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ORIGINAL RESEARCH

An improved dynamic deployment technique based-on genetic algorithm (IDDT-GA) for maximizing coverage in wireless sensor networks

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Abstract
Recently, many researchers have paid attention to wireless sensor networks (WSNs) due to their ability to encourage the innovation of the IT industry. Although WSN provides dynamically scalable solutions with various smart applications, the growing need to maximize the area coverage with decreasing the percentage of deployed sensor nodes is still required. Random deployment is preferable for large areas that require a maximal number of nodes but result in coverage holes. As a result, mobile nodes are used to reduce coverage holes and maximize area coverage. The main objective of this study is to present an Improved Dynamic Deployment Technique based-on Genetic Algorithm (IDDT-GA) to maximize the area coverage with the lowest number of nodes as well as minimizing overlapping area between neighboring nodes. A two-point crossover novel is introduced to demonstrate the notation of variable-length encoding. Simulation results reveal that the superiority of the proposed IDDT-GA compared with other state-of-the-art techniques. IDDT-GA has better coverage rates with 9.69% and a minimum overlapping ratio with 35.43% compared to deployment based on Harmony Search (HS). Also, IDDT-GA has minimized the network cost by 13% and 7.44% than Immune Algorithm (IA) and Whale Optimization Algorithm (WOA) respectively. Besides, it confirms its stability with 83.04% compared to maximizing coverage with WOA.

Keywords Coverage · Deployment techniques · Genetic algorithm (GA) · Whale optimization algorithm (WOA) · Wireless sensor network (WSN) · Quality of service (QoS)

1 Introduction

Wireless sensor networks (WSNs) (Ezhilarasi and Krishnaveni 2018) are a group of sensor nodes with limited processing and low power capacity (Su and Zhao 2017). These nodes are spatially scattered in an ad-hoc manner for collecting physical information from the surrounding environment and relaying collected data to the sink node as well. Different environmental conditions can be recorded by WSNs such as sound, wind, pressure, room temperature, humidity, and pollution level. On other hands, WSNs heavily affect real-time applications (Sengupta et al. 2013), which comprises intelligent transportation systems (ITS), security monitoring, military surveillance, battlefields , health care, transportation, environmental monitoring, industrial monitoring (Aponte-Luis et al. 2018), and agriculture.

As a part of the WSNs scenario, the environmental applications which aim to track and record the environmental changes, whether indoor or outdoor. The indoor applications may fall into the category of urban applications (including

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pollution, healthcare, and lighting tracking). By contrast, outdoor applications involve open nature surveillance [(e.g. chemical and biological risks, volcanos, earthquake, and flood detection, and weather forecasting, habitat tracking, transportation, agriculture monitoring, and underwater exploration applications (Priyadarshini and Sivakumar 2019)] (Ali et al. 2017). Besides, WSNs play an efficient role in remote and catastrophe monitoring such as military applications (Mahamuni 2016). Sensor nodes in military applications are randomly deployed (Tian 2019) in the target field which results in areas of varying density. Therefore, maximizing sensing area coverage is an essential requirement.

Many challenges and issues are facing WSNs such as the limitation of equipped battery power, memory, processing and communication cost. Moreover, sensor nodes are subject to failure due to a lack of manufacturing, environmental, weather conditions, and drain battery power (Bala et al. 2018). As a result, Deploying a sufficient number of sensor nodes to maximize area coverage is considered as a critical issue for implementing WSNs (Tripathi et al. 2018). Currently, deployment techniques can be found in (Banoori et al. 2018; Boualem et al. 2018) which classified them into random deployment, deterministic and semi-random deployment techniques. In the case of sensor nodes are drawn randomly from aircraft in large open and hostile environments such as earthquakes, oceans, and volcanoes, random deployment techniques are usually used. However, it may result in areas with different densities and coverage holes. Therefore, random deployment is not guaranteed for achieving maximum coverage. In deterministic deployment sensor nodes positions are fixed, and it is used in small areas (indoor) environments. It minimizes network cost, network lifetime and guarantees maximum area coverage. Semi-random deployment is a hybrid deployment that gathers the advantages and minimizes the drawbacks of random deployment and deterministic deployment.

Every sensor node has a sensing range (r_s) which influences area coverage and communication range (R_c) that indicates communication between nodes. The area is fully covered (More and Raisinghani 2017) if and only if every target point in the monitoring area is covered by at least one sensor (within r_s). Besides, sensor nodes are connected and sharing data with their neighbors which are located within their communication range to ensure connectivity. Coverage and connectivity are considered measures of WSN's quality of service (QoS). In most cases, to achieve maximum coverage, a massive number of sensor nodes are required. Based on the nature of the application, coverage has many types (Nehra et al. 2019) including area coverage, point of interest coverage and barrier coverage (Khoufi et al. 2016). The area coverage has two types, full area coverage and partial area coverage (Hanh et al. 2019). The main coverage challenge as to how to deploy the minimum number of sensor nodes that achieve maximum area coverage (Jha and Eyong 2018). Maximizing coverage is considered as Non-deterministic Polynomial-time hard (NP-hard) problem (Gupta et al. 2016).

Depending on the nature of the application, nodes can be mobile, static, heterogeneous (Mostafaei and Obaidat 2017) or homogeneous (Singh and Sharma 2014). In the case of deploying static nodes, their position is fixed and may be deployed randomly or deterministically according to the requirements of the application. Lack of mobility in static nodes takes advantage of saving cost and energy. However, during the operation of WSN, few sensor nodes expire because of energy depletion and the area coverage can be partially broken down. This is called a coverage hole, Fig. 1 shows an example for the coverage hole. Therefore, mobile nodes are moved to fill up those holes. Mobile nodes are usually deployed randomly after the initial deployment of static nodes. But, the mobility feature consumes more battery power and increase implementation cost (Chien et al. 2012). Regardless of sensor type, coverage and connectivity techniques can be classified into three main categories (Farsi et al. 2019): classical deployment strategies, meta-heuristic strategies, and self-scheduling strategies.

Determining the optimal sensor nodes locations within the area helps in achieving maximum coverage of the target area. Hence, coverage maximization is considered as an optimization problem, which can be solved with soft computing tools. There are many researchers focused on meta-heuristic based techniques because they can achieve high stability and performance for WSNs. Besides, meta-heuristic techniques can optimize multi-objective functions like power consumption, coverage, and connectivity. Therefore, the main contribution of this paper is to investigate an Improved Dynamic Deployment Technique based on Genetic Algorithm (IDDT-GA), which guarantees maximum coverage with a minimum number of nodes. Reducing the amount of deployed nodes directly impacts the reduction of network costs. Rather than using additional and redundant nodes that boost costs, IDDT-GA uses sufficient nodes to cover the entire region. Besides, an efficient derivation for an objective function is presented that ensures two main objectives. The first objective is maximizing area coverage. The second objective is minimizing the number of sensor nodes that contributes to minimizing the overlapping area between sensor nodes. Also, random deployment is considered for implementing the system. Random deployment produces regions of variable intensity, high-density regions while others with lower intensity but rich in data that may be lost owing to lack of optimum coverage. Therefore, the mobility feature is used to eliminate coverage holes and increase area coverage. Furthermore, connectivity between nodes is considered to guarantee 1-connectivity between sensor nodes. An implementation is performed based on GA with an improved two-point crossover for making the chromosome length adaptive and

