



# Energy efficient active/sleep scheduling of sensor nodes in target based WSN using genetic algorithm with dither creeping mutation

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## Abstract

Scheduling of sensor nodes in an energy-efficient manner is one of the most effective ways for extending the lifetime of wireless sensor networks (WSNs). In energy-efficient scheduling, only a subset of the deployed sensor nodes is enabled to monitor the targets. As sensor nodes have restricted communication and sensing range, coverage and network connectivity should be considered while scheduling with fewer sensor nodes. For guaranteed transmission of sensing data from every target point to the base station, connectivity and coverage are the most pivotal issues in the scheduling of sensor nodes. In this research article, we have presented the energy-efficient active/sleep scheduling of the sensor nodes using a genetic algorithm (GA) with Dither Creeping mutation in which only few sensors are activated that ensures the coverage to all targets as well as communication with the sensor nodes and base station (BS). The novelty of the proposed GA with crossover and Dither Creeping mutation (GACDCM) is that the mutation probability is generated randomly rather than the fixed value for each string. As a result, for the same generation, the various strings of the proposed algorithm will be subjected to various creeping mutation probabilities and the same string is subjected to various creeping mutation probabilities at successive generations. The proposed algorithm replaces the traditional bitwise mutation. For exploring the search space in case of extremely constrained problems, Dither Creeping Mutation is more efficient than bitwise mutation. We have simulated the proposed algorithm extensively with several WSN scenarios. The simulation results are analyzed with the existent algorithms to validate the efficiency of the presented algorithm. The experimental result showed that the lifetime of the suggested GACDCM is increased by 53.27% than traditional GA, 27.93% than GANCDM, 13.23% than NSGA-II, and 4% than algorithm proposed by Harizan and Kula (Wireless Netw 25(4):1995–2011, 2019).

**Keywords** Wireless sensor networks · Connectivity · Coverage · Node placement · Genetic algorithm

## 1 Introduction

### 1.1 Background

Wireless Sensor Network (WSN) comprises huge numbers of resource-constrained, low cost, tiny sensor nodes. The sensor nodes sense the physical parameters from the environment without human interference and transmit them directly

or by multi-hop transmission to the BS (Lv et al. 2021). The sensor nodes are placed randomly or in a pre-planned fashion in the target area. When sensor nodes are deployed randomly in the target area, there may be the possibility of some portion of the target area being covered with a few nodes or some portion may be densely placed with sensor nodes. When less sensor nodes are used to cover the target area, most of the portion of the target area leave uncovered, which consequently requires more energy for transmitting the sensed data as the nodes are far away from each other. If the sensor nodes are placed densely in the target area, more energy will be consumed as more sensor nodes are in route participating in the data transmission (Farsi et al. 2019).

The random node deployment is mainly used where the area of interest is not easily accessible, for example, the applications like surveillance of the military realm, harsh environment monitoring, forest monitoring, etc. The

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pre-planned deployment is used where the area of interest is easily accessible, for example, the applications like agriculture, environment monitoring, healthcare, etc. (Boardman and Sullivan 2021). The deployment cost and the management of network is easy in the pre-planned deployment technique as compared to random deployment as the area of interest is covered with a less sensor nodes. In both the deployment techniques, connectivity and full coverage are very much important.

In WSN, the battery with the restricted energy source is the most stimulating issue. Once the sensor nodes are deployed, replacement or recharging of batteries is challenging or even impossible because of the large network size and harsh environment (Goyal and Tripathi 2022). Therefore, proper energy utilization has become a challenging issue for decreasing the power consumption and increasing the network lifetime.

As fewer nodes are used to cover the target area, most of the portion of the target area leave uncovered. Therefore, the sensor nodes need to be deployed densely. But because of the dense deployment of sensor nodes more energy will be consumed. This issue can be resolved by energy-efficient active/sleep scheduling of the sensor nodes. Various techniques and meta-heuristic based scheduling algorithms have been presented in the last few years. The majority of the existing scheduling algorithms take only one of two constraints into account: coverage or connectivity. For determining an optimal schedule, only few proposed techniques taken into account both coverage and connectivity constraints. The greedy-based scheduling algorithms have extended network lifetime, connectivity and coverage. However, the real-time implementation is challenging because of multiple packet losses, collisions, and pre-computed energy consumption rate that varies in real-time scenarios (Cardei and Cardei 2008a, b). The NSGA-II (Jia et al. 2009a, b) based technique has been successfully used to select the fewest sensor nodes out of all the randomly deployed nodes which ensure the coverage to the region of interest. But they considered the range of communication of sensor nodes is twice that of the sensing range. However, in a target-based network, the targets may be spread over the application area, this assumption is not valid. The bio-inspired techniques such as Ant Colony Optimization (ACO) have shown noteworthy improvement in the node scheduling (Lee et al. 2011). The target tracking algorithm presented in (Lerstean et al. 2018) provides node scheduling to monitor the moving targets. The proposed algorithm finds the schedule with fewest sensor nodes which ensures coverage of moving targets and minimizes the energy consumption for target tracking. The selected sensor nodes are considered to be in the communication range with one another for data transmission. However, because of the limited communication range selected sensor nodes in

large network area may not be connected and thus affect data forwarding.

