powerful sensor deployment strategy will obviously improve performance and resource management. The deployment strategies can be classified according to three criteria: the first is the placement methodology that can be either random placement or grid-based placement (deterministic placement).the second is the optimization of performance metrics such as connectivity, sensing coverage, energy consumption and lifetime. Finally, the roles the deployed node, which can be regular, relay, cluster-head, or base-station plays [2]. The placement techniques can be further categorized into static and dynamic according to whether the optimization is performed at the time of deployment or when the network is working, respectively. The choice of the deployment schema depends on many properties [2].

The coverage problem is one of the most basic issues in wireless sensor networks, it directly affects the capability and the performances of the sensor network [3]. The quality of coverage is immediately influenced by the choice of the deployment strategy. Most of the applications using WSN, especially those requiring permanent measurements collection, demand a low-energy consuming network. Also, for the sensors network itself, energy consumption is a critical issue since sensor nodes rely on limited power resources. As a result, an optimal deployment topology should achieve a trade-off between the coverage requirement and the energy constraint. In general, there exist conflicts between minimizing energy dissipation and maximizing coverage. To maximize the area of coverage, sensor nodes must be placed far away from the sink node (data collection point) which means that the sensor signals need higher power in order to reach farther distances. Multi-objective optimization approaches (MOOAs) are generally used to solve optimization problems with conflicting objectives. The multi-objective optimization (MOO) works on several objective function vectors simultaneously. Unlike, the single-objective optimization, the solution of MOO is a set of solutions, known as the set of pareto optimal solutions [4].

The connectivity metric in WSN is satisfied if, and only if, there exists at least one path between each pair of nodes. This requirement is at the same level of importance with the coverage requirement. Actually, these two metrics should be strongly related in order to ensure wider monitored area without connectivity holes.

Nature constantly inspires research in the field of optimization. While genetics, ants and particle swarm algorithms are famous examples, other nature inspired optimization algorithms emerge regularly. Flower Pollination Algorithm (FPA) is a novel global optimization algorithm inspired from pollination process of flowers. FPA is simple and very powerful; in fact, it can outperform both genetic algorithm (GA) and particle swarm optimization (PSO) according to [5].

In this work, we proposed a new deployment approach based on the multi objective version for FPA (MOFPA) [6] for WSN. Our approach aimed to find the optimal deployment topology taking into account the aforementioned objectives, i.e., minimizing energy consumption and maximizing total coverage while maintaining connectivity constraints.

The remainder of this paper is organized as follows. In Section 2, the related work is outlined. The problem formulation is presented in Section 3. Section 4 introduces the proposed approach. In Section 5, simulation results and discussion are given. Finally, Section 6 concludes the paper.

II. Related work

Many literature surveys are available where optimization methods have been used to solve several nodes placement issues for WSNs. The authors in [7] proposed an improved version of Artificial Bee Colony algorithm to maximize the coverage rate in WSN. This algorithm modified the updating equation of onlooker bee and scout bee. In fact, some new parameters, such as forgetting, neighbor factor and probability of mutant were introduced to enhance coverage rate and accelerate the convergence speed. Sengupta et al. [8] achieved an optimal tradeoff between coverage, energy consumption and lifetime in WSN using the multi-objective evolutionary algorithm (MOEA). They developed an enhanced version of Multi-objective evolutionary algorithm based on differential evolution (MOEA/D-DE) known as MOEA/DFD, which includes the fuzzy dominance. The authors in [9] proposed three algorithms, specifically integer linear programming models, a local search algorithm and a genetic algorithm in order to solve the deployment problems of WSNs. Theirs approaches aimed at finding the optimal deployment in terms of area of coverage and number of wireless sensor nodes by taking into account the connectivity constraint. Likewise, they compared the three models with some regular sensor deployment patterns. The problem of the probability node deployment is less important than the distribution of the asymmetrical nodes. Zhang et al. [10] addressed the sensor nodes deployment issues for Directional Sensor Networks (DSNs). They proposed a novel placement approach based on PSO in order to enhance the coverage probability of the monitoring field. The probability coverage model was adapted as a sensing model.

III. Problem Formulation

Considering the severe resources constraints of sensor nodes and the levels of QoS required for the WSNs, an optimal placement process has to be considered. In this work, we aimed at finding the coordinates of the sensor nodes in a two−dimensional sensing area that insure the maximal coverage rate and minimal energy dissipation. The deployed sensors should be connected in an efficient way so that each deployed sensor can find a connection path to reach the sink node. Consequently, our deployment problem was modeled as a multi-objective optimization problem with two objective functions, namely total coverage ratio and energy consumption, and one problem constraint, namely the network connectivity.

A. Preliminary Definitions

Sensor nodes in WSN are characterized by their positions in the 2D plane (x, y), sensing radius R_s and communication radius R_c. Given a multi-hop WSN, where all nodes collaborate in order to ensure cooperative communication such network, can be defined as a linked graph, G = {V, E}, where V is the set of vertices representing sensors and E is the set of edges representing links between the sensors. Let u ϵ V and v ϵ V, (u, v) belongs to E if, and only if, u can directly send a message to v (we say that v is neighbor of u). We assume that R_c is identical for all nodes. Let d(u, v) be the distance between the nodes u and v, the set E can be defined as follows:

$$E = \left\{ (u,v) \in V^2; \qquad d(u,v) \le R_C \right\}$$

The network coverage is defined by the sensing radius of the sensor node, whereas the network connectivity is specified by the communication radius of the nodes.

B. Multi objective optimization

Formulating an optimization problem as a multi objective problem is necessary in some cases, especially when the problem involves more than one objective functions and several constraints. The objective functions are typically conflicting; the task of MOOA is to find a tradeoff between the conflicted objectives. Unlike single-objective problem optimization, the results of MOOA are usually a set of solutions [4].

Definition 1. Multi-objective optimization problem
A multi-objective optimization problem is a problem of the following form:

$$\begin{cases} \text{Minimize/Maximize } f(x) = \left[f_1(x),\, f_2(x),\, \ldots f_n \right]^T \\ \text{Subject to } q_j(x) \ge 0, \qquad j=1, 2, \ldots, m, \\ h_d(x) = 0, \qquad d=1, 2, \ldots, l, \end{cases} \tag{1}$$

Where, xϵ E^n is the decision variables, n is the number of objective functions, l is the number of equality constraints and m is the number of inequality constraints [4].

Definition 2. *Pareto optimality*
MOO problem has actually many solutions in the feasible region that all fit a predetermined definition for an optimum solution. The predominant concept in defining an optimal

point is that of Pareto optimality. This is specified as follows:
A point, $y^* \in Y$, is Pareto optimal if there is not another solution point $y \in Y$, such that $f(y) \leq f(y^*)$ for at least one function [4].

Definition3. *Non-dominated solution*
A feasible solution is non-dominated if there is not another feasible solution better than the current one in some objective function.

C. *Energy Model*

The energy consumed by WSN is considered as the first objective function. Here, our purpose was to minimize the total energy consumed by the network. Supposing that E_0 is the initial energy capacity for each sensor and e_i is the energy consumed by each node i, e_i can be formulated as follows:

$$e_i = ME_i + TE_i \times P_{si} + RE_i \times \alpha_i \tag{2}$$

Where ME_i is the maintenance energy, TE_i is the transmission energy, Psi refers to the cost of minimum path from a sensor node i to the sink node, RE_i is the reception energy and α_i represents the number of sensors in which node i receives data and transfers it to the sink node in multi-hop communication.
The network total energy consumed is defined as the sum of the energy consumed by each node. So, our first objective function is given as follows:

$$f_1 = \text{Minimize}\left(\sum_{i=1}^{N_S} e_i\right) \tag{3}$$

With N the number of sensor nodes.

D. *Coverage Model*

Coverage in WSN can be defined as the total area covered by a collection of sensor nodes deployed in the region of interest (RoI). Coverage problems are commonly classified into two types: target coverage problem and area coverage problem. The former ensures the monitoring of only certain specific points which have fixed positions in the area of interest, while the latter is concerned with the supervision of the whole deployment area. In this paper, an area coverage problem was considered. The sensing area was considered as m × n grids, each grid point size was equal to 1 and denoted as G(x, y). The zone covered by a sensor node was a disk with a radius equal to the sensing radius of the sensor (R_s) (Figure 1). The binary sensing model was considered. For this model each grid point within the sensing radius of a node can be taken as covered with probability equal to "1" and point out of the sensing range was set as "0" since it cannot be covered.

