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Research paper

A Multi-Objective Particle Swarm Optimization for Wireless Sensor Network Deployment

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Abstract

The use of wireless sensor networks nowadays is imperative for different domain of interests. One of the challenging task in deploying such networks lies on the efficient deployment that guarantees least number of sensors while assuring the connectivity and the coverage among these sensors. This would significantly contribute toward longer lifetime of the network. Several studies have addressed this problem by proposing various meta-heuristic approaches. One of these approaches is the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) which has been extensively used for WSN deployment. However, such approach suffers of the inaccurate fitness values provided for criteria in the same front. Therefore, this paper aims to propose an alternative approach which is called Multi-Objective Particle Swarm Optimization (MOPSO). The proposed method has been compared against the NSGA-II and the results showed that the proposed method has superior performance.

Keywords: *Genetic Algorithm; Multi-Objective; Pareto-based; Particle Swarm Optimization; Region of Interest; Wireless Sensor Network.*

1. Introduction

The rapid development of wireless communication nowadays has led to the popularity of implementing wireless sensor networks (WSNs) for different applications where the environments are vary such as monitoring facilities including shopping malls, hospitals, and other military and civilian constructions [1]. The deployment of such networks is still suffers of multiple limitations such as the energy consumption, connectivity between the nodes, quality of data transmission and covering the Region of Interests (ROIs) [2]. Hence, the problem has become an optimization task where the aim is to identify an efficient deployment of WSNs that guarantees less energy consumption, meanwhile, maintaining the connectivity among the nodes and assuring wide range of coverage. Such pre-mentioned problems are crucial in WSN deployment where the quality of data transmission is significantly associated with the Quality of Service (QoS), while maintaining minimized consumption of the energy such as reducing the battery and memory consumption would lead to longer lifetime of the network [3]. Therefore, researchers have been attracting by these gaps in which some researches were focusing on specific problem independently [4].
However, tackling separate problem would lead to improve one issue but affecting others. For instance, focusing on assuring wide range coverage would require more energy consumption. Hence, balancing among these issues would be a challenging task in which a trade-off WSN deployment is imperative [5]. This is called Pareto optimization in which multiple criteria are being addressed for decision making problems [6].
In fact, researchers have taking the advantages of heuristic and meta-heuristic approaches which are algorithms that have been inspired by the nature. Such algorithm aims to identify optimal solution for specific problems [7]. One of these algorithms is the Genetic Algorithm which has been widely used in the optimization problems. In particular, a modified version of this algorithm for pareto-based problem has been proposed which is called Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Such algorithm has been extensively used for pareto-based WSN deployment task. However, it has a drawback which can be represented by the inaccurate fitness given for multiple points in the same front [8]. Therefore, this study aims to propose an alternative approach which is called Multi-Objective Particle Swarm Optimization. The proposed method aims to minimize the number of nodes while preserving a maximum number of coverage area among the sensors.
The paper has been organized as Section 2 discusses the related work, Section 3 presents the proposed method, Section 4 depicts the experiment results obtained by the proposed method, and finally, Section 5 provides the final conclusion.

2. Related Work

In fact, the earliest research efforts in the domain of WSNs deployment have focused on a specific problem using heuristic and meta-heuristic approaches. For example, Yoon & Kim [9] have proposed a genetic algorithm for optimizing the coverage among the nodes in WSN. The authors have conducting several simulations where the proposed optimized deployment using GA has been compared with the random deployment. Results showed that the proposed GA has contributed toward significant fast deployment, at the meantime, maintaining the coverage among the nodes.
Similarly Banimelhem et al. [10] have proposed a GA optimization method for maximizing the coverage among nodes in WSN. The authors have addressed the heterogeneous networks where some

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wireless nodes are static and others are dynamic. They compared the proposed deployment using GA with the random deployment. Apparently, results showed that the GA has contributed toward efficient deployment.

On the other hand, Al-Turjman et al. [11] have addressed the problem of balancing connectivity and energy consumption for the 3-dimensional deployment of WSN. Such 3D WSN would indeed have unique characteristics which leads to a challenge task of optimizing the deployment. Therefore, the authors have proposed an approach called Optimized 3D Deployment with Lifetime Constraint (O3DwLC). Several simulations have been conducted in order to evaluate the proposed method. Results showed superior effectiveness of the proposed method.