In this article, we have proposed energy-efficient scheduling where out of total deployed nodes, only a subset of the nodes is in active mode to monitor the targets and the rest of the nodes are in sleep mode. The subset of nodes continues to monitor and transmit the data till the energy of one or more nodes is drained. Then, from the remaining set of nodes, it activates a new subset of nodes. The same process is repeated until no more subsets can be formed to provide coverage to all target points as well as communication among sensor nodes and the BS. Thus scheduling the active and sleep modes of the sensor nodes saves energy that improves the network lifetime. Thus active/sleep scheduling of the nodes helps to preserve the valuable energy of the sensor nodes by activating only fewest nodes out of the densely deployed nodes. The nodes are not only selected on the basis of the fewest node count but also consider the residual energy, coverage to all the target points as well as connectivity between the sensor nodes and base station to transmit the data sensed by nodes to the base station.

The sensing and transmission range is limited for the sensor nodes. For the guaranteed data transmission from the targets to the BS, full coverage, communication among the nodes and the base station are very stimulating issues in the WSN. Therefore, full coverage and communication between the sensor nodes and base station are equally considered while scheduling the sensor nodes. Residual energy is also considered along with the fewest nodes, connectivity and coverage. The node with the higher residual energy is selected. Because of this frequent formation of scheduling is not required, which in turn it will avoid the overhead on the network.

The coverage to the target points as well as the connectivity between sensor nodes with minimum nodes is a multi-objective and NP-hard problem. The metaheuristic approach is highly preferred to determine the optimal solutions for such multi-objective optimization problems. The GA is found very simple, touristy, and widely used algorithm for finding out solutions to multiobjective problems. Here in our proposed work, a Genetic algorithm is employed to determine the optimal solution for scheduling the sensor nodes in active and sleep modes based on the multiobjective function. In our work, we proposed an algorithm for energy-efficient active/sleep scheduling. The proposed algorithm aimed to enhance the overall performance of the WSN.

The contributions of this paper are as follows:

1. We have implemented the energy-efficient active/sleep scheduling of the sensor nodes using the GA with Dither Creeping mutation algorithm with a crossover as well as without crossover.

2. In 2013, Angus Simpson and his team have developed and analysed, the Non-crossover dither creeping mutation-based GA for the optimization of pipe networks in civil engineering where they have represented chromosomes in integer numbers. But in our work, first time we have used GA with dither creeping mutation for WSN and we have represented the chromosomes in binary.
3. The schedule for active/sleep modes of the sensor nodes is done with the following fitness function with four objectives:
  - i Select the fewest active nodes from all deployed nodes.
  - ii Complete coverage to all the targets.
  - iii All the active sensor nodes are in the communication range of each other along with the BS.
  - iv Residual energy.

We have simulated the proposed algorithm extensively with several WSN scenarios. To validate the efficiency of the presented algorithm, the simulation results are analysed with the existing algorithms.

## 1.2 Organization of the paper

The paper is organized as follows: Sect. 1 begins with an introduction. Section 2 is of the literature review. Section 3 briefed about the system model, problem statement, and terminology used. Section 4 concisely describes the GA. The proposed work describes in Sect. 5, the detailed experimental setup discussion and simulation findings are described in Sect. 6, and finally, there is a conclusion of the paper.

## 2 Literature survey

The energy-efficient active/sleep scheduling of the sensor nodes in target-based WSN is one of the prominent research areas in WSN. Many researchers are using multi-objective optimization techniques for node deployment and active/sleep scheduling of the sensor nodes in an energy-efficient way for improving network lifetime and reducing energy consumption.

Harizan and Kuila (2019) presented an energy-efficient algorithm for the sensor nodes scheduling based on the improved genetic approach which is aware of coverage to targets and connectivity in target-based WSN. In this paper, the authors presented the novel mutation for quicker convergence and improved performance. The cost function is derived from the fewest active node count, full coverage, connectivity among the active nodes, and residual energy. Kaur and Kautish (2016) presented a strategy to resolve the issue of coverage based on the VORONOI\_PSO. The