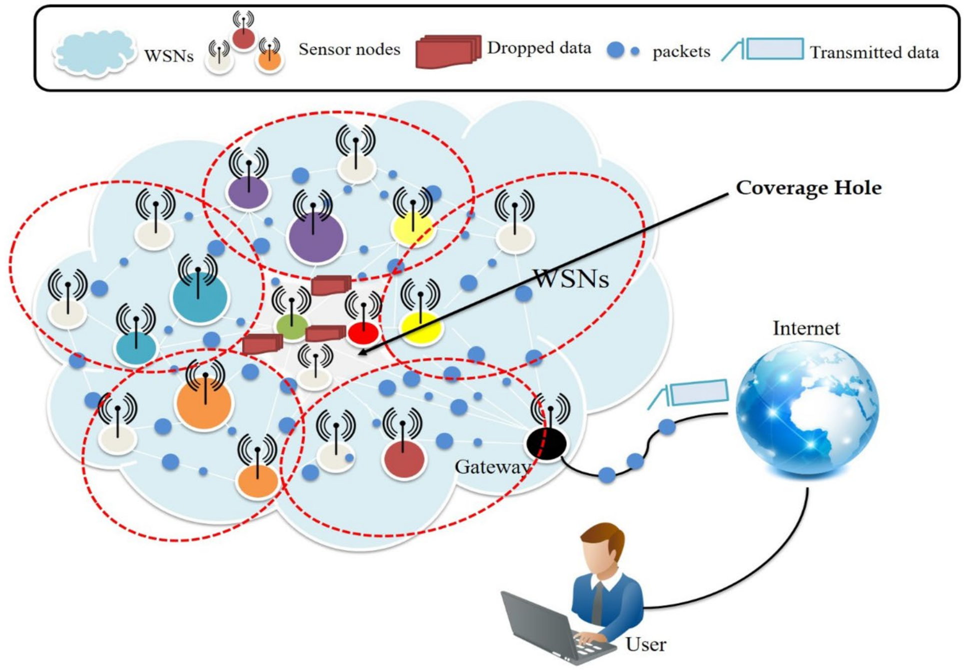


Fig. 1 An example of coverage hole

allows the algorithm to search for the minimal number of sensor nodes that could be able to cover the area. The simulation results prove the superiority of the proposed IDDT-GA over the related state-of-the-art techniques.

The main contributions of this paper can be summarized as follows:

- Proposing a deployment technique based on the GA algorithm that achieves maximum coverage with a minimum number of nodes.
- An improved two-point crossover is introduced to adapt the length of the chromosome and permit GA to search for the minimal number of sensor nodes that maximizes the area coverage.
- Ensuring 1- connectivity between sensor nodes.
- Deriving an efficient objective function with two main objectives, maximizing coverage and minimizing the number of sensor nodes.

This paper is organized as follows: Sect. 2 summarizes the related work. Section 3 presents the problem formulation. Section 4 illustrates the proposed IDDT-GA technique. Section 5 provides the simulation results and comparisons. Section 6 concludes the paper.

2 Literature review

Node deployment techniques are considered one of the most significant techniques to enhance WSN coverage. Even though there are many kinds of research conducted on the node deployment problem of WSN, efforts still needed so that a unique solution can be realized. Random deployment techniques can use hybrid nodes (static and mobile nodes) or use mobile nodes only (Sharma et al. 2016). In both cases, optimization techniques can be used to determine the best node locations that maximize area coverage and ensuring connectivity to the sink node. A considerable number of meta-heuristics are used to solve this problem with different methods.

The dynamic deployment problem using mobile sensor nodes is employed with Artificial bee colony (ABC) algorithm in (Öztürk et al. 2012). Their investigated algorithm has high performance in area coverage maximization. However, they do not give attention to nodes connectivity with the sink node or network cost. Abo-Zahhad et al. (2014) proposed coverage maximization for WSNs using Immune node deployment algorithm (CM-IA). An objective function considering maximizing area coverage and minimizing energy consumption is derived. As node mobility consumes more power, this power is minimized through the reduction of root mean squared moved distances for all sensor nodes. Simulation results showed that their algorithm outperforms other algorithms in terms of the coverage area and the redundant covered area. Besides, it minimizes the moving consumed energy per each node. However, it did not ensure network connectivity or achieving coverage with the minimum number of deployed nodes.

Ensuring k-coverage and m-connectivity between sensor nodes using a genetic algorithm in target-based WSN introduced in (Gupta et al. 2016). Their proposed algorithm provided representation for each chromosome as 0 and 1 string with the same length of the number of potential positions. Besides, the derivation for an efficient fitness function is presented, which guarantees coverage and connectivity up to 3 and 2 for k and m respectively. Besides, their proposed algorithm is simulated with various WSNs scenarios with variation in the number of potential positions. The proposed algorithm proves its superiority with the minimum number of selected potential positions compared to a greedy approach (Rebai et al. 2015).

Moh'd Alia and Al-Ajouri (2017) proposed a Harmony Search (HS)-based deployment technique that maximizes coverage with minimum nodes deployed deterministically in the target area. For the representation of a variable number of nodes in each candidate solution, a variable-length encoding is used. Besides, the coverage ratio, a distance between sensor nodes, and the number of deployed nodes were the main terms of the derived fitness function. The proposed technique proved its effectiveness, stability, and superiority in achieving full coverage with minimal cost compared to GA. However, connectivity and consumed power per node didn't consider.

El Khamlichi et al. (2017) investigated a hybrid deployment technique for WSNs with a minimum number of nodes for both barrier and area coverage problems. It is a hybrid of simulated annealing (Du and Swamy 2016) and a gradient algorithm. This technique has achieved 1- coverage and 1- connectivity for small and large maps, with size 100×100 pixels and 500×500 pixels respectively. Also, it has the ability for optimizing nodes' locations, nodes count, and guarantee the highest coverage to meet application requirements.

Mobile nodes with random deployment presented in ÖZDAĞ and CANAYAZ (2017). It proposed a dynamic deployment algorithm using a whale optimization algorithm for coverage ratio optimization (MADA-WOA). Besides, MADA-WOA achieves more optimal coverage rates with a minimum number of nodes compared to the maximum area detection algorithm based on electromagnetic (MADA-EM). Moreover, it has fast convergence and high stability. Although, this algorithm did not draw attention to network connectivity.

Coverage maximization with a Firefly optimization algorithm for mobile WSNs introduced in Tuba et al. (2017). The proposed algorithm contributed to minimizing nodes' power consumption by reducing the root mean of the sum squared moved distances of all nodes as the same as Abo-Zahhad et al. (2014). Furthermore, simulation and comparisons with other state-of-the-art techniques prove the superiority of Firefly with maximum coverage and less power consumption.

Enhanced Cuckoo Search and Chaotic Flower Pollination are proposed in Binh et al. (2018) for maximizing area coverage with heterogeneous sensor nodes. The results of experiments demonstrated the strength of these two algorithms in computational time, fast convergence and in the reliability of the solution compared to the state-of-the-art.

To minimize the number of deployed sensor nodes, some researches focused on area partial coverage instead of area full coverage. Area partial coverage addressed cases where a small area of interest is necessary to be constantly monitored. An efficient Learning Automata-based algorithm (PCLA) (Mostafaei et al. 2016) is introduced to minimize the number of sensor nodes for covering a certain portion of the target area and maintaining sensor connectivity. Simulation results proved that PCLA can effectively choose the minimum number of sensor nodes that meet constraints imposed. PCLA ensured a good performance in terms of both the ratio of active-nodes and lifetime of WSN over state-of-the-art partial coverage techniques.

Coverage Scheduling and Power-Aware Connectivity (CSPAC) is introduced in Elma and Meenakshi (2019). Based on heterogeneous WSN, a dynamic cluster structure technique is used for grouping the sensors into clusters. The Artificial Bee Colony (ABC) optimization algorithm is used to determine the minimum active set needed for achieving the Q-coverage and ensure network connectivity. Besides, power-aware scheduling and battery discharge quality are used for maximizing the network timespan. Simulation results prove the ability of CSPAC for improving the coverage and connectivity in heterogeneous WSN with a minimum number of active nodes.

As sensor deployment has a direct impact on WSN performance and routing reliability, a new technique to optimize the deployment of sensor nodes over an area is proposed in Musa et al. (2019). They optimized the network lifetime, ensure network connectivity, and provides solutions for short-term and long-term monitoring applications. The results indicate that the proposed technique outperforms the state-of-the-art in terms of optimal positioning sensors and energy consumption follows a uniform distribution over the network.

To minimize power consumption per sensor nodes during data communication, an energy optimization in WSNs based on a genetic algorithm introduced in Jha and Eyong (2018). GA implemented on three different energy models for finding the optimal GA by selecting a proper combination of selection, crossover and mutation methods. Over 200 iterations, stochastic uniform selection method, two-point crossover and uniform mutation method with mutation rate 0.04, it achieves minimum energy consumption rates among other methods.

Briefly, state-of-the-art techniques contributions have limitations in the following points:

– Achieving maximum network coverage using different optimization techniques is considered by all of them however, to the best known of the authors, only one work has considered network connectivity between nodes.