Lin et al. [12] have proposed a multi-agent system for optimized WSN deployment. The agents would utilize an online incremental algorithm based on Voronoi partition in order to identify the maximum coverage while preserving the connectivity among the nodes. Different simulations have been conducted in order to validate the proposed method. Results showed that the proposed method has outstanding performance.

Jameii et al. [13] have concentrated on the balancing task between the coverage and connectivity among the nodes in the deployment of WSN. The authors have proposed a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) in order to optimize the deployment. Simulation has taken a place by considering the number of active nodes, as well as, the coverage among the nodes. Experimental results have showed that the proposed NSGA-II has produced superior performance compared to the state of the art.

Khalesian & Delavar [6] have proposed an evolutionary method in order to optimize the deployment of WSNs. The authors have concentrated on the trade-off between multiple objectives in terms of optimizing the implementation of WSNs. In this regard, optimizing a wide range coverage would affect the connectivity or the energy consumption and vice versa. Therefore, the authors have proposed a modified version of Genetic Algorithm (GA) which is called Constrained Pareto-based Multi-objective Evolutionary Approach (CPMEA). The proposed method was intended to alter the workflow of GA by making it serves multiple objectives. The proposed method has been compared with the original GA and showed substantial performance.

Abo-Zahhad et al. [14] have focused on the trade-off between the coverage and energy consumption for deployment of Mobile Wireless Sensor Networks (MWSNs). The authors have presented an approach called Centralized Immune-Voroni deployment algorithm (CIVA). Such proposed method is utilizing the probabilistic in terms of maximizing the coverage while maintaining minimum energy consumption by adjusting the active nodes. The proposed method has been compared with other techniques and showed competitive performance.

Finally, Senouci et al. [15] have focused on the quality of the acquired data from sensors within a WSN for surveillance applications. In fact, the implementing a finite number of unreliable sensors would relatively cause high extent of false alarm when the detection of object could be failed. Therefore, the authors have proposed a fusion-based approach in order to identify the best implementation of sensors which leads to lower the false alarm. Results of simulations have showed that the proposed fusion-based method has contributed toward reducing the false alarm rate.

3. The Proposed MOPSO

The proposed method is basically inspired by the standard Particle Swarm Optimization which is a meta-heuristic algorithm. PSO aims to mimic the swarm nature or, in other word, the moving objects in order to solve the specific problem by optimizing the solution. Hence, this study aims to modify the workflow of PSO in order to meet the multi-objectives of deploying the WSN.

First, the proposed MOPSO aims to produce random number of sensors with a range that identifies the minimum and maximum number, these numbers will considered to be the solutions. Then, a random coordinates will be produced by the proposed method in order to assign the ROI sensors. Note that, a Voronoi method has been used in order to guarantees that the number of ROI will not exceed the number of solutions (i.e. number of whole sensors). In other words, this will assure the coverage of the whole environment. This can be depicted in Fig. 1.

In this regard, if the solution satisfies the coverage constraint, a graph would be built which depicts the sensor network in which the two sensors that have a distance that is less than the maximum number of ROIs will be connected. Consequentially, the proposed method will assign the ROI nodes by considering the distance between the nodes in accordance to the sink.

Now, after generating the solutions, the evaluation of each solution will take a place. The evaluation will consider two criteria including global pareto front, local pareto front and iteration pareto front. The global pareto front aims to analyze the solutions in resulted from all the iteration in order to rank them and combine them. This would enable the algorithm from exploring larger areas in the search space. Whereas, the local pareto front aims to analyze the solution from the current iteration and previous iteration in order to rank and combine them. Finally, iteration pareto front aims to analyze the solutions from the current iteration. This can be depicted in Fig. 2.

