Efficient Deployment Approach in WSNs Using Heuristic Technique

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Abstract

Several researchers have paid attention to designing deployment algorithms in WSNs. In fact, there are many different ways to deploy sensors in sensors' fields. Selecting one of them mainly is based on the application for which WSN design. However, two main factors should be considered when designing a deployment approach in WSN: coverage and connectivity. In this paper, we present a genetic algorithm (GA) to enhance the sensor deployment in WSNs while concurrently improving the coverage and connectivity rate. The most popular deployment approach is to deploy sensor nodes randomly in the field. Although this approach is simple and easy, it may not achieve good results. In the proposed GA algorithm, the metaheuristic algorithm is used to deploy sensors. Simulations demonstrate that GA achieves a good deployment result compared to other research papers by ensuring maximum network coverage and connectivity rate by achieving efficient coverage and connectivity.

Keywords: WSN; Nodes deployment; Connectivity; Coverage

1. Introduction

A wireless sensor network (WSN) is a distributed network of sensor nodes deployed in a spatially diverse manner to facilitate data gathering, analysis, and transmission of diverse data formats. WSN nodes suffer from many limitations: small communication range, limited energy, low coverage, and/or redundant node deployment [1][2]. However, communication range and power unit capacity are manufacturing factors, and they are out of the scope of this study. Coverage indicates that a given WSN can gather data from anywhere in the targeted area based on the sensing range and number of deployed nodes. At the same time, redundancy means a high ratio of nodes overlapping by the term of sensing range. Connectivity indicates that any node in the given WSN should always have neighbor nodes within its communication range. Without missing that node, communication range is different from node sensing range. Optimizing these issues has always been the most significant interest of researchers in this topic. In WSNs, the problem of coverage optimization is to ensure there are no blinded holes inside a designated monitoring region [18]. While connectivity optimization is to ensure all nodes can deliver data to the sink node somehow [19], both coverage and connectivity measure how well the wireless sensor network is performing its intended purpose. An efficient node placement design has the potential to significantly enhance network performance as well as reduce costs [3]. Placing sensor nodes randomly throughout the targeted monitoring region typically results in low coverage and connectivity [16], while deterministic deployment is a strategic approach aimed at optimizing coverage while minimizing resource use [17]. Expanding WSN coverage is crucial for the future growth of the applications of wireless sensor networks. Heuristic techniques provide promising solutions for multi-variable optimization. Based on techniques such as particle swarm optimization PSO, genetic algorithms GA, and ACO ant colony optimization, etc., various approaches have been developed by the literature. Most of these approaches take into consideration the optimization of the proposed distribution plan only, neglecting how these virtual plans are projected using available techniques. In this study, both planning and deploying are optimized and evaluated using simulation. This introductory section constitutes one of six segments comprising the remaining content of the article. The second section delves into pertinent literature. Section 3 demonstrates metaheuristic algorithms. A proposed algorithm is delineated in the fourth section. The fifth section

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offers a detailed examination of the results obtained. The final section, Section Six, elucidates and draws conclusions from the primary concepts discussed.