- Maximizing coverage with a minimum number of nodes is considered by little of them, although the number of nodes affects the network's cost directly.
- Deploying sensor nodes deterministically is considered by many works, while little works interested in random deployment.
- Stability and reliability of the system were observed by a few of them, although it is an important factor in judging the performance of the system.

Table 1 provides a comparison among previous techniques, considering which of them touched the following issues: coverage, connectivity, minimizing the number of deployed nodes and power consumption per node. Besides, advantages and limitations were discussed.

Therefore, there is a crucial need for maximizing area coverage in WSNs using minimum cost besides, ensuring network connectivity between them for the success of WSN's operation.

3 Problem formulation

Maximizing network coverage in WSN is a critical issue for WSN's performance metrics. Achieving maximum coverage with a minimum number of sensor nodes is the main target for this research. Hence, maximum coverage can be realized through the optimal deployment of sensor nodes in the target area. Accordingly, this paper proposed a deployment technique based on GA for maximizing coverage for randomly deployed nodes in the target area. Assume area A with size $M \times N$ grid points and a set of WSN sensor nodes S=s_1,s_2,s_3 ,…,s_n . The binary disk model and the probabilistic sensor model (Zhu et al. 2012) are the most common models for

Table 1 Comparison among different state-of-the-art techniques

Factors	Coverage	Connectivity	Minimum number of nodes	Power	Advantages	Disadvantages
ABC (Öztürk et al. 2012)	✓	✗	✗	✗	Increase the coverage of the monitoring area	Didn't ensure network connectivity High power consumption
Immune algorithm (Abo-Zahhad et al. 2014)	✓	✗	✗	✓	Increase the area coverage Minimize the redundant area between sensor nodes	Maximize network cost
GA (Gupta et al. 2016)	✓	✓	✓	✗	Ensure k-coverage and m-connectivity with minimum number of sensor nodes	Suitable for target based-WSNs not for random deployment
Harmony search (Moh'd Alia and Al-Ajouri 2017)	✓	✗	✓	✓	Maximize area coverage with less number of sensor nodes	Designed only for deterministic deployment Didn't ensure network connectivity
SA (El Khamlichi et al. 2017)	✓	✓	✓	✗	Solve area and barrier coverage with the minimum number of sensor nodes	Complex and maximize processing time
WOA (ÖZDAĞ and CANAYAZ 2017)	✓	✗	✓	✗	Maximize area coverage with less number of sensor nodes More stable	Didn't ensure network connectivity High processing time
Firefly (Tuba et al. 2017)	✓	✗	✗	✓	Increase area coverage Minimize nodes' power consumption	Increase network cost
CSPAC (Elma and Meenakshi 2019)	✓	✓	✓	✓	Improve coverage and connectivity Minimize the number of active nodes	Not suitable for random deployment with mobile nodes
CSPAC (Musa et al. 2019)	✓	✓	✗	✓	Ensure network connectivity Maximize network lifetime	Complex

representing the coverage of sensor nodes in WSNs. Binary disk model is used in this paper that considers the sensor such as a sensing disk with radius r_s as its sensing range. Any grid point is said to be covered if and only if it is within the sensing range of the sensor. Assume that there is a sensor s_i deployed at (x_i, y_i), and a grid point p located at (x, y), the Euclidean distance between grid point p and sensor s_i is defined as:

$$d(s_i, p) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{1}$$

Where i ranges from 1 to N_s and N_s represents the number of deployed sensor nodes in area A.

Equation 2 (Zhu et al. 2012) denotes the binary disk model that represents the probability $p(x, y, s_i)$ of a grid point p is covered by sensor s_i.

$$p(x, y, s_i) = \begin{cases} 1, \text{ if } d(s_i, p) < r_s; \\ 0, \text{ otherwise;} \end{cases} \tag{2}$$

3.1 Derivation of the objective function

A multi-objective function consisting of the coverage ratio and the number of nodes is derived. First of all, nodes locations that will be randomly deployed are bounded by the lower and upper boundaries of the target monitoring area. They defined according to Eqs. 3, 4 and 5 as follows:

$$lb \le x_i \le ub_M \quad \text{where } i = 1, 2.....N_s. \tag{3}$$

$$lb \le y_j \le ub_N \quad \text{where } j = 1, 2.....N_s. \tag{4}$$

$$lb = \frac{r_s}{2}, \quad ub_M = M - \frac{r_s}{2}, \quad ub_N = N - \frac{r_s}{2}. \tag{5}$$

where lb, $ub_{(M,N)}$ represent lower and upper bounds of the area under consideration. Also, M and N are the width and the height of the target area, N_s is the number of sensor nodes and r_s represents the sensing range of the sensor node.

3.2 Coverage ratio

The probability that a grid point $p(x, y)$ is covered by the set of sensor nodes S can be written as:

$$p(x, y, S) = 1 - \prod_{i=1}^{N_s} (1 - p(x, y, s_i)) \tag{6}$$

The total percentage of the coverage area (Cov) is given by:

$$COV_{percentage} = \frac{\sum_{x=1}^{M} \sum_{y=1}^{N} P(x, y, S)}{M \times N} \tag{7}$$

Where $M \times N$ is the total area size.

The goal of the proposed technique is to maximize area coverage ($f_1 = COV_{percentage}$).

3.3 Number of deployed sensor nodes

The second goal of the proposed technique is to achieve maximum area coverage with a minimum number of deployed nodes. The number of sensor nodes is defined between the upper and lower bound of a predefined range. Those bounds are defined according to Eq. 8:

$$L_s \le N_s \le U_s \tag{8}$$

where N_s is the number of deployed nodes and L_s, U_S are the predefined lower and upper bounds respectively. Therefore, the second goal is to minimize the number of deployed sensor nodes in the area under consideration as defined in Eq. 9.

$$f_2 = 1/N_s \tag{9}$$

3.4 Overlapping area between sensor nodes

Minimizing the number of sensor nodes contributes to significantly reducing the overlapping area between nodes. Figure 2 describes two sensors s_1 and s_2 overlapped a point $p(x, y)$. The probability that the two sensors s_i and s_j to overlap grid point $p(x, y)$ is given by:

$$P_{Overlap}(x, y, s_i) = \begin{cases} 1, \text{ if } d_{ps_i} < r_s \text{ and } d_{ps_j} < r_s, i \ne j; \\ 0, \text{ otherwise;} \end{cases} \tag{10}$$

Where $d_{(ps_i)}$,$d_{(ps_j)}$ are Euclidean distance between sensors s_i, s_j and the grid point p that is given by:

$$d_{psi} = \sqrt{(x - x_i)^2 + (y - y_i)^2}, d_{psj} = \sqrt{(x - x_j)^2 + (y - y_j)^2} \tag{11}$$

Where i, j=1,2,....,N_s,$i \ne j$.

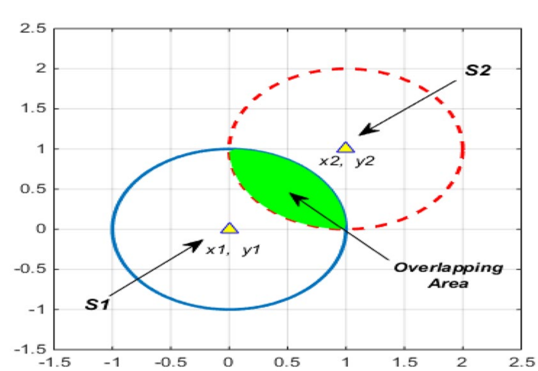


Fig. 2 Overlapping region between two sensors s_1,s_2

The redundant covered area percentage (RED) of nodes in the target area is defined as:

$$RED_{area}(f_2) = \frac{\sum_{x=1}^{M} \sum_{y=1}^{N} (\sum_{i=1}^{N_s} P_{Overlap}(x, y, s_i))}{M \times N} \tag{12}$$

To verify the effect of including the minimization of the number of sensor nodes on reducing the overlapping area in the proposed objective function, simulation with different parameters is performed. Simulation with area $50 \times 50\ m^2$, r_s=10 m, and N_s=20 is used for this purpose. The first simulation is tested without minimizing the number of sensor nodes as described in figure 3a. It is observed from Fig. 3a that eliminates the number of sensor nodes from objective function, result in maximizing the number of deployed sensor nodes to achieve full coverage. It requires 17 nodes to achieve 100 % coverage with an overlapping percentage of 68.24 %. While another simulation requires only 12 nodes when comprises the number of sensor nodes in the objective function. This achieves 99.76 % coverage for the same area with an overlapping percentage of 34.72 % as shown in Fig. 3b. That is means that, including minimizing the number of sensor nodes contributes to minimizing the network cost and overlapping percentage area with 25 % and 49.12 % respectively.