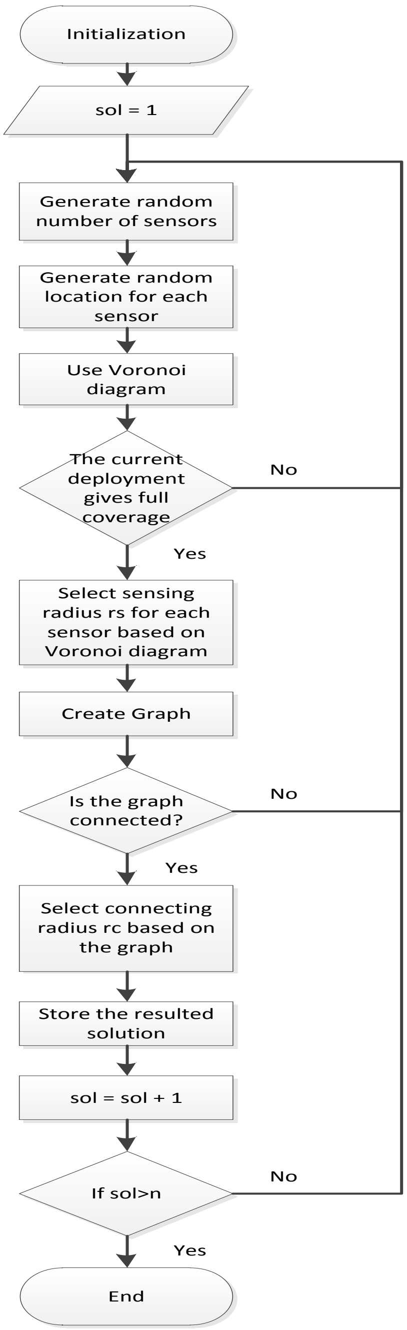


Fig. 1: General workflow of MOPSO

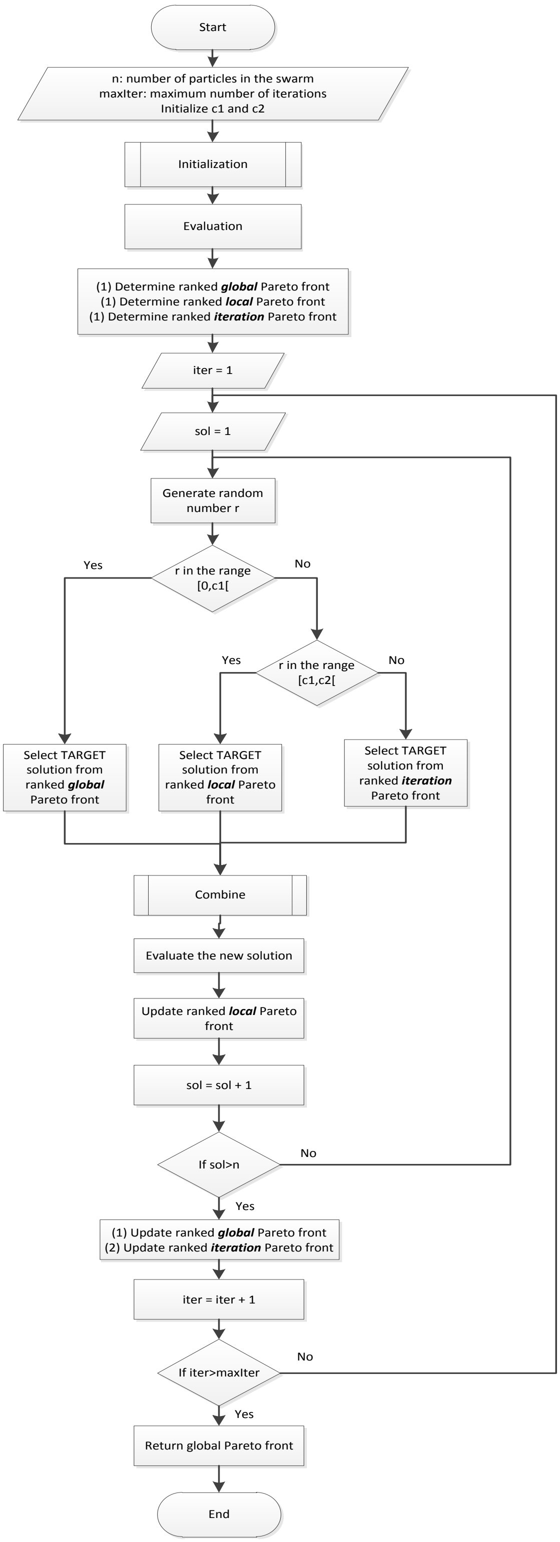


Fig. 2: Evaluating the solutions

During the execution of the algorithm each solution is combined with another solution to create a new solution. The process of selection depends mainly on the parameters c_1, c_2 which determine the probabilities of selection from global, local, or iteration pareto front [16,17,18].

The process of combining the solutions can be explained as combining current solution with the target solution. This can be conducted by firstly determining the nearest sensor in the target solution which can be represented in the following equation:

$$(x_{new}, y_{new}) = (x, y) + Rand \times ((x_{target}, y_{target}) - (x, y)) \qquad (1)$$

Hence, the process of selection of sensors would take a place for the new solution by finding the sensor that achieves the maximum coverage and get an access to the sink node [19,20]. Once such sensor is being identified, it will be added to the new solution. In this regard, the process of combining solution will attempt to minimize the number of sensors while maintaining maximum coverage. This process can be depicted in Fig. 3.

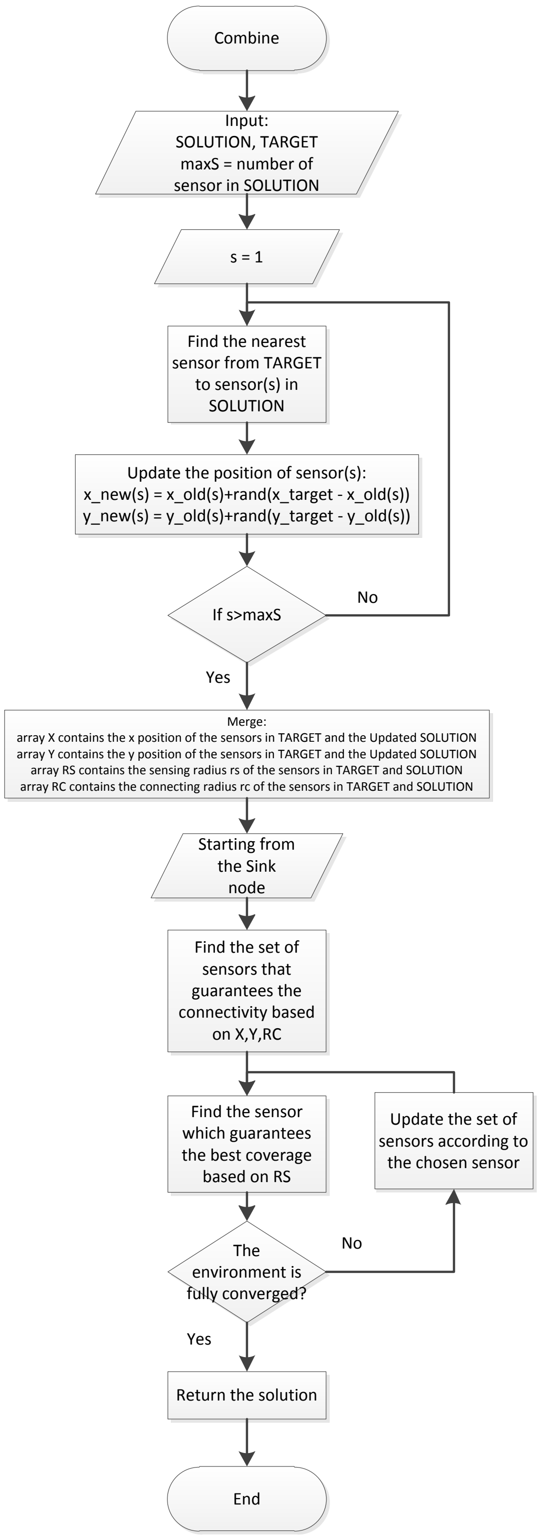


Fig. 3: Combining solutions

In order to validate the proposed method, this study will use three evaluation metrics. These metrics can be illustrated in the following sub-sections.

3.1. Number of Non-Nominated Solutions (NDS)

Assume P_s a pareto set of all non-dominated solutions that is produced by the proposed method *M*. NDS aims to identify the size of P_s as in the following equation [6]:

$$NDS(M) = |P_s| \quad (2)$$

The greater value of NDS refers to the existence of appropriate number of choices.

3.2. Hypervolume metric (HV)

This metric is also called as S-metric and aims to give information about both closeness and diversity within the set of non-dominated solutions P_s. It aims to calculate the volume covered by the solutions in the objective space. Hence, the worst possible point would be used as a reference point *W* in the objective space. Let *x* be a solution within P_s, the HyperCube(x) will be initiated by taking into the account both *W* and *x* as the corners of the hypercube in the objective space. In this regard, HV can be computed by the volume of the union of the hypercubes as in the following equation:.

$$HV = volume\left(\bigcup_{x \in P_s} HyperCube(x)\right) \quad (3)$$

In fact, the greater value of HV indicates superior performance.