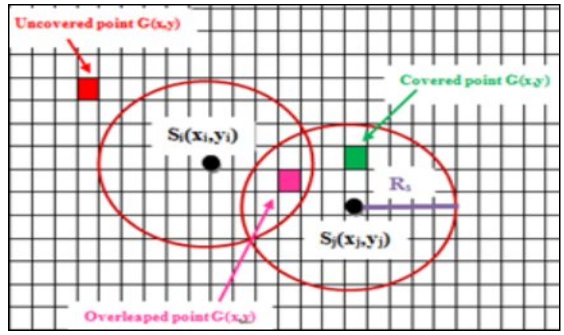

Figure 1. Sensor coverage in sensing field

Thus, the coverage of the whole area is proportional to the grid points that can be covered by at least one sensor $S_i(x_i, y_i)$ [17].

$$P(x,y,S_i) \begin{cases} 1, \text{ if } & \sqrt{(x-x_i)^2-(y-y_i)^2} \leq R_S \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Supposing that a WSN consists of N_S sensor nodes, the probability that a point G(x, y) is covered can be given by:

$$P(x,y,S) = 1 - \prod_{i=1}^{Ns} (1 - P(x,y,S_i)) \tag{5}$$

And the Coverage Ratio (R_{cov}) is given by:

$$R_{cov} == \frac{\sum_{x=1}^{m} \sum_{y=1}^{n} P(x,y,S)}{m*n} \tag{6}$$

The second objective function is to maximize the total coverage area. But, since energy consumption has to minimized, coverage metric should be modeled as a minimizing problem. So, our objective function has to be expressed as minimizing the non-coverage ratio which is equal to 0 in case of full coverage.

$$f_2 = \text{Minimize}(1 - R_{cov}) \tag{7}$$

E. *Connectivity Constraint*

The network connectivity is satisfied if there exists, at least, one path from the sensor node to the sink node. Here, connectivity is considered as a problem constraint.

Definition 1. *Node Degree*
Given an undirected graph G, the degree Deg (u) of a vertex $u \in V$ is specified as the number of neighbors of u [11].

Definition 2. *k-Node Connectivity*
A graph is considered to be connected if for every pair of nodes, there exists a single hop or a multi-hop path connecting them otherwise the graph is called disconnected. A graph is considered to be Q-connected if for any pair of

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nodes there are at least Q reciprocally separate paths connecting them [11].

IV. PROPOSED APPROACH

Our objective was to enhance the performances of WSN by optimizing both coverage [14] and energy consumption metrics without affecting the network connectivity. Here, we dealt with area coverage problem for a centralized random placement topology with a predefined number of sensors. The proposed approach is a multi objective approach based on FPA. This section presents the different rules and steps of the proposed approach.

A. Multi-Objective Flower Pollination Algorithm

Meta-heuristics algorithms are often inspired from nature and designed to solve challenging optimization problems. Here, we considered one of the most recent meta-heuristic algorithms named FPA, developed by Xin-She Yang in 2012 [5] for the global optimization problems. FPA inspired from the flower pollination process of flowering plants. In nature, flowers pollination process resulting from the transfer of pollen, typically, by pollinators such as insects, birds, bats and other animals. In this work, we presented a multi objective approach based on MOFPA [6] to solve deployment problems for WSN. FPA has the following four rules:

1. *Cross-pollination is a global pollination process with pollen carrying pollinators doing Lévy flights.*
2. *Self-pollination is considered as local pollination.*
3. *Flower constancy can be defined as the reproduction probability proportional to the similarity of the two flowers involved.*
4. *Global and local pollination is controlled by a switch probability p ϵ [0, 1].*

The fitness function used for this work is given by the following equation:

$$f \quad \text{Minimize}\ (f_1, f_2) \tag{8}$$

With f_1 and f_2 described above.

The pseudo code of the proposed approach is presented in Figure 2. Where N_f represents the number of flower, ε is the scaling factor, p is the switching probability, $\mathbf{F}^{\mathbf{t}}_{\mathbf{i}}$ is solution vector $\mathbf{F_i}$ at iteration t and g* is the current best solution found among all solutions at the current generation/iteration. Thus, to imitate the movement of the pollinator, FPA uses Lévy flight. Therefore, we draw L > 0 from a Lévy distribution:

$$L \sim \frac{\lambda\Gamma(\lambda)\sin(\frac{\pi\lambda}{2})}{\pi}\frac{1}{s^{1+\lambda}} \quad (s \gg s_0 \gg 0) \tag{9}$$

Begin
Read N_f, solution space, Max Iteration Max_T , ε, p, Iteration count Tcount=0, and Flower count Fcount=0.

Step1: Create initial population of N_f Flowers F (**Algorithm 2**).
Step 2: Find fitness of each flower using f, then find the Global Flower g* which have minimum fitness function value.
Step 3: For each flower except the g* generate a random number r.
If (r<p) **then**
Pollinate current flower with global flower g*:
$F_i^{t+1} \leftarrow F_i^t + L(g^* + F_i^t)$
Else
Pollinate current flower with any other flower in the population:
$F_i^{t+1} \leftarrow F_i^t + \varepsilon(F_k^t + F_j^t)$
End if
$F_{count} = F_{count}+1$
Step 4: **if** new solution F_i^{t+1} better than current solution **then** update them in the population, **if** new solution F_i^{t+1} better than g* **then** update the global solution.
Step5: if ($T_{count} < Max_T$) **then**
$T_{count} = T_{count}+1$
Else
Go to **Step 3**
End if
End

Figure 2. Pseudo-code of MOFPA

B. Initial population

To implement the proposed approach, we needed to create an initial population for FPA. In this work, we considered that each individual or flower represented the vector of all sensor nodes position (x, y) in RoI.

To create the initial population, we began by generating the position of the sink node at the centre of RoI for each flower. Then, we deployed the remaining sensors randomly after verifying the connectivity constraint. Actually, the network connectivity is assumed to be full if the distance between two sensors is less than the communication radius (Rc) of the sensor. Rc is set at $2R_S$ to guarantee the network connectivity [12]. The distance is defined as the Euclidean distance between two sensors. In addition, to ensure a sufficient distribution in RoI, we controlled the number of neighbors of each deployed node that should be less than a predefined number N_e. Here, N_e was set to 1. So, we dealt with 1-connected network.

The pseudo code of the initial population is presented in Figure 3. With S_i is the sensor node i, N_f is number of flowers, Rc is the node communication radius and N_e is the maximum number of neighbors.

```
Begin
Read Nf, NS, Solution space , flower count Fcount=0, sensor count Scount=0,
Rc and neighbors Ne.

Step1: for each Flower F: Deploy (Sinki).
Step2: for each Flower F:
Scount=0
While ( Scount <=NS )
Generate-Random-Position(Sk)
if ∃ Sj While Dkj < Rc then
  if Neighbors (Sk) ≤ Ne then
   Deploy(Sk)
   k←k+1
  End if
End if
End
```

Figure 3. Pseudo code of Initial Population Creation

V. SIMULATION AND RESULTS

To validate the performances of the proposed approach, some simulations were performed. Here, the binary sensing model was taken and sensor nodes of the initial population were randomly distributed.

TABLE I. DEFINITIONS AND VALUES OF SIMULATION PARAMETERS.

Parameter	Definition	Value
x_m	Maximum width of RoI	100m
y_m	Maximum length of RoI	100m
R_c	Communication radius	30 m
R_S	Sensing radius	15 m
N_S	Number of sensors	15
Ne	Maximum number of neighbours	1
IE	Initial energy for each sensor	1Ah
ME_i	Maintenance energy for node i	13 mA
TE_i	Transmission energy for node i	20 mA/m
RE_i	reception energy	2 mA
N_f	Number of flower	20
p	Switching probability	0.8
$NCov_{pop0}$	Non-coverage ratio of initial population	0.4777
E_{pop0}	Energy consumption of Initial population	8042 mA

The network is homogeneous, i.e., all sensors have the same deployment parameters such as the sensing and communication radius. Simulations were carried out using MATLAB R2016a. The algorithm was run a maximum number of iterations of 1500 for 5 runs.

Figure 4 presents all solutions (dominated and non-dominated) obtained over five runs of the proposed algorithms. The simulation shows that 90% of non-dominated solutions (see Figure 4) offered the following pairs of values: (217.09, 0.166) and (199.36, 0.168), for Energy Consumption and non-Coverage Ratio, respectively.

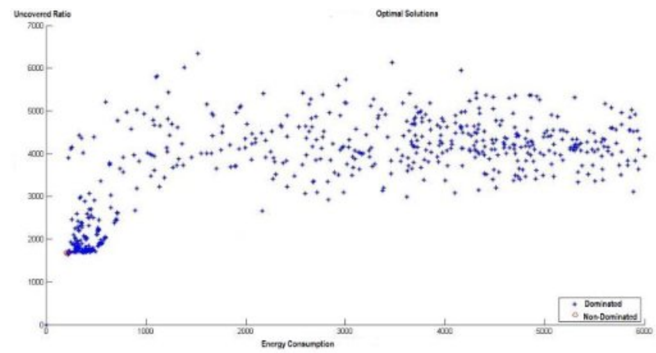

Figure 4. Non-Dominated Solutions of MOFPA

Tab I presents the definitions and the values of simulation parameters. The non-dominated solutions were close but not overlapping. Comparing the simulation results with the initial values, i.e. those of initial population, we can notice the amelioration offered by our approach in terms of the considered objective functions. Actually, the proposed approach was 38.62 and 2.86 times better in minimizing energy consumption and non-covered area, respectively.

In this work, the simulation results of MOFPA were compared with those of PSO algorithm [13] in different instances. PSO was tested by considering the same initial simulation parameters (See Tab I). Figure 5 and Figure 6 show the results of MOFPA compared with those of PSO algorithm.

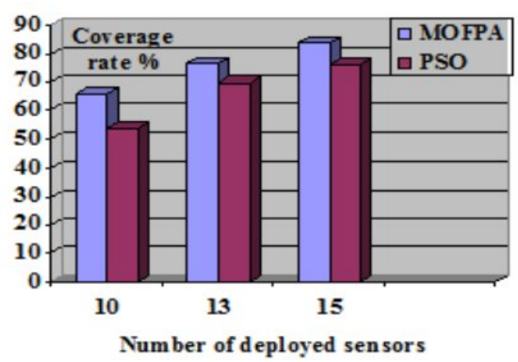

Figure 5. Average of Coverage rate of non-dominated solutions

Figure 5 presents the average of coverage rate of non-dominated solutions found after 1500 iterations of the two algorithms for different instances. We notice that the total coverage rate of RoI increases when the number of deployed nodes increases. The proposed approach outperforms the PSO in all instances and produces maximum coverage area.

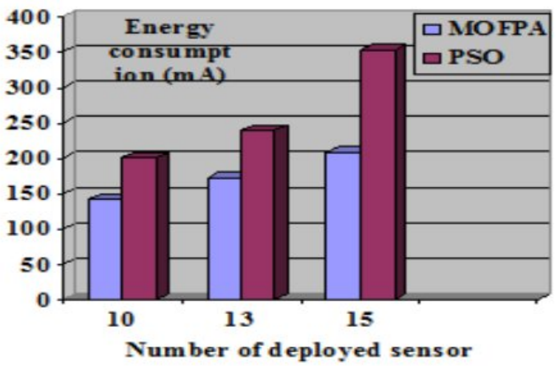

Figure 6. Average of energy measure of non-dominated solutions

Figure 6 presents the average of energy consumption of non-dominated solutions found after 1500 iterations of the two algorithms for different instances. We notice that the total energy consumption increases when the number of deployed nodes increases. The proposed approach outperforms the PSO in all instances and consumes minimum net energy.

VI. CONCLUSION

The multi-objective optimization algorithm aims to determine a set of optimal solutions which establish a trade-off between the different objective functions. This paper presented a new multi-objective approach for node deployment problem in WSN. The proposed approach tried to deploy sensor nodes in the RoI while maximizing coverage area, minimizing energy consumption and maintaining net connectivity. Simulation results prove that MOFPA out-performs PSO as it allows better network in terms of both coverage and energy consumption. In a future work, we will incorporate other QoS metrics like sensor lifetime.

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