It is worth mentioning that maximizing area coverage required a large number of nodes. However, minimizing the number of deployed nodes is the main factor of this paper. So, these two objectives are conflicting with each other. The objective function is built in the way to integrate those objectives using the weight sum approach (WSA) (Gupta et al. 2016). WSA is used for solving multi-objective optimization problems by multiplying preference w with each objective and make a summation of all objective terms to get the final objective value as shown in Eq. 13. Due to its simplicity, WSA is used with less computational complexity and low network overhead.

$$Z = w_1 \times f_1 + w_2 \times f_2 \tag{13}$$

Where w_1, w_2 are the weight values and w_1+w_2=1.

To summarize this section:

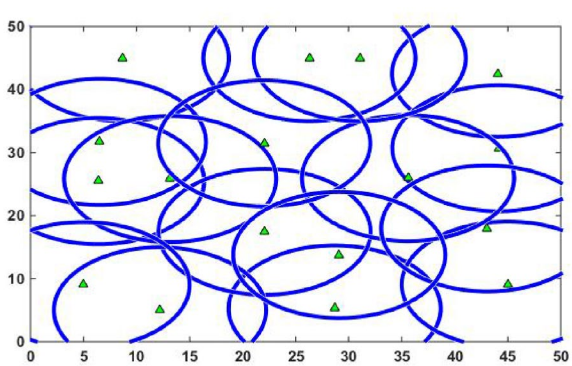
Objective function
Objective
Maximizing the area coverage percentage (f_1)
Minimizing the number of deployed nodes (f_2)
Subject to
Minimizing the overlapping area between nodes.
Ensuring 1-connectivity between sensor nodes.

If the constraints are violated, the objective function will be assigned penalties.

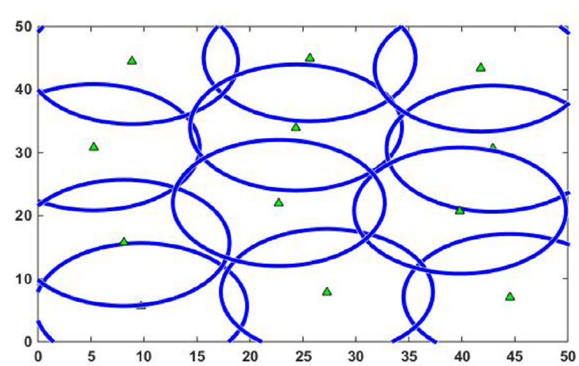
3.5 Connectivity between sensor nodes

Sensor nodes communicated with each other via communication range (R_c) for exchanging data until reaching the sink. This is called connectivity, where the network said to be connected if and only if there is at least one path (k = 1) between each sensor node and the sink. Moreover, if there are multiple and different paths between each sensor and the sink, this is called k-connectivity where k > 1 (Farsi et al. 2019; Zhu et al. 2012). For simplicity, the two sensors s_i and s_j are connected if the Euclidean distance between s_i and s_j [$d(s_i, s_j) <= R_c$] as described in Eq. 14.

$$Con(s_i, s_j) = \begin{cases} 1, \text{ if } \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} <= R_c, i \neq j; \\ 0, \text{ otherwise}; \end{cases} \tag{14}$$



(a) Coverage without minimizing overlapping area and 100% coverage rate.



(b) Coverage with minimizing overlapping area and 99.76 % coverage rate.

Fig. 3 The effect of minimizing the number of sensor nodes on reducing the overlapping area

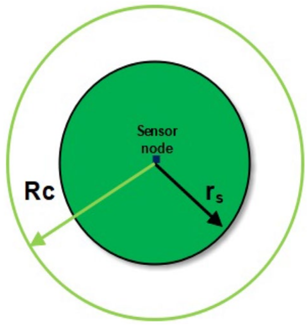


Fig. 4 Sensing range (r_s) and communication range (R_C)

where $R_C = 2 * r_s$, and according to Eq. 13, the proposed technique has verified connectivity between sensor nodes to be 1-connectivity by adding a penalty to the objective function that ensures ($k = 1$). Figure 4 shows the relationship between R_C and r_s.

3.6 Plan of the solution

The following assumptions regarding sensor nodes are fixed in the proposed technique:

- All sensor nodes are homogeneous (have the same sensing range).
- There are two dimensions of the target A with width M and height N, and it is assumed to be an obstacle-free region.
- All sensor nodes are aware of their location via GPS or another device for location determination
- All nodes can move within their range of mobility to other locations.

Steps for solution are summarized as follow:

- Initially randomly deploy nodes within the boundaries of the area (initial population)
- Select a row from the population as a candidate solution (selection of parents to produce children)
- Apply a modified two-point crossover to enable variable-length encoding for each parent.
- Perform mutation
- Calculate objective function (maximizing coverage and minimizing the number of sensor nodes with overlapping and 1-connectivity constrains)
- Update population for the next generation
- Get the best solution as final nodes coordinates

The details of the proposed technique will be discussed extensively in the next section.

4 Proposed dynamic deployment technique using Genetic algorithm(IDDT-GA)

The most important characteristics of GA compared to other state-of-the-art techniques are (Sivanandam and Deepa 2008):

Firstly, GA combines different solutions to boost the best one that provides a variety of potential solutions. This variety results from the crossover stage. Secondly, the algorithm's solidity should also be stated as something an essential parameter to the success of the algorithm. Solidity means the ability of the algorithm to resolve a wide range of problem types well consistently. Thirdly, GA is simple to implement and has a small computational cost. Also, it has a good compromise between exploration and exploitation. Finally, according to No Free Lunch theorem (Wolpert and Macready 1997), no optimization algorithm outperforms any other algorithm for all problems, but an algorithm performs well in a specific application. All of these features make a genetic algorithm is a powerful tool for the optimization process.

The proposed IDDT-GA is detailed in this section. Foremost, all nodes are deployed randomly within the target area. Then, the population matrix is generated which each row represents a candidate solution. Each row has several columns that determined based on the number of deployed nodes. These columns contain randomly generated positions of the sensor nodes within a predefined range as described in Eq. (5). A variable-length encoding is used to construct each row. Each row has a variable length for a different number of sensor nodes, which are created within range as shown in Eq. 8. Therefore, a candidate solution has chosen from the population. After that, performing GA steps including selection, crossover, and mutation until reach termination conditions and get the best value for the fitness function. Finally, get final nodes locations and calculate coverage ratio for the area under consideration. A comprehensive description of GA steps is outlined in subsections 5.1 to 5.3 below. Algorithm 1, illustrates steps for the proposed technique.

Algorithm 1: Proposed technique Pseudo-code

Input: $M, N, r_s, P_c, P_m, N_s, w_1, w_2$.
// P_c is crossover probability and P_m is mutation probability.
Output: $final_{locations}, Cov_{ratio}, N_s$

Set M, N, r_s;
Set $P_c = 0.8, P_m = 0.01, w_1 = 0.7, w_2 = 0.3$;
Set population size(P_s),ITR; // Initialize initial population (algorithm 2).
$IP = initial_{population}()$;
i=0; // Index of iteration number.
$Z = fitness_{evaluate}(IP)$; // Calculate objective function for chromosome using algorithm 3.
while $(i \leq ITR)$ **do**
    $iter+ = 1$; // Increment for next iteration.
    $X = Roulette - Wheel(IP)$; // roulette-wheel selection of parents.
    if $(rand() \in (0,1) \leq P_c)$ **then**
        $Y = Improved_{crossover}(X)$; // Improved two-point crossover to generate children 4.3.
    end
    if $(rand() \in (0,1) \leq P_m)$ **then**
        $M = Gaussian_{mutation}(Y)$; // Gaussian mutation.
    end
    $Z = fitness_{evaluate}(M)$ // Calculate objective function using algorithm 3.
    $Update(M, IP)$ // Update IP to add M for the best populations
    $best_{individuals} = Better(Z)$; // Get new population for next iteration.
end
$final_{locations} = best_{solution}(Z)$; // Store the best solution as final nodes coordinates
$N_s = length(final_{locations})$; // Get the optimum number of the sensor nodes
$coverage_{ratio}(final_{locations})$;

4.1 IDDT-GA—initial population

The initial population is created as a matrix in which each row represents a chromosome. Each row has a set of columns that represent randomly generated positions of sensor nodes. Each chromosome has a variable row length l_c which equal to the double of the randomly generated number of sensor nodes ($l_c = 2 \times N_s$). The first half of the chromosome represents x coordinates for nodes, while the last one represents node's y coordinates as described in Fig. 5. Algorithm 2, shows in detail the generation of the initial population matrix.