2. Related Work

Numerous methodologies have been suggested by scholars to tackle the deployment of sensors in Wireless Sensor Networks (WSNs), a predominant challenge within the realm of WSNs that stands as a critical concern. In [4], Frantz Tossa et al. introduced a genetic algorithm to determine the optimal placement of sensors to achieve effective network coverage over a two-dimensional Euclidean area with a given number of sensors. In [5], Birtane, S., Sahingoz, O. K., & KorkmAZ, H., employed a technique known as the vibrational genetic algorithm to enhance the efficiency of sensor node placement. In an unevenly shaped area, using heterogeneous sensor nodes is chosen over other research in order to maximize the coverage rate. The experiment findings show that, in more realistic and complicated application scenarios, the suggested approach provides an efficient means of attaining maximum coverage. In [6]. Akram, A., et al. addressed the layout optimization problem using the meta-heuristic multi-objective firefly method (MOFA). Here, they examined a number of goals related to the optimal design for homogenous WSNs, including coverage, connection, longevity, consumption of energy, and the sensor node number. Simulation studies demonstrated that MOFA generated optimal Pareto front of non-dominated solutions with enhanced hyper-volumes and spread of solutions when compared to particle swarm optimizers (OMOPSO, SMOPSO) and multi-objective genetic algorithms (IBEA, NSGA-II). Therefore, MOFA can be used to increase the large-scale WSNs' quality of monitoring and detecting power in real-time deployment applications. In [7]. Barnawi, A., and A. Bawazir proposed two heuristic optimization methodologies, namely (BPSO) binary particle swarm optimization and genetic algorithm (GA), for the three-dimensional multi-objective deployment of wireless sensor networks (WSNs). The node sensors, clusterheads, and base station that make up the proposed WSN's two-layer hierarchy and multidimensional (3-D) structure. Finding an ideal or nearly ideal clusterhead placement is the goal in order to meet the intended goals. According to experimental findings, if the three objectives are taken into account, the suggested strategy can improve network deployment. In [8], Singh, A., et al. delved into the investigation of optimization methodologies for achieving optimal coverage within wireless sensor networks through the utilization of nature-inspired algorithms. The integration of Lion Optimization (LO) with the Binary Ant Colony Algorithm and Enhanced Genetic Algorithm was carried out. Findings indicated that LO exhibited a superior convergence rate and enhanced network coverage, accompanied by reduced generation counts. In [9], Shuming Sun et al. proposed a combination of the GA and (RWOA) reinforced whale optimization algorithm to maximize the effectiveness of algorithm exploration and development. In [10], Sibel Birtane et al. presented the vibrational genetic algorithm as a new method to more effectively optimize the positioning of sensor nodes. Heterogeneous sensor nodes are the best option to enhance the area's coverage rate. In [11], Bader Alshaqqawi et al. suggested a novel optimization method that combined the Particle Swarm Optimization (PSO) algorithm and a greedy technique. The greedy algorithm is a crucial component to provide effective guidance during PSO convergence. It supports the PSO algorithm with the required information to efficiently alleviate the complexity of the PSO search space and locate RNs in the spots of critical significance. Vahid Kiani et al. [15] presented a (BVFPSO) bi-objective virtual-force local search PSO algorithm to decrease sensor battery energy consumption while increasing coverage rate. In this study, it has been tried to ensure maximum coverage and connectivity of the wireless sensor network using a genetic algorithm by simulating the plan of best location of sensor nodes and simulating them in a real environment.

3. Methodology

This section describes in detail the phases of proposed system, the deployment phase and finding the best plan of it , the grid based deployment and the evaluation phase of the model ,as shown in figure 1.

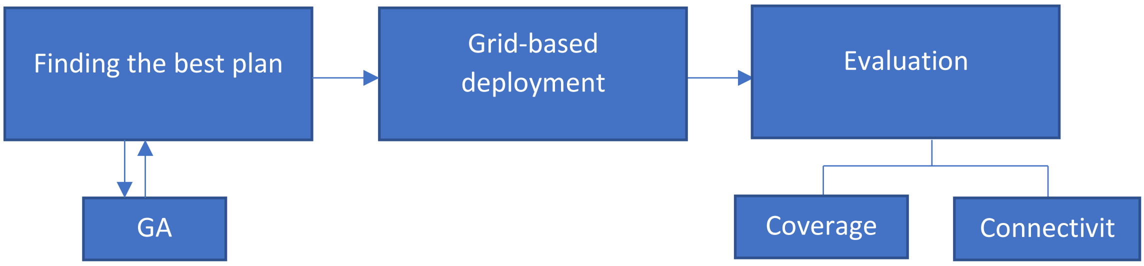

Figure 1. Proposed system's phases

1. Finding the best plan phase

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Deploying nodes uniformly at random in a specific area (W×H) m2. It is necessary to deploy a sink. The sink node should be represented by one of these sensor nodes, which should be placed in the center of the area. As shown in Fig 2., the sink node is represented with a pink color, and the unknown nodes are represented with a circle shape and a white color. In this deployment, the results are unsatisfactory, so we apply the GA as an optimization method to get the best coverage and connectivity.

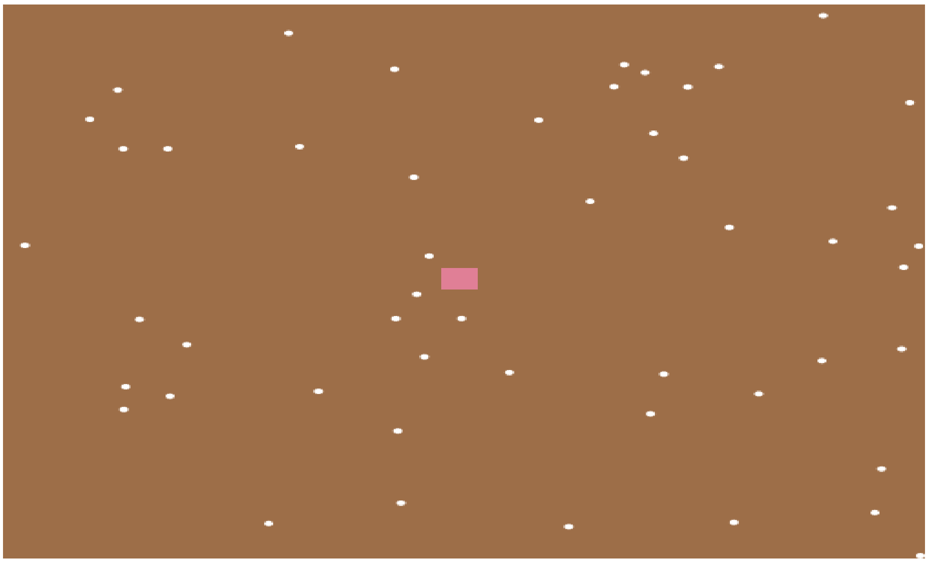

Figure 2. Deployment Sensor Nodes

A. **Genetic Algorithm**

The GA algorithm is an evolutionary technique for optimization issues. GA uses Darwin's natural selection basics to find the best formula to predict or anticipate the model. In general. GA are based on iteration, with most of the parts being selected as random methods. In nature, superior generations outcome from the better chromosome's combination. There are sometimes mutations in the chromosomes to enhance the next generation, which can also be used to solve problems. GA begins its entire procedure with random samples. Each sample represents a possible solution to the problem. All samples are evolved via sequential iterations, called generations, and assessed each generation in relation to fitness criteria. Genetic operators and the iteration process continue until the desired state is attained to create the population that follows the next generation [20]. Stochastic algorithms incorporate unpredictability into their search processes. This increases the likelihood of discovering a global optimum by enabling them to break out of local optima and investigate new areas of the solution space. Genetic algorithms simulated annealing, ant colony optimization, particle swarm optimization, and tabu search are a few examples of well-known metaheuristic algorithms. Metaheuristic algorithms have, effectively solved many optimization issues, including scheduling, routing, resource allocation, machine learning, and engineering design. Their ctivenesscan vary based on the problem and parameter settings, sothey cannot be relied upon to discover the best answer. Consequently, it is critical to assess and optimize metaheuristic algorithm performance for individual problems. To sum up, metaheuristic algorithms are effective instruments for optimization. GA is an optimization and search technique that imitates natural selection. GAs try to find the best solution within a search area by utilizing methods including crossover, mutation, and natural selection. GAs often tackle complex optimization problems such as resource allocation, route optimization, mission scheduling, and node placement. [11, 12, 13, 14] In GA, the efficiency of the algorithm is immediately impacted by the genetic operator choices made, and the algorithm's performance is directly impacted by the genetic operator design. Inadequate genetic operator design can cause the algorithm to become unstable and even stop trying to converge on the best answer. The most fundamental and significant genetic operations in GA that establish an individual's fitness within a population are selection and crossover. Several people can be combined through cross operations to increase group variety. Manipulating variations can increase population fitness on an individual basis. The algorithm's performance is directly impacted by the way genetic operators are designed in GA.