3.3. Set coverage metric (C-metric)

This metric aims to accommodate a comparison among two optimal pareto sets by computing the ratio of non-dominated solutions in the second set dominated by non-dominated solutions in the first set. Let P_{s1} and P_{s2} are the two pareto sets, the C-metric will be calculated as in the following equation:

$$C(P_{s1}, P_{s2}) = \frac{|\{y \in P_{s2}\ \exists\ \boldsymbol{x} \in P_{s1}: x > y\}|}{|P_{s2}|} \quad (4)$$

Now if C(P_{s1}, P_{s2}) < C(P_{s2}, P_{s1}) the set P_{s2} would have better solution compared to P_{s1}.

3.4. Simulation

In order to validate the proposed method using the pre-mentioned evaluation metrics, 13 scenarios have been adjusted in order to examine different parameters of the proposed MOPSO. Each scenario contain 10 experiments. Table 1 shows the parameters of each scenario.

Table 1: Parameters of the scenarios

Scenario	C1	C2	Tlag	No. solutions	No. generations
1.	0.33	0.66	3	50	100
2.	0.25	0.5	3	50	100
3.	0.25	0.75	3	50	100
4.	0.5	0.75	3	50	100
5.	0.33	0.66	6	50	100
6.	0.33	0.66	9	50	100
7.	0.33	0.66	12	50	100
8.	0.33	0.66	3	100	100
9.	0.33	0.66	3	150	100
10.	0.33	0.66	3	200	100
11.	0.33	0.66	3	50	125
12.	0.33	0.66	3	50	150
13.	0.33	0.66	3	50	200

4. Experimental Results

Based on the pre-mentioned evaluation metrics and the simulation setting, this section will show the average NDS, HV and C-metric for all the scenario as shown in Fig. 4, 5 and 6 respectively. As shown in Fig. 4, both scenario 9 and 10 have achieved the highest value of average NDS compared to other scenarios. Similarly, in Fig. 5 scenarios 9 and 10 have obtained the highest average value of HV compared to the other scenarios. Finally, in terms of C-metric Fig. 6 shows the average outperformance for each scenario. Basically, the set coverage metric is associated with comparison among the scenarios for example, scenario 1 will be compared with all the other scenarios based on C-metric. Hence, Fig. 6 shows how many time scenario 1 has outperform the other scenario. In this regard, it is obvious that both scenario 9 and 10 have showed the maximum outperformance over the other scenario.

In order to justify the outperformance of both scenario 9 and 10 for all the metrics against the other scenarios, it is necessary to examine the parameters of these scenarios (See Table 1). One would notice that both scenario has larger number of solutions. This means that increasing the number of solutions in the algorithm would significantly facilitate discovering more areas in the search space which lead to acquire better non dominated solutions.

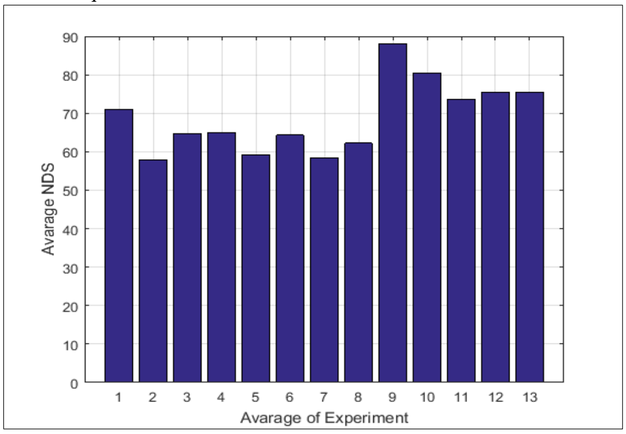


Fig. 4: Average NDS for all scenarios

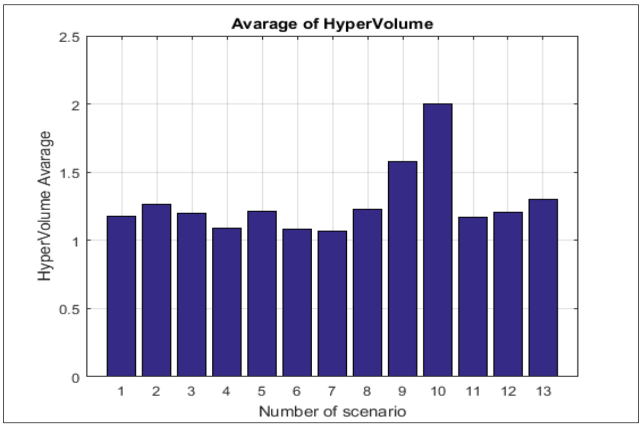


Fig. 5: Average HV value for all scenarios

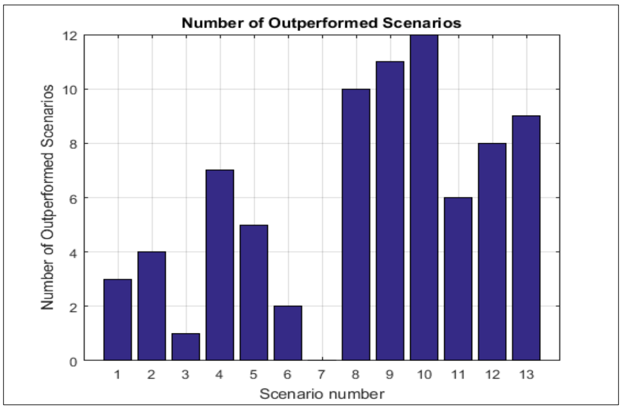


Fig. 6: Average C-metric for all scenarios

Now, in order to declare the novelty of the proposed method, it is necessary to accommodate a comparison against the state of the art. For this purpose, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) will be applied in contrast to the proposed method. 10 experiments have been conducted using both algorithms. Note that, the proposed method will be applied using the parameters of scenario 10 (see Table 1) which demonstrated the best performance. While the parameters of NSGA-II can be depicted as in Table 2.

Table 2: Parameters of NSGA-II

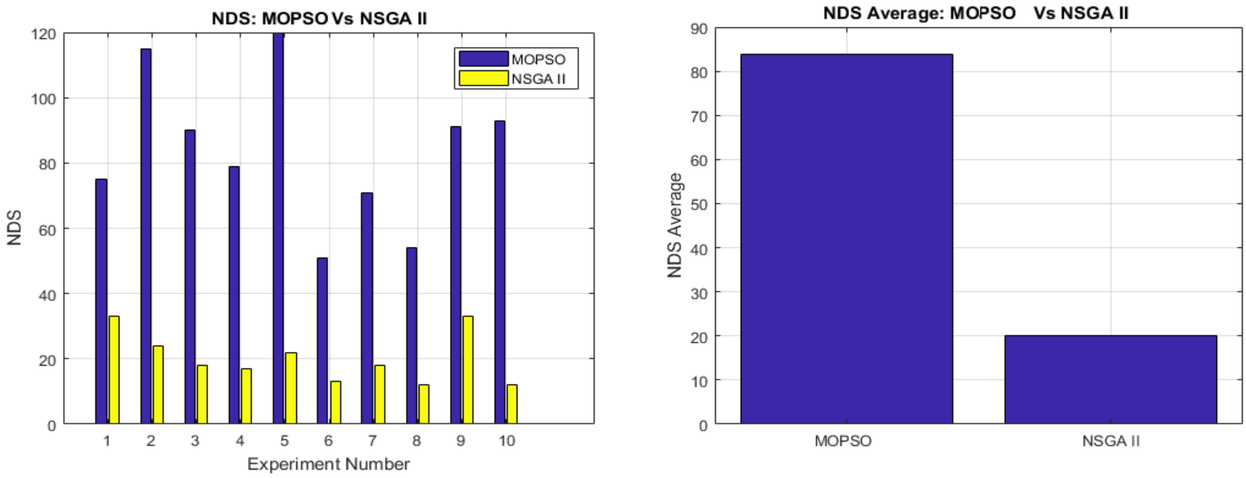
Number of solutions	200
Number of generations	100
Crossover probability	0.85
Mutation probability	0.01

In terms of the NDS, the proposed MOPSO has outperformed the NSGA-II for all the ten experiments as shown in Fig. 7(a). This lead to an average NDS produced by MOPSO higher than the one produced by NSGA-II as shown in Fig. 7(b).

In terms of HV, the proposed MOPSO has outperformed the NSGA-II for the majority of the experiments (except for experiments 1, 2, 3, and 5) as shown in Fig. 8(a). However, the average HV of both algorithms has shown a superiority for the proposed MOPSO over the NSGA-II as shown in Fig. 8(b).

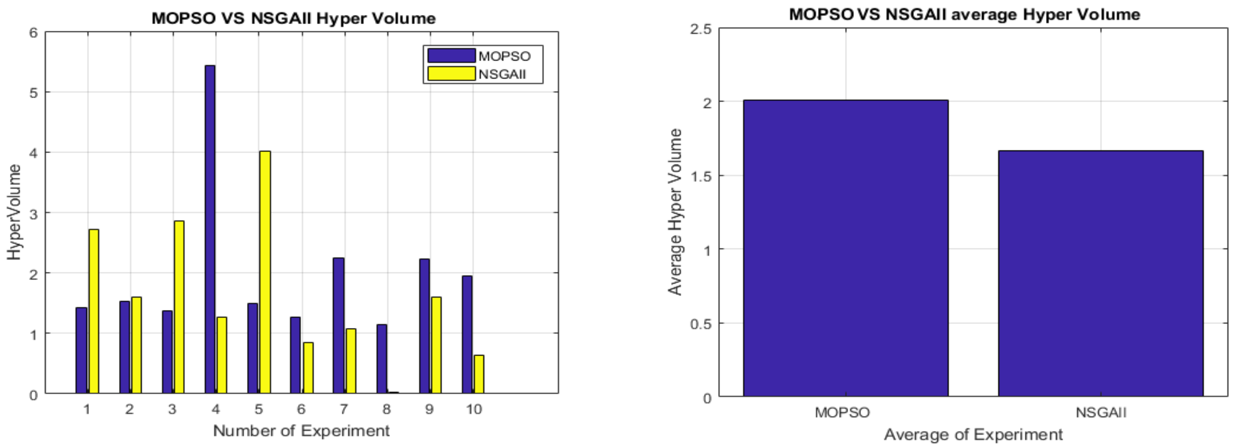
Finally, in terms of the C-metric, the set coverage of NSGA-II in accordance to the MOPSO has greater values than the set coverage of MOPSO over NSGA-II as shown in Fig. 9. This means that the proposed MOPSO has better performance based on C-metric.

These results have demonstrated that the proposed MOPSO has the ability to provide efficient coverage with the minimum number of sensors. This would assure the balance among the connectivity and coverage [21].



(a) (b)

Fig. 7: (a) Results of NDS for each experiment conducted by both MOPSO and NSGA-II, **(b)** Average NDS for all experiments conducted by MOPSO and NSGA-II



(a) (b)

Fig. 8: (a) Results of NDS for each experiment conducted by both MOPSO and NSGA-II, **(b)** Average NDS for all experiments conducted by MOPSO and NSGA-II

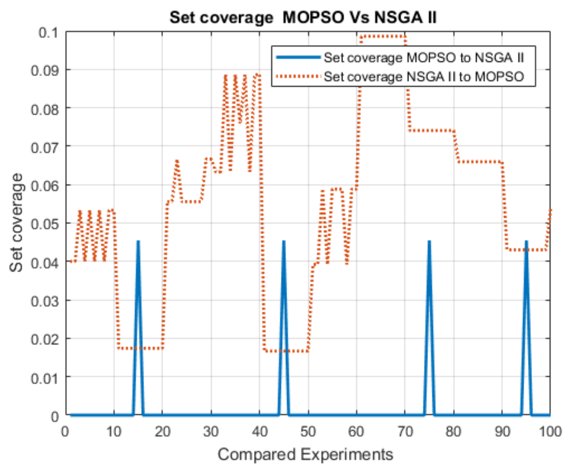


Fig. 9: Set coverage of MOPSO in accordance to NSGA-II and vice versa

5. Conclusion

This study has addressed the problem of trading-off among the connectivity and coverage within wireless sensor networks toward efficient deployment. This has been accomplished by proposing a Multi-Objective Particle Swarm Optimization (MOPSO). The proposed method has intended to minimize the number of nodes while preserving the maximum area coverage. Different experiments have been yielded in order to examine various parameters of the proposed algorithm. Once the best practice has been identified from the experiments, a comparison with the state of the art has been performed. Results showed an outperformance of the proposed method. For future direction, examining the dynamic WSN or the mobile WSN would be a challenging task.

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