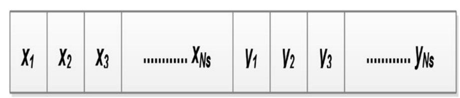


Fig. 5 Chromosome representation

Algorithm 2: Generation of initial population pseudo-code

Input: M, N, r_s, L_s, U_s.
Output: IP.

Begin
Set M, N, r_s, L_s, U_s; // Set area width, area height, sensing range and lower and upper bounds of the number of sensor nodes
Set population size(P_s); // Define length of population matrix
Evaluate $lb = \frac{r_s}{2}$; // Determine lower bound of the target area
Evaluate$ub_M = M - \frac{r_s}{2}, ub_N = N - \frac{r_s}{2}$; // Determine upper bound of the target area
t=0; // Index to generate population matrix
while $(t \leq P_s)$ **do**
    t=t+1; // Increment for next iteration
    k=0;// Index to indicate the number of sensor nodes
    while $(k \leq N_s)$ **do**
        k=k+1; // Increment for next iteration
        $x_{coordinates(k)} = lb + (ub_M - lb) * rand()$;// Generate random x coordinates
        $y_{coordinates(k)} = lb + (ub_N - lb) * rand()$;// Generate random y coordinates
    end
end
$IP = [x_{coordinates}, y_{coordinates}]$; // Form population matrix

Algorithm 3: Objective function evaluation

Input: w_1, w_2, IP.
Output: Z.

Begin
Set w_1, w_2, P_s;
t=0;
while $(t \leq P_s)$ **do**
  t=t+1; // Increment for next iteration
  $B = IP(t)$ // B is Individual row from population
  if $length(B) > 0$ **then**
    Evaluate $P(x, y, S)$; // probability that a grid point $p(x, y)$ is covered using (6)
    Evaluate $COV_{percentage}$ (f_1); // Calculate area coverage percentage using (7)
    Evaluate (f_2) // Calculate minuimum number of sensor nodes using (9)
    Evaluate $(Z = w_1 * f_1 + w_2 * f_2)$ // Evaluate objective function using (13)
  end
end

4.2 IDDT-GA—selection

Selection is an important process within the genetic algorithm. It is used to select parents for the next generation. Individuals that have better objective value have a better chance to be selected as parents to produce offsprings through crossover operation. There are many selection methods as rank selection, roulette-wheel selection, stochastic, tournament selection, etc. (Gupta et al. 2016). The proposed technique uses a roulette-wheel selection.

4.3 IDDT-GA—crossover and mutation

Crossover is the exchange between two parents (parent/individual: Each row has a variable length that equals to the double of the randomly generated number of sensor nodes. The first half of the row represents x coordinates for nodes, while the last one represents the node's y coordinates) to produce child individuals for the next generation. A modified two-point crossover is presented for representing individuals with the notion of adaptive length encoding to demonstrate a variable set of sensor nodes. Initially, each row (parent) is divided to isolate the x coordinates and the y coordinates. Then, two crossover points are randomly selected for the first parent (x and y coordinates) within its length according to Eq. (15). For the second parent, the two points are selected relative to the points of the first parent, but within the range of the second parent's length as defined in Eq. (16). After that, the parents' chromosomes swap the parts between the two points.

$$CrossPoint(P_1)_{1,2} = round((ub_1 - lb) * rand() + lb) \tag{15}$$

Where $CrossPoint(P_1)_1$ and $CrossPoint(P_1)_2$ are the first and second cross points for the first parent respectively, and $CrossPoint(P_1)_1 < CrossPoint(P_1)_2$. Besides, ub_1 is the length of the first parent and lb is the lower bound of the first parent's length that equals 1. We can calculate the cross points for the second parent based on the following:

$$\begin{aligned} CrossPoint(P_2)_1 &= \frac{ub_2 * CrossPoint(P_1)_1}{ub_1}, \\ CrossPoint(P_2)_2 &= \frac{ub_2 * CrossPoint(P_1)_2}{ub_1} \end{aligned} \tag{16}$$

Where $CrossPoint(P_2)_1$ and $CrossPoint(P_2)_2$ are the first and second cross points for the second parent, and ub_2 is the length of the second parent. Figure 6 shows an example of an improved two-point crossover.

As shown from Fig. 6, the first parent has a length of 20. The first ten values represent x coordinates of sensor nodes while the last values correspond to y coordinates of sensor nodes. With the same concept, the second parent has a length of 14 represents x and y coordinates for 7 sensor nodes. Based on Eq. 15, the first and second cross points for the first parents are generated randomly at locations 3 and 8 respectively. After that, relative to Eq. 16 points 2, 7 are cross points for the second parent. Finally, following swapping the parts between the two parents, child 1 with length 18 and child2 with length 16 are produced.

Mutation (Kramer 2017) provides diversity in the search space. It creates small changes in individuals and creates a mutated child. It occurs according to a user-defined mutation rate P_m during the evaluation process. This rate is usually set to low. If it is set too high, the search will turn into a random search space. A gaussian mutation is used, which adds a random number taken from Gaussian distribution with mean 0 to each element of the parent vector.

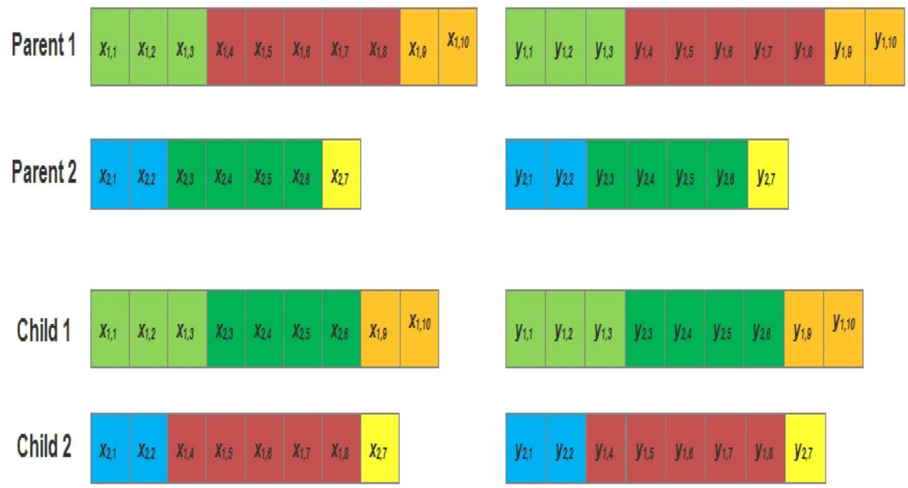


Fig. 6 Improved two-point Crossover example

5 Simulation results and comparisons

To prove the validity and superiority of the proposed deployment technique, it has implemented using MATLAB 2014 X64 on a system with Core (TM) i5, 2.6 MHZ, 6 GRAM, windows 7 as a platform. The target area is considered as mentioned above to be $M * N$ grid points. So, the number of grid points need to be covered equally to $M * N$. Initially, sensor nodes deployed randomly, with sensing range r_s. The proposed technique is compared to three related works CM-IA (Abo-Zahhad et al. 2014), HS-based deployment (Moh'd Alia and Al-Ajouri 2017) and MADA-WOA (ÖZDAĞ and CANAYAZ 2017) because they are the most recent techniques related to minimal cost coverage and cited by different research works. Different area size $M * N$, sensing range r_s and the number of nodes N_s is used for simulation for similarity conditions with related works. Table 2 shows the simulation parameters used for comparisons with related works. For simulation, different values for preference weight w_1, w_2 were tested. It is observed from Table 3 that $w_1 = 0.7$ and $w_2 = 0.3$ has good comprise for both coverage and the number of deployed nodes. As they achieve maximum coverage with the minimum number of sensor nodes and acceptable overlapping rates. In addition, the proposed technique considered crossover probability $P_c = 0.7$ (Mnasri et al. 2015) and mutation probability $P_m = 0.01$ (Kalayci et al. 2007).

Table 2 Simulation parameters

Parameters	Values
Area size ($M * N$)	50, 100
Sensing range (r_s)	5–10
Number of sensor nodes (N_s)	4–100
Population size (P_s)	30
Number of iterations (ITR)	500
Crossover probability (P_c)	0.7
Mutation probability (P_m)	0.01

Table 3 Different weight values for coverage rates, the number of sensor nodes ,and overlapping rates for $5 =< N_s <= 10$

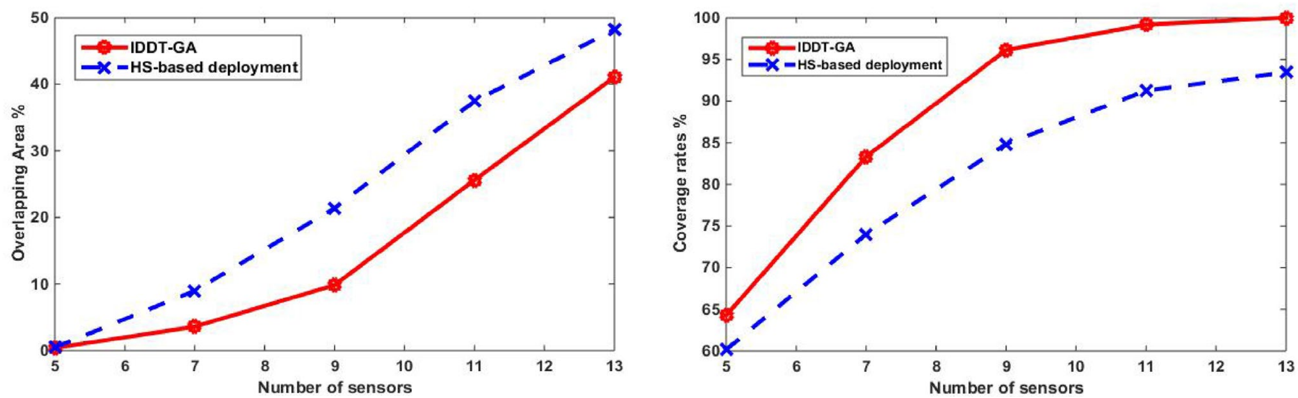
w_1	w_2	Coverage (f_1) %	Ns (f_2)	Overlapping area %
0.9	0.1	93.6	9	14
0.8	0.2	93.94	9	12
0.7	0.3	93.05	8	8
0.6	0.3	93.19	9	13
0.5	0.5	92.38	8	7
0.4	0.6	88.72	8	8
0.3	0.7	82.61	7	5
0.2	0.8	67.13	5	0.32
0.1	0.9	64.24	5	0.28

First of all, IDDT-GA is compared with coverage maximization with minimum cost using HS-based deployment (Moh'd Alia and Al-Ajouri 2017). For this purpose, area size $50 \times 50\ m^2$ and $100 \times 100\ m^2$ is used with $r_s = 10\ m$. To eliminate the simulation error due to randomization, this simulation was run for 10 independent runs and the average of results is estimated.

It is shown from Table 4 that, IDDT-GA outperforms HS-based deployment in terms of coverage ratio with the minimum number of nodes. For area $50 \times 50\ m^2$, the proposed technique requires only 13 nodes for 99.75% area coverage while the last covered 96.8 % of the target area with 15 nodes. Also, for a large area 100×100, the proposed technique covers 97.25 % of the target area with only 45 sensor nodes. However, HS-based deployment requires 50 nodes for covering 86.69 % of the target area. It is shown from Fig. 7 that IDDT-GA has better coverage rates and

Table 4 Comparison between HS-based deployment (Moh'd Alia and Al-Ajouri 2017) and IDDT-GA

Area	Ns	HS-based deployment				IDDT-GA			
$M-N$	$L_s - U_s$	Coverage %	Overlapping %	N_s	STD	Coverage %	Overlapping %	N_s	STD
50 - 50	4–10	88.38	29.4	10	0.0161	90.83	6.8	8	0.0176
50 - 50	10–15	96.8	53.76	15	0.0084	99.75	42.04	13	0.00077
100 - 100	20–30	69.92	20.43	30	0.013	81.74	5	28	0.0111
100 - 100	30–50	86.69	46	50	0.0097	97.25	33.67	45	0.0073



(a) Overlapping rates for $50 * 50\ m^2$ **(b)** Coverage rates for $50 * 50\ m^2$

Fig. 7 Difference between IDDT-GA and HS-based deployment in terms of the number of sensor nodes, coverage rates, and overlapping rates

minimum overlapping ratio with 9.69 % and 35.43 % (on average) compared to HS-based deployment respectively. HS-based deployment was designed for a deterministic deployment technique with a limited number of grid points. However, in this paper network is designed for random deployment that has better coverage for a large and small number of grid points with a minimum number of nodes. Besides, IDDT-GA is always stable and reliable as it has a small standard deviation over most of the runs beside it has fast convergence as shown in Fig. 8. IDDT-GA contributes to minimizing STD values with 90.83 % for an area with size $50 \times 50\ m^2$ and 19.68 % for an area with the size $100 \times 100\ m^2$ compared to HS-based deployment. Figures 9 and 10 show nodes distribution with the proposed technique and HS-based deployment for a different number of nodes.

In addition to the above, IDDT-GA is compared with CM-IA (Abo-Zahhad et al. 2014). The same amount of sensor nodes and field size is endorsed. In other words, the number of nodes varies between 20 and 60 in the same area field of $50 \times 50\ m^2$ with sensing range r_s=5 and 7 m. This simulation was run for 10 times and the average is calculated. It is observed in Table 5 that compared to CM-IM, IDDT-GA has approximately the same coverage rates with the minimum number of sensor nodes. Besides, IDDT-GA contributes to minimizing the network cost (the number of sensor nodes) by 13 % on average compared to CM-IA. Also , IDDT-GA improved the overlapping area between nodes by 65.80 % than CM-IA as shown in Fig. 11. Along with all simulations, IDDT-GA has small STD values 0.0178, 0.0056 and 0.0117 for N_s=20, 60 and 23 respectively, that confirms its stability and superiority. Figure 12 describes nodes distribution with IDDT-GA using a different number of nodes. Although we must mention that for areas with a lower number of nodes that do not satisfy maximum coverage conditions, some nodes could not meet connectivity requirements. Because of the minimum number of nodes that could not cover the area efficiently as shown in figure 12a.

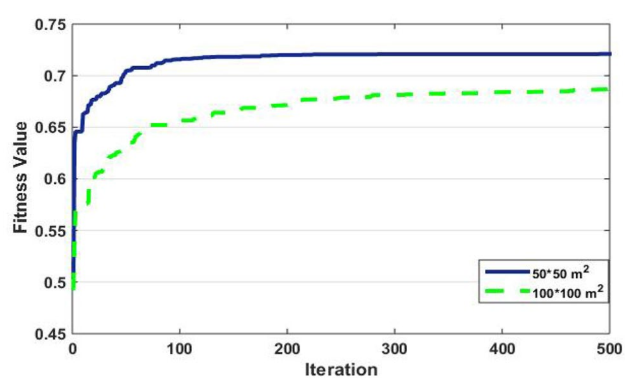
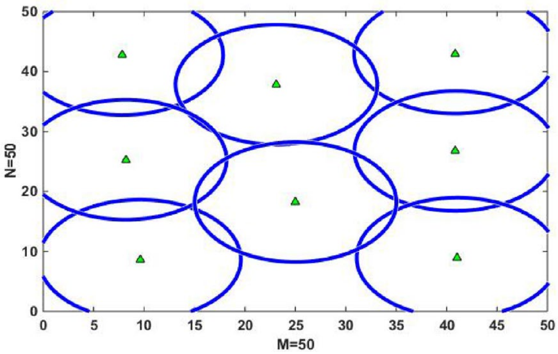
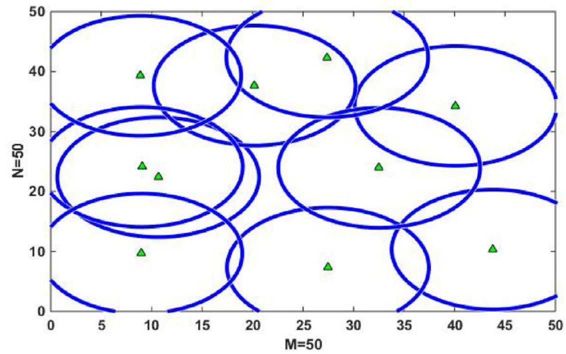


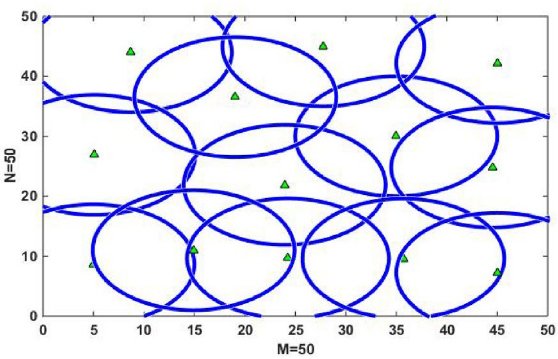
Fig. 8 IDDT-GA Convergence for $50 \times 50\ m^2$ and $100 \times 100\ m^2$



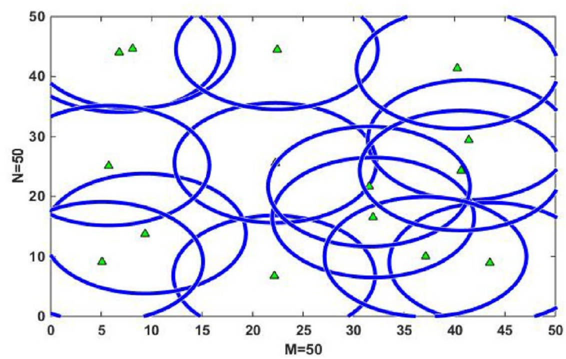
(a) Node distribution with IDDT-GA for $N_s = 4 - 10$ with 90.83 % coverage rate.



(b) Node distribution with HS-based deployment for $N_s = 4 - 10$ with 88.38 % coverage rate.



(c) Node distribution with IDDT-GA for $N_s = 10 - 15$ with 99.75 % coverage rate.



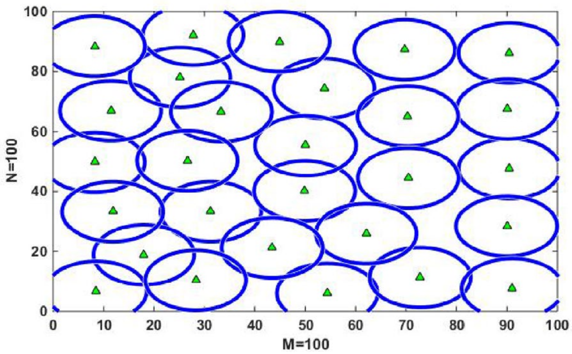
(d) Node distribution with HS-based deployment for $N_s = 10 - 15$ with 96.80 % coverage rate.

Fig. 9 Node distribution with IDDT-GA and HS-based deployment for area size $50 \times 50\ m^2$

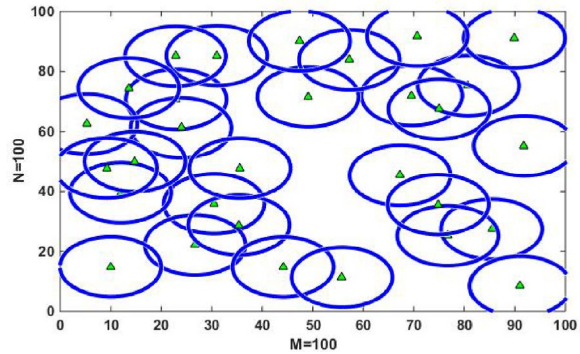
Finally, the performance of IDDT-GA is compared with MADA-WOA (ÖZDAĞ and CANAYAZ 2017). For this purpose network with size $100 \times 100\ m^2$ is considered and $r_s = 7$, which have set of randomly deployed mobile sensor nodes in the range 20-100 sensor nodes. This simulation was run for 5 independent runs and the average of results is calculated. As can be seen from Table 6, the performance of the IDDT-GA is compared to MADA-WOA in terms of coverage ratio with a different number of sensor nodes. IDDT-GA covered 30.07 % of the target area with only 19 nodes while MADA-WOA required 20 nodes for covering 29.2 % of the area. IDDT-GA has improved the network cost (minimum number of nodes) by 7.44 % than MADA-WOA because IDDT-GA has similar coverage rates with a minimum number of sensor nodes compared to MADA-WOA as described in Fig. 13a. Besides, the proposed technique is more stable than MADA-WOA, as it always has a small standard deviation value. This means that, coverage rates at all iterations are close to each other and that it has fast convergence than MADA-WOA. IDDT-GA contributes to minimizing STD values with 83.04 % compared to MADA-WOA. Figure 13b shows standard deviation values for both algorithms with the number of sensor nodes. Nodes distribution for this simulation with IDDT-GA is described in Fig. 14.

6 Conclusion and future work

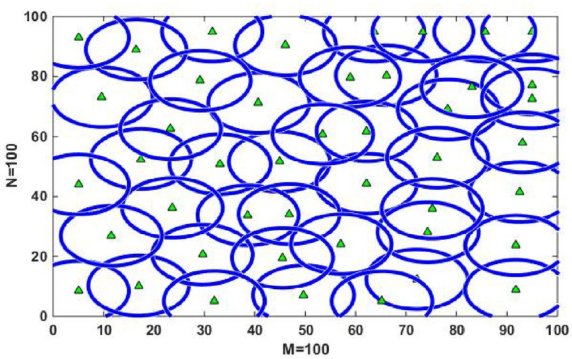
This paper introduced an Improved Dynamic Deployment Technique based on the Genetic Algorithm (IDDT-GA) for maximizing area coverage. This technique was designed to maximize the network coverage by reducing the number of sensor nodes in the random deployment. The IDDT-GA



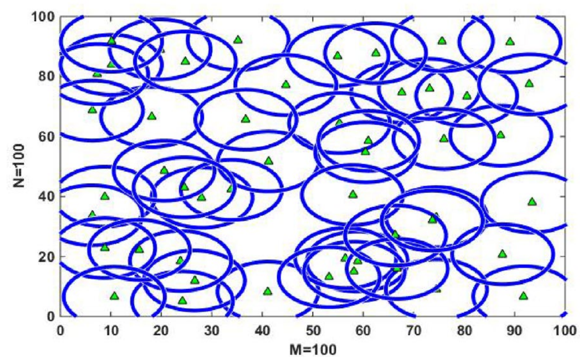
(a) Node distribution with IDDT-GA for $N_s = 20 - 30$ with 81.74 % coverage rate.



(b) Node distribution with HS-based deployment for $N_s = 20 - 30$ with 69.92 % coverage rate.



(c) Node distribution with IDDT-GA for $N_s = 30 - 50$ with 97.25 % coverage rate.



(d) Node distribution with HS-based deployment for $N_s = 30 - 50$ with 86.69 % coverage rate.

Fig. 10 Node distribution with IDDT-GA and HS-based deployment for area size 100×100 m^2

Table 5 Comparison between CM-IA (Abo-Zahhad et al. 2014) and IDDT-GA

Common parameters	IDDT-GA		CM-IA	
	N_s	Coverage %	N_s	Coverage %
$M = 50$, $N = 50$,$r_s = 5$	19	62.51	20	62
	48	98.28	60	99.4
$M = 50$, $N = 50$,$r_s = 7$	20	96.45	23	97.4

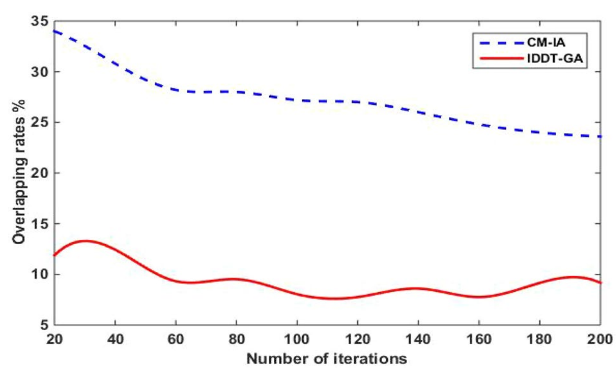
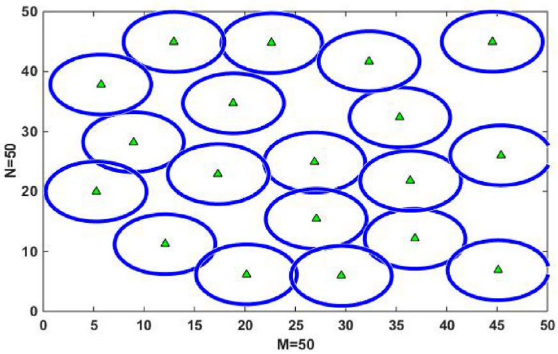


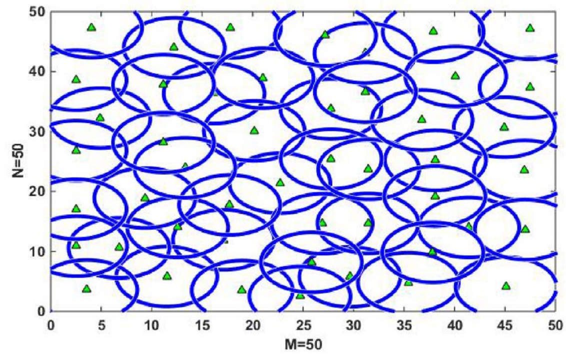
Fig. 11 Overlapping rates for IDDT-GA and CM-IA

was introduced in this work as the promising solution not only to demonstrate the notation of variable-length encoding through an improved two-point crossover but also to guarantee 1-connectivity between sensor nodes.

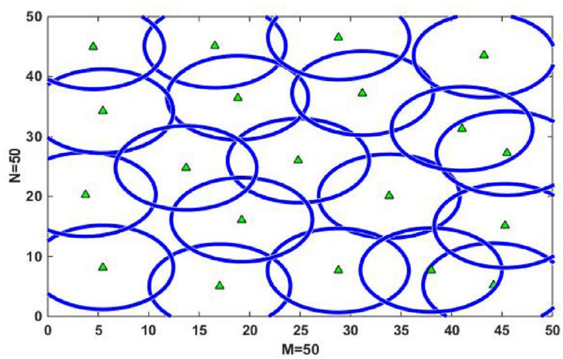
In the simulation results, the proposed technique was confirmed its superiority and efficiency as it has better coverage rates and the minimum overlapping ratio with 9.69% and 35.43% compared to HS-based deployment. Moreover, IDDT-GA was contributed to minimizing the network cost and the overlapping area between nodes by 13% and 65.80% than CM-IA. It also demonstrates its stability and reliability



(a) Node distribution with IDDT-GA for N_s=19 ,r_s=5 with 62.51% coverage rate.,



(b) Node distribution with IDDT-GA for N_s=48 ,r_s=5 with 98.28 % coverage rate.



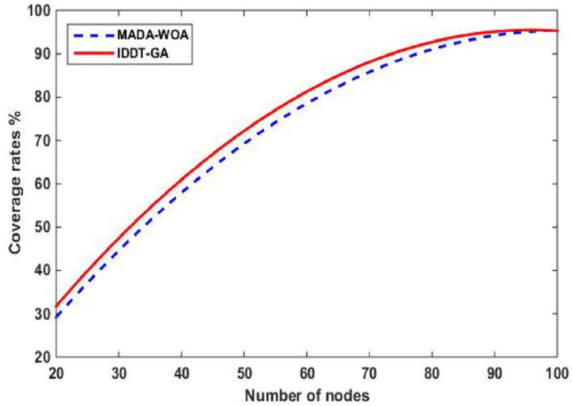
(c) Node distribution with IDDT-GA for N_s=20 ,r_s=7 with 96.45 % coverage rate.

Fig. 12 Nodes distribution with different number of nodes N_s and sensing range r_s for $50 \times 50\ m^2$

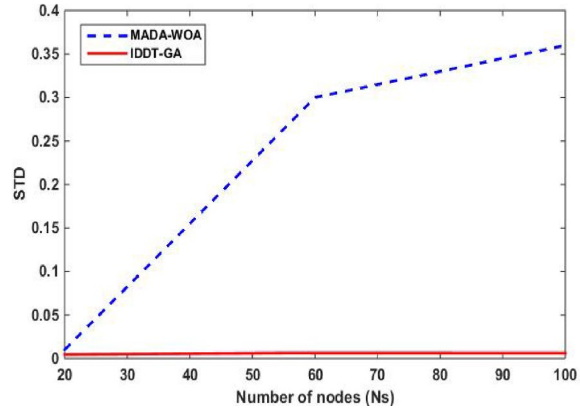
Table 6 Comparison between MADA-WOA (ÖZDAĞ and CANAYAZ 2017) and IDDT-GA

MADA-WOA			IDDT-GA		
N_s	Coverage %	STD	N_s	Coverage %	STD
20	29.2	0.01	19	30.07	0.0047
60	78.55	0.3	55	77	0.0064
100	95.4	0.36	91	95.32	0.0063

as opposed to other techniques, it usually has small STD values. Although the effectiveness of the IDDT-GA was investigated in the simulation results in terms of minimizing the network cost and maximizing the coverage area, the development is still required in future work by applying IDDT-GA with a probabilistic detection model and power consumption reduction.

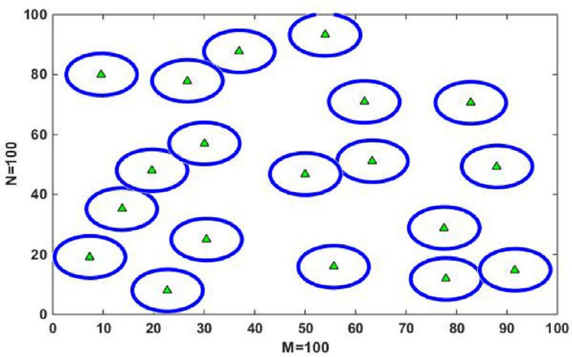


(a) Coverage rates for proposed IDDT-GA and MADA-WOA.

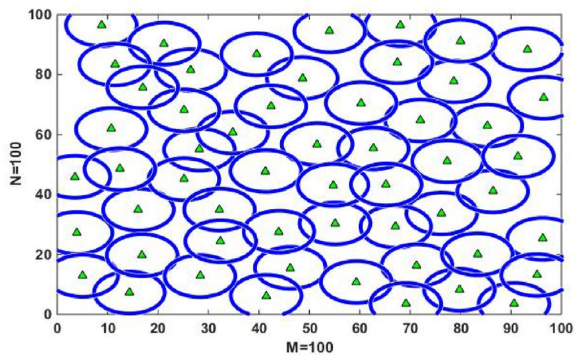


(b) Standard deviation values for proposed IDDT-GA and MADA-WOA.

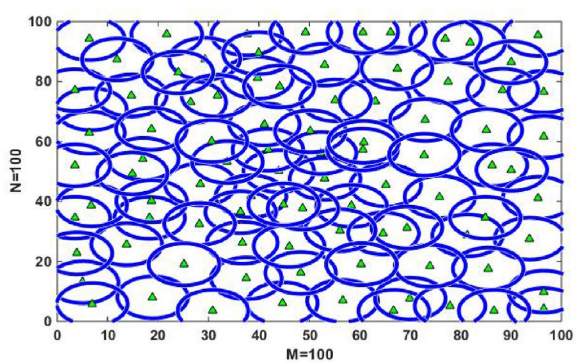
Fig. 13 Coverage rates and standard deviations for proposed IDDT-GA and MADA-WOA



(a) Node distribution with IDDT-GA for $N_s = 19$ with 30.07 % coverage rate.



(b) Node distribution with IDDT-GA for $N_s = 55$ with 77 % coverage rate.



(c) Node distribution with IDDT-GA for $N_s = 91$ with 95.32 % coverage rate.

Fig. 14 Nodes distribution with a different number of nodes N_s for $100 \times 100\ m^2$

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