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Algorithm 1 Genetic Algorithm

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Input:
        size of population, n
        max iterations number, max
Output:
        best global solution, Ybt
begin:
generate initial population of n chromosomes Yi (i=1,2,3,...,n)
set iteration counter t = 0
Compute the fitness value of each chromosomes
Th
While (t < Max )
Select two chromosomes from old population with best fitness
Apply crossover operation on selected pair with crossover probability
Apply mutation on the offspring with mutation probability
Replace old population with newly generated population
Increasing the current iteration t by 1 .
End while
Return the best chromosome, Ybt
End
```

2. Grid-based deployment phase

In this phase, we divide the area into a grid and compute the sensor nodes in each grid that were deployed in the first phase and use a drone as a deploying tool that moves on the entire field and deploys a number of sensor nodes in the grid. Evaluate the result of this phase by two factors: coverage and connectivity.

3. Evaluation phase

In a WSN, the evaluation phase is extremely important for assessing the network's performance and ensuring its effectiveness in monitoring and gathering data. Two key metrics in this phase are coverage and connectivity.

4. Proposed Genetic Algorithm based Deployment Approach GAbDA

To address the issue of node deployment, we proposed a genetic algorithm-based deployment approach, GAbDA.

In this section, we suggested a GAbDA algorithm in this study. The goal of the suggested algorithm is to maximize the sensor nodes' coverage and connectivity rate. Combining these objectives in one objective function, a good balance between these two goals can be obtained. GAbDA is a bi-objective memetic algorithm. In a memetic meta-heuristic algorithm, in addition to collective evolution mechanisms such as recombination and crossover, individuals in a population have the opportunity to improve themselves with the local improvement mechanisms. The basis of this approach is a few basic concepts. First, it starts with a random selection of individuals from the population, each individual representing an alternative answer to the problem. Each solution appears as a phenotype and is coded by genotype or chromosomes. After that, create an evaluation function (fitness) that finds out the phenotype with the best performance. Most likely, these latter could use their genotype on the next generation. Genetic operators are known as those rules that govern this gene transmission. These include three operators: The selection operator that specifies the procedure used to pick the candidates for recombination; the primary operator, crossover, matches the process of combining the parents in a certain order to produce offspring; the mutation operator is a tool for increasing population variety. We represented a chromosome in the proposed genetic algorithm as a set of n sensors with distinct geographic coordinates. A chromosome's structure is seen in Fig 3. Method, find the optimal solution for the following linear programming problem (1):

Sensor 1		Sensor 2			Sensor n	
X_1	Y_1	X_2	Y_2	....	X_n	Y_n

Figure 3. Chromosome representation

A crossover operation performs genetic recombination of parent chromosomes taken after selection to form new chromosomes. The selection phase is crucial for determining which individuals from the current population will be chosen to breed and produce the next generation. Roulette wheel selection was chosen in this study. Roulette

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wheel selection represents a fundamental technique in the field of genetic algorithms that finds the right balance between exploration and exploitation. It biases selection towards the fitter individuals but keeps some level of randomness in it. The view of inner mechanics will provide a deeper understanding of how genetic algorithms can be applied to optimization problems. In this study, other individuals were formed from the axis using the uniform crossover technique for crossover. In this technique, several genes are assumed to be taken from both parents at random, and one new individual is formed. In GA a crossover probability, pc is first specified. This probability shows how many times the crossover will be performed in a population. Fig 4 shows the crossover operation.

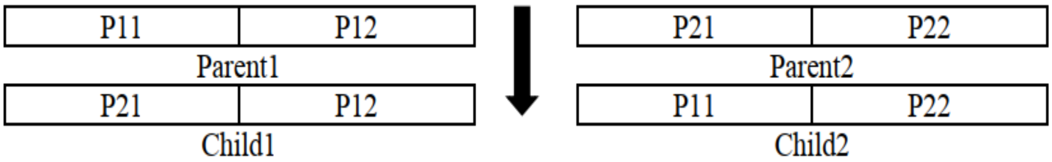

Figure 4. Crossover process

The mutation operator, applied to any solution in the population, randomly selects a sensor and mutates its position (x,y), enhancing population diversity and exploring the search space. Fig.5 demonstrate the mutation process.

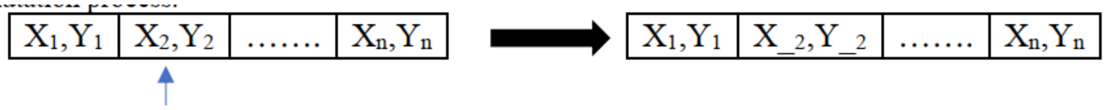

Figure 5. Mutation process

The fitness function demonstrates how well the solutions are solved. The fitness function is not the same for all the problems. In this case, the fitness function is aimed at selecting the best, most appropriate chromosome to augment the coverage and the connectivity of the WSNs. In this work, it evaluates coverage and connectivity with a specific weight. The sensing range Sr of the sensor node and the point coverage are also reflected by a. The point covering is located within the area contains at least one of the nodes distributed within the area, as seen in Equation (1). It is possible to integrate coverage with connectivity in equation (2) into one single seamless form. However, data and the results obtained about each of them are different in significance; this means merging two objective functions together called multi-objective function. The values of the objects must be normalized and checked to make sure they are between 0 and 1 in order to create a single multi objective function with both objectives. Then assign weights to each of the objectives as per the application rationale and objectives. Equation (3) explains weighted multi-objective function.

$$Net_{coverage} = \sum_{\substack{i=1 \\ j=1}}^{n,m} 1 \quad if\ d(a_{i,j}, s_{k,l}) > Sr \qquad (1)$$

Where a is point in the field and s is sensor.

$$Net_{connectivity} = \frac{\begin{cases} 1, & if\ \exists\ p\ from\ si\ to\ sink \\ 0 & otherwise \end{cases}}{s} \times 100 \qquad (2)$$

Where p is path.

$$Fitness\ Fun = Net_{connectivity} * W_1 + Net_{coverage} * W_2 \qquad (3)$$

Where W1+W2=1

The advantage of employing weighted multi-objectives is the ability to manipulate the weights of objectives such that you create biased solutions towards certain objectives over the others. While a balanced solution is produced by giving equal weight for the objectives.

5. Results and Discussion

The proposed deployment algorithm, GA, is simulated using NetLogo version 6.3. The GA and simulation parameters are set according to Table 1.

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Table 1: Values of the Genetic Algorithm and Simulation Parameters

Parameter	**value**
Population size	20
Number of genes or sensors	25,50,75
Crossover method	Uniform Crossover
Probability of Crossover	0.2
Mutation method	1X Mutation
Probability of Mutation	0.01
Iterations	20
Network size	100*100 m^2
Number of sink nodes	1
Communication range	20 m
Sensing range	10 m
Patch size	1*1 m^2

In the finding best plan phase, we chose sensor locations uniformly at random for set sensors of (25, 50, and 75) with communication range (CR) = 20 m and sensing range (SR) = 10 m. Fig. 6 shows the relationship between coverage, connectivity, and the number of sensors (# sensors). Different experiments are conducted with a set number of sensors set at (25, 50, and 75). The result shows that increasing the node number causes an increase in coverage and connectivity. The optimized deployment of sensors is the reason for increasing coverage and connectivity.

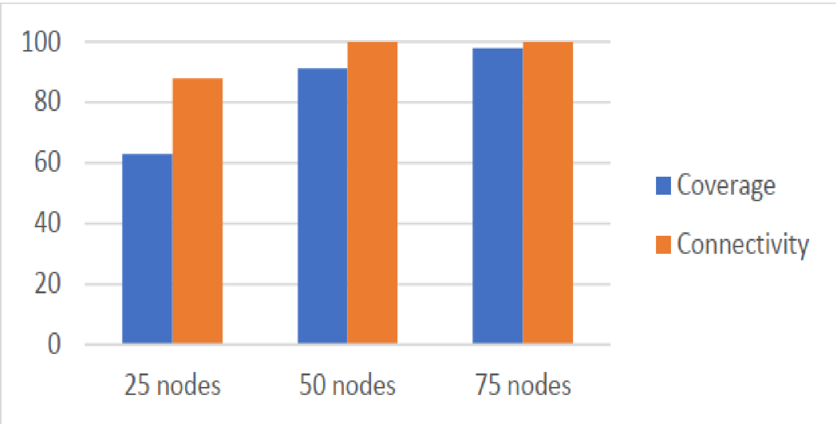

Figure 6. The Relationship between # sensors, coverage, and connectivity after GA

Fig. 7 illustrates the relationship between coverage, connectivity, and # sensors in the grid-based deployment phase. For the deployment approach, we suggest using a drone that moves to distribute the sensors in the best positions of virtual deployment after applying GA as an optimization method to optimize the coverage and connectivity of the network to get the best position to apply the grid-based deployment. The distribution process is affected by the way, in which sensors are dropped in the field and the path taken by the drone. In addition, we find the result that shows getting optimal coverage and connectivity with the same parameters of finding the best plan.

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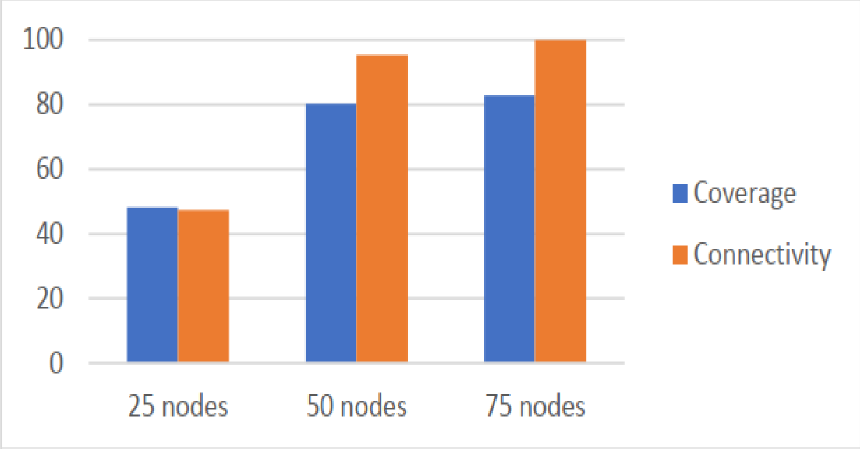

Figure 7. The Relationship between # sensors, coverage, and connectivity before GA

Fig. 8 shows that increasing the number of nodes led to a gradual increase the coverage in the finding the best plan phase of the proposed system.

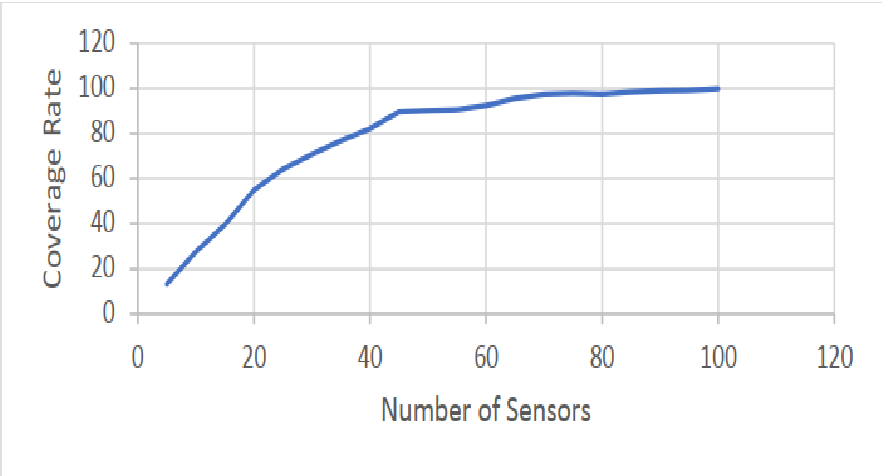

Figure 8. The relation between # sensors and the coverage in finding the best plan phase

Table 1: Values of the Genetic Algorithm and Simulation Parameters

Algorithm	Year	# sensor	Coverage	Connectivity
GA BPSO	2023 [7]	200	————	97 100
BVFPSO	2023 [15]	30 40 50 60	78 91 98 10	————
GA Algorithm	2024	25 50 75	58.64130967552201 85.62885991569455 87.56004313302618	73.91304347826086 93.47826086956522 98.36065573770492

6. Conclusion

In this paper, a genetic algorithm-based deployment approach (GAbDA) was proposed to deploy sensor nodes of the WSNs. It considers two objectives: optimizing the wireless sensor network's coverage and connectivity rate.

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The simulation results showed that, when compared to the competing techniques, the proposed algorithm provides a more efficient deployment. In our work, applying the deployment, we get a distribution plan of the best location of sensors in the WSNs and simulate it as grid-based deployment; however, we do not take the energy consumption of the distributing tool (drone) and time into account.

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