coverage issue is addressed by determining the optimal coverage based on the best node location. Liu and He (2014) have presented a greedy-based approach using an ant colony optimization, which aims to cover the pols with fewer sensor nodes while maintaining connectivity. In this approach, the authors considered grid-based coverage with minimum cost and assured connectivity. The experimental results demonstrated that the presented approach reduces the deployment cost and also balances the energy consumption and maximizes the network lifetime. Xiang et al. (2019) suggested a cuckoo search-based hybrid WSN node placement algorithm. Here the authors mainly designed the algorithm to increase the regional coverage and decrease the energy loss. The regional coverage of WSN is improved with the CS algorithm and target location optimization is used to decrease the energy loss during the node movement. El Khamlichi et al. (2017) introduced the optimization model that can handle barrier coverage as well as the area coverage problems. To tackle the node placement problem with the fewest active sensor nodes, the authors suggested a node deployment methodology which is the combination of the simulated annealing algorithm and gradient approach. The proposed model outperforms the extent algorithm in terms of full coverage to the targets with the fewer sensor nodes, according to simulation findings. Mini et al. (2012) tackled the M-connected target points coverage issue in WSN where the connectivity and coverage level is high or low as per the requirement. The authors presented a method in which the connectivity and coverage requirements are fulfilled using fewer sensor nodes. Yoon and Kim (2013) investigated the coverage deployment challenges in WSN and also examined problem properties and its solution space. They proposed the GA using the normalization method. The evaluation function is designed with the Monte Carlo method. According to simulation findings, it is observed that the GA is not only twice faster but also showed an improvement in performance quality. Liu et al. (2010) aimed to improve the network lifetime with redundant sensor node coverage and connectivity. They have proposed two algorithms Heuristic Algorithm and Network Flow Algorithm for attaining energy conservation along with connectivity and coverage. Rebai et al. (2015) introduced a GA-based algorithm to search the various positions for the placement of an optimum count of sensor nodes which provides guaranteed full coverage and connectivity between the active nodes. The cost function is derived from the less number of active sensor nodes needed to furnish the necessary coverage and connectivity. Singh et al. (2016) presented the analytical method for prolonging the network lifetime by keeping the disjoint groups of sensors. At a time only one group is active and renders guaranteed coverage. The analytical and experimental results show that the network lifetime increased two times than the original lifetime. Gupta et al. (2016a, b) have developed a scheme based on

GA, that identifies the minimal number of probable positions for node placement to satisfy the  $m$ -connectivity and  $k$ -coverage of the sensor nodes in the target-based WSN field. The suggested scheme based on GA performs better than the previous schemes based on count of selected potential positions. Bendigeri and Mallapur (2015) have developed an energy-efficient scheme for the placement of nodes. It provided uniform deployment of the sensor nodes. The authors have considered the random, grid, and circular patterns of the sensor node for the simulation. The simulation results show that there is less power consumption in a circular pattern in comparison to the random placement of the node. Yang and Chin (2016) tackled the new issue of the minimum energy harvesting nodes placement for energy-neutral connectivity and coverage. The authors aimed to find out the positions to place the minimum sensing and relaying nodes that can cover all the target points, and have connectivity with the base station. Gupta et al. (2016a, b) investigated a node deployment approach based on GA to render  $k$ -connectivity to each target. They have also presented a greedy approach to node deployment policy. The GA-based algorithm outperforms the greedy approach for node deployment. Sengupta et al. (2013) focused to determine the node deployment with full coverage, minimal consumption of energy, maximum lifetime of the network, and full connectivity using the minimal active nodes. The authors proposed a concept of fuzzy Pareto dominance and the decomposition type of evolutionary algorithm. Li and Lei (2009) addressed the node deployment issues. To solve that problem, they presented an improved particle swarm optimization algorithm. The experimental results reveal that the performance factors like power consumption, coverage ratio, and the network lifetime are better than the extent algorithm. Fan et al. (2014) have presented a strategy for predetermined node placement of two tired WSN to minimize the network cost through the fewest active nodes, optimal cluster size, and minimum energy consumption. The authors build the network with the hexagonal cell architecture which ensures guaranteed connectivity and full coverage using the minimum active nodes. Singh and Sharma (2015) presented algorithm based on the theorems, Position, and Hop-count. The algorithm ensures complete coverage and connectivity with minimal node selection. The algorithm is designed to provide three connectivity in the network. The suggested method outperforms the extent algorithm in terms of full coverage using fewer nodes according to simulation findings. Kung et al. (2008) have implemented two novel node deployment methods slow-start and the square-encircled method to carry out node placement investigations for the deployment of the unknown obstacle-filled region with less overlapping rate. The authors proved the correctness of the methods mathematically. These

two methods resolve guaranteed  $k$ -coverage issues using the divide and conquer concept.

Various meta-heuristic algorithms are used in many fields for the optimization problems like GA based Noncrossover dither creeping mutation for the optimization of pipe networks in civil engineering (Zheng et al. 2014), Fuzzy mathematical programming and hybrid model based on the Artificial Fish Swarm Algorithm for flow shop scheduling (Tirkolaee et al. 2020a, b), fuzzy multi-trip location-routing problem for medical waste management (Tirkolaee et al. 2020b).

## 3 System models

### 3.1 Network model

We have considered the WSN where the sensor nodes and targets are spread in a two-dimensional area. