

Evolutionary Multi-Objective Based Approach for Wireless Sensor Network Deployment

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Abstract—This paper is a study about deployment strategy for achieving coverage and connectivity as two fundamental issues in wireless sensor networks. To achieve the best deployment, a new approach based on elitist non-dominated sorting genetic algorithm (NSGA-II) is used. There are two objectives in this study, connectivity and coverage. We defined a fitness function to achieve the best nodes deployment. Further we performed simulation to verify and validate the deployment of wireless sensor network as an output from the proposed mechanism. Some performance parameters have been measured to investigate and analyze the proposed sensor-deployment. The simulation results show that the proposed algorithm can maintain the coverage and connectivity in a given sensing area with a relatively small number of sensor nodes.

I. INTRODUCTION

A wireless sensor network (WSN) is a wireless network composed of sensors to respond physical or environmental circumstances, such as temperature, pressure, vibration, pollutants, motion or sound, at different places. Each sensor in a sensor network is characteristically equipped with a radio communication, a small micro-controller, and a limited energy source.

Both in research and commercial area, WSN has become a critical technology fascinating increasing interest in recent years. They are being deployed flexibly and quickly for many applications such as monitoring and control, surveillance, search and rescue, battlefield operations, etc [1].

Coverage and connectivity are two underlying issues in WSN. The aim of coverage is to guarantee that the area of target is absolutely sensed, while connectivity is to make certain event in the area of target is successfully transmitted and received at base station and afterwards captured by users or remote users. Both coverage and connectivity collectively can be treated as a measure of quality of service (QoS).

For a target area that out of reach, a random deployment method is the only fashion. When the target area is reachable, a deterministic sensor deployment method should be more effective. Such a strategy would minimize the total number of sensors required and achieve the specific needs of applications in terms of their expected quality of coverage and connectivity. Significant changes may occur in the topology with long deployment. Moreover, the connectivity of the nodes can change

because of jamming, interference, noise, or other obstacles. Therefore, the coverage of a sensor, hence, of the network is closely related to its line of sight. This fact results in different challenges for coverage problems in WSN.

Most prior researches on WSN deployment with assured coverage and connectivity are based on simple sensing and communication models with sensing range of R_s and communication range of R_c . It is common that the result of $R_c = 2R_s$ is better than $R_c = R_s$ [2]. However, this is not absolute. In [4], Y. Li et al. provided deeper study on R_c , R_s and the need of more nodes to cover the area of interest.

Coverage is thus an important aspect of QoS in wireless sensor networks. One important question arise is that given an area to be observed and some coverage requirements, what number of sensors is needed and where should they be placed? This research question, hence forward marked as the deployment problem, can be posed under certain compelling constraints, i.e cost constraints, existence of obstacles, availability of various types of sensors, and so forth.

In this paper, our proposed algorithm imitated one of the most well-known Genetic Algorithms (GAs) and has been found to be effective for a number of applications to establish the framework for solving the multi-objective optimization problem (MOP) in WSN deployment, NSGA-II [3].

The objective of this work is to obtain the optimum connectivity and coverage and also the minimum number of sensor nodes in the given sensing area which can offer optimal (or near-optimal) performance, and also to recognize the primary challenge in QoS over WSN. In addition, the developed algorithm lead to a fewer required sensors to be deployed to achieve full sensing coverage in the monitoring area.

The rest of this paper is organized as follows. Section II reviews related work. Section III discusses the proposed work for nodes self-deployment. Simulation setup and result are discussed in Section IV and conclusion of the paper is presented in Section V.

II. RELATED WORK

The problem of coverage in WSN is tightly connected to the deployment, for the fact that a good deployment can enhance all the functionalities of the network. A necessary prerequisite

is that the possible event locations are covered by the sensing ranges of a number of sensors. The required node density depends on the sensors sensing ranges, the shape of the sensing regions, and environmental conditions.

The deployment approach for obtaining coverage and connectivity in wireless sensor networks is studied in some related works [7], [8] and [10]. Simulation results indicated that NSGA-II can fulfill the needs of the desired coverage area and preserve the connectivity with a comparatively small number of sensor nodes.

Deployment strategies can be classified into three categories: random deployment, regular deployment and on-demand deployment. The choice of deployment method strongly depends on the type of sensors, application and environment or function of sensor. Controlled deployment (regular deployment and on-demand deployment) is often required when sensor's price is too expensive or when the operation is strongly influenced by their position. However, in some applications of WSN, random deployment is the only option. This is especially due to environment with difficult access, such as a battlefield or disaster area. According to the distribution node and the level of redundancy, random deployment of the sensors can possibly achieve the required performance [4].

Authors in [5] identified algorithms as an inclusive to random deployment, incremental deployment and movement-assisted deployment. Random deployment is the fastest and most practical way to deploy a network, even if it does not guarantee a similar dispersion. For this reason it is often used, in our case, only in the initial population phase. Incremental deployment is a centralized approach, which locates nodes one at a time. The computing of ideal position for each node is based on the output gathered by the nodes that are already deployed. Therefore, computation and time costs erupt when number of nodes raises. Recently, the most used method to deploy a network is the movement-assisted approach, because it can obtain a uniform coverage with reasonable time and costs.

In [6] and [7], the methods for coverage are classified into three categories: force based, grid-based and computational geometry based. Each method can be acknowledged as a subgroup of the movement-assisted method.

Authors in [19] have presented the design, the development and the performance of a wireless sensor network for rural and jungle environments fire detection and verification. They have studied how many nodes, i.e. cameras, multisensors and access points, are required to cover a rural or forest area.

Lloret et al [17] discussed the energy consumption and gave some reviews that should be taken into account in deploying a wireless local area sensor network. Later, they proposed a new protocol based on a group association to be completed in these types of networks to reduce the energy consumption and save the energy wasted.

According to [16], the developers choice is not incidental, because not all combinations of hardware or software are available. This is because hardware solutions are definitely

more in number than software. Some hardware platforms are supported by both ContikiOS and TinyOS operating systems which give some degree of freedom to the developer. Another approach is to add a new hardware port to an existing operating system, but such a task may turn out to be complicated and takes time.

III. THE PROPOSED ALGORITHM

This section presents the proposed algorithm based-on NSGA-II for WSN deployment. As a well-known algorithm, NSGA-II follows some basic steps of genetic algorithm (GA). The population is first initialized and then sorted based on the non-domination into each front by using a fast sorting algorithm. Every individual in any front is referred as a fitness (or rank) value which is equivalent to its non-domination degree. Once the non-dominated sorting is complete, the crowding distance is also assigned. The crowding distance is a measure of how close an individual is to its neighbors. Large number of average crowding distance will result in a better diversity in the population. Parents are selected from the population by using a binary tournament selection based on the rank and crowding distance. The offspring population is combined with the current generation population and the selection is performed to set the individuals of the next generation. The selected parents generate offspring by using crossover and mutation operators. The new generation is monitored by each front subsequently until the population size exceeds the maximum population size. Since all the previous and current best individuals are added in the combined population, elitism is ensured in NSGA-II [3].

The flowchart in Figure 1 describes the most relevant steps of the nodes self-deployment algorithm.

A. Initial population

The area considered for deployment is a grid of size $X \times Y$, in this case $100 m \times 100 m$. To create the initial population P_0 , a random approach is used to create the initial population which is composed of several individuals. Knowing that an individual represents a deployment of wireless sensors.

Deployment strategy could be designated by a matrix D of size 10×10 with element $d_i = N_{ID}$ (Node ID) indicating that sensor node with identifier ID is deployed. In this case, $d_i = 0$ indicates that there are no sensor deployed on that area, as seen in Figure 2. The random deployment is defined by:

$$d_i = \begin{cases} N_{ID}, & rand < Den \\ 0, & empty \end{cases} \quad (1)$$

Where Den is an adjustable parameter that control the density of nodes in a deployment and $rand$ belongs to $[0,1]$. N_{ID} is a unique identifier of sensor in each deployment. Figure 2 shows an example of the deployment with the grid size of $100 m \times 100 m$ and the size of each cell is $10 m \times 10 m$.

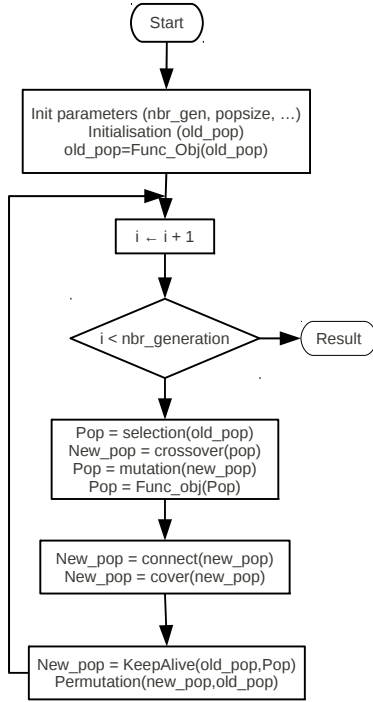


Fig. 1. Flowchart of NSGA-II based for WSN Deployment

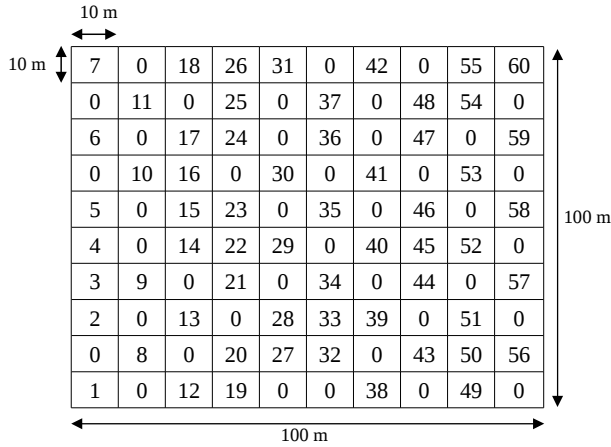


Fig. 2. Sample of Initial Population

B. Genetic Algorithm

An intermediate population of size n_p is created by employing the following genetic operators.

Selection. Selection is a genetic operation that is performed to create new deployments. In this study, the tournament selection method is chosen. This method consists of selecting two individuals randomly, and among these individuals, one with the best value (minimum is the best) of fitness based on the best ranking will be taken. This operation is repeated in the population of generation until it gets the new population P . Parents are selected from the population by using a binary tournament selection based on the rank. This is based on the

principle that parents with better chromosomes can reproduce better offsprings.

Crossover. The crossover operator is applied after the selection operator with a probability of p_c on the population P . In this phase two types of crossover are used. The first type is sensor interconnected from a selected deployment, later it is replaced by another randomly chosen part of another deployment. If they are not interconnected sensors, the second type of crossover is applied, which is to select a random part of the individual (deployment) and replace it by another party without any verification. Multiple crossover points is chosen, whose locations are calculated using a random number generator (RNG), to create a new population with probability of p_c .

Mutation. With mutation probability of p_m , randomly chosen chromosomes are mutated. The mutation is to add or remove chromosomes (sensors in this case) of an individual (deployment). The first method selected is a random point. If the cell contains a sensor in the active state, then turn it into a passive state or otherwise. Although, if the cell contains no sensor, the algorithm will select a sensor randomly in the active state and puts it in another box (change location). Mutation is applied with a probability of p_m .

Fitness Function. Once the initial population is created, the functions compute the set goals for each solution (each deployment) using the following equations for each of solutions:

$$\min F_1 = \sum_{i=1}^{X \times Y} d_i, \quad (2)$$

$$\min F_2 = \sum_{i=1}^{X \times Y} 1 - e^{-(R_c - R_s)}. \quad (3)$$

Where R_c is the communication range of a node, and R_s is the sensing range with the Euclidean distance between two sensors. Function F_1 calculates the number of sensors used (active) deployment. However, the function F_2 has been proposed to provide two objectives, first, to ensure that each sensor is positioned within the communication range of at least one other sensor, second, to prevent sensor nodes become too close to each others. It means that the distance between the two sensors should be less than R_c . After calculating the objectives and constraints, connectivity and coverage, each individual solution contains a rank (Pareto Fronts), and all non-dominated individual sets with the same rank in a category. Crowding distance is calculated to maintain the diversity of solutions in the Pareto Fronts. As a result, after the evaluation of objectives, the different stages of the genetic algorithm proposed will achieve one optimal solution.

The application of the fitness function to optimize the deployment of sensors from one generation to another. The convergence of the algorithm is to give an optimum solution which depends on the number of sensors and the size of sensing area. For example, for an initial deployment of 100

random nodes, the optimal solution ($F_1 = 50, F_2 = 0$) for all active sensors.

IV. SIMULATION AND RESULT

This section will present the simulation setup and the result. The main parameter of interest is the coverage achieved by the scheme in respect of the achievable coverage. Nonetheless, the mechanism of genetic transmission and learning that lie behind the usage of the fitness function has been investigated. The approach used in this work can be view as two phases.

Phase I: In this phase, we perform simulation of NSGA-II to achieve the best deployment of generation according to the relocation of sensor nodes in the area of $100\text{ m} \times 100\text{ m}$. The sensor nodes are generated and randomly deployed in the given sensing area according to Figure 2. In this case, the communication range R_c of sensor nodes is the same for all, which is 10 m . The output of this phase is the best deployment with minimum number of nodes and minimum fitness value which is defined by equation (2) and (3).

The output of this phase are the best generation which mean the minimum fitness value and the minimum number of nodes needed to be deployed with its position respectively to other node position.

Phase II: This phase is used to measure and validate the output of phase I.

In this scenario of simulation, the simulation time is 500 seconds. We use two deployment methods of wireless sensor network i.e. random position and proposed position. For random position we use 100 sensor nodes, 75 nodes and 50 nodes. On the other side, for proposed node position, we use 50 nodes. The position of nodes are defined based-on the result of the proposed algorithm in phase I. The cover area used in this simulation is $100\text{ m} \times 100\text{ m}$. The output of this phase are trace files and network animators. Then we analyze the trace files to achieve the performance.

A. Simulation Setup

The proposed scheme is evaluated by simulation using C language for phase I, which is an open source framework for simulation design, and NS-2 network simulation for phase II. The Network Simulator, NS-2, is a discrete event simulator targeted at networking research. Table I and II, we reported the NSGA-II and simulation parameters used in this work. We consider a 10×10 cells fields, where a variable number of nodes is deployed according to a randomly uniform distribution while initiate the population as shown in Figure 3.

B. Simulation Result

This section will present the simulation result and the performance evaluation of the proposed algorithm.

Figure 4 shows the number of required nodes of different deployment methods under different R_c/R_s ratios. We compare the proposed algorithm with some algorithms i.e. Genetic Algorithm (GA) [13], Tabu Search (TS) [12], grid deployment and random deployment. For particular method, as the R_c/R_s ratio raise from $5/4$ to $11/4$, the number of nodes required

TABLE I
NSGA-II PARAMETERS

Parameter	Value
Population size	300
Number of generation	100
Passing crossover	0.8
Percentage of mutation	50
Distribution index crossover (di)	10
Distribution index mutation (dim)	20
Crossover type	Binary

TABLE II
SIMULATION PARAMETERS

Parameter	Value
Simulation time	500s
Routing Protocol	AODV
MAC Type	802.15.4
Data type	CBR
Packet size	50 Bytes
Data rate	[0.5,1.0,1.5,2.0]Mb
Nodes with random deployment	100,75,50
Nodes with proposed deployment	50
Simulation area	$100\text{ m} \times 100\text{ m}$

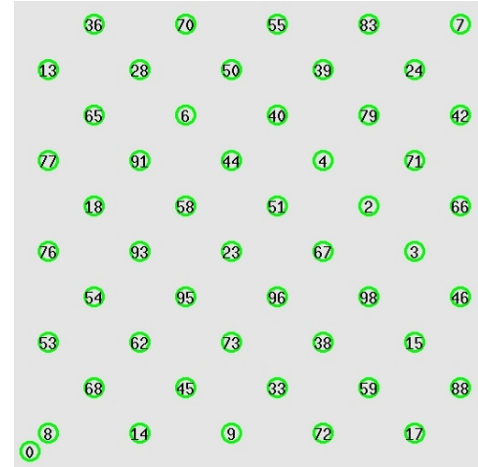


Fig. 3. Proposed Nodes Deployment

sequentially decreased and completely coincides to a minimum value. This is because the range sensing (R_s) parameters remain the same. There should be a minimum number of nodes ensuring the coverage requirement. The increase of R_s cannot help to improve coverage the area. We can see that the proposed algorithm achieved less number of nodes while R_s increase. However TS requires minimum number of sensors, it cannot fulfill the connectivity necessity, because it does not support multi-objective optimization problem properly.

Next results are the outcome based on the simulation using NS-2. In this part, some performance parameters are measured. Figure 5 shows the average delay for proposed and random deployment. For random deployment, the average

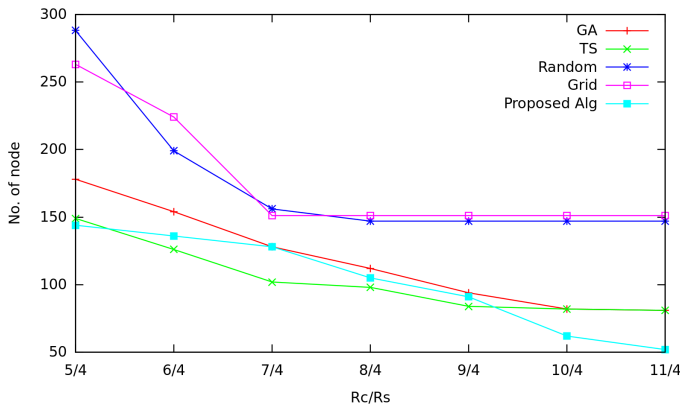


Fig. 4. Required Number of Node for Different Deployment vs Rc/Rs Ratio

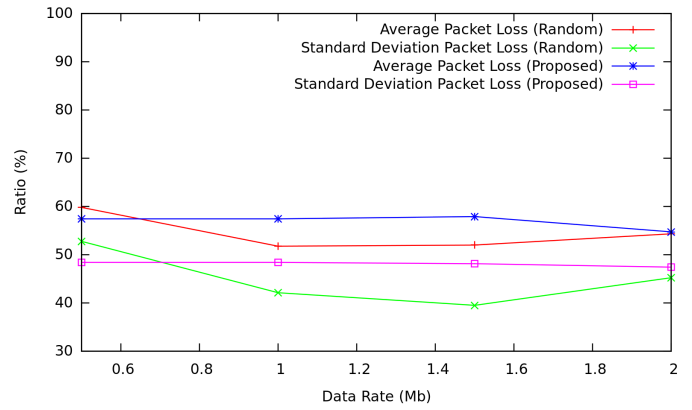


Fig. 7. Average and standard deviation of packet loss between random and proposed deployment.

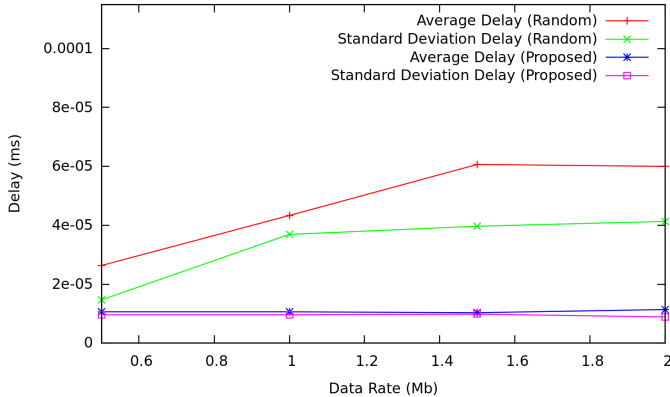


Fig. 5. Average and standard deviation of delay between random and proposed deployment.

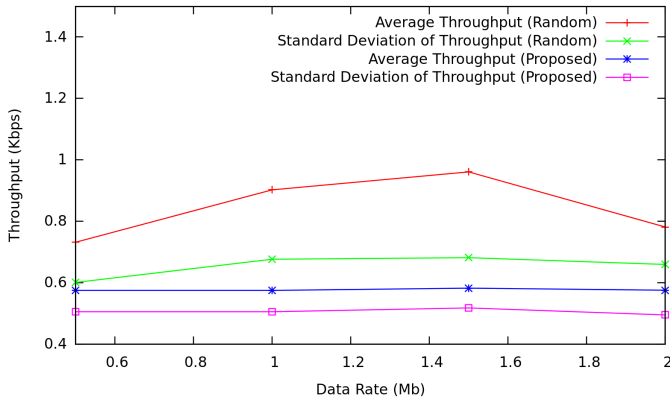


Fig. 6. Average and standard deviation of throughput between random and proposed deployment.

delay increases proportional to increase the data rate from 0.5 Mb to 1.5 Mb. However after 1.5 Mb up to 2.0 Mb the delay becomes stable.

The graphs depicted in Figure 6 presents the average and standard deviation of throughput for random and proposed deployment respectively. For random deployment, the highest throughput is achieved when the data rate is 1.5 Mb and the lowest throughput is recorded for random deployment

scenario during period 1 - 1.5 Mb of data rate. However, for proposed deployment, the average throughput is lower than the random deployment. We can see that the average throughput for proposed deployment scenario is more stable than random deployment. For the scenarios of proposed deployment, the average throughput achieved is between 0.576 kbps and 0.582 kbps respectively. In addition, the standard deviation of throughput of random deployment scenario is also not steady proportional to the average throughput. This is caused by the network deployment topology that always changes in every generation. The standard deviation of throughput of the proposed deployment is based on the algorithm produces a value that does not have a lot of differences from random deployment method.

Packet loss ratio is another performance parameter that we consider. The highest ratio of packet loss is reached by defined deployment scenario, see Figure 7. It is normal that the average packet loss ratio of proposed algorithm is larger than the random scheme, because the random scheme has more number of nodes deployed than proposed deployment. For proposed deployment based on the algorithm, the packet loss ratio is higher than the random deployment scenario in the data rate of 1 Mb and 1.5 Mb. However, for 0.5 Mb of data rate, the random scheme has the highest packet loss ratio among all scenarios.

V. CONCLUSION

This paper proposes a sensor deployment algorithm based on NSGA-II that efficiently deals with the multi-objective problem and likely acquires the target of full coverage with the deployment of small number sensors. Simulation results show that the proposed algorithm significantly reduces the number of deployed sensors and improves the performance. In the future, we could consider a team of sensors that cooperatively perform the same deployment duty in a distributed manner and also take into account the obstacle. Moreover, a wireless sensor network is believe strongly to work for a long period of time. Another possible work in the future could focus on developing an efficient sensor redeployment algorithm that

nurtures the full coverage by deploying the minimum sensors within a reasonable duration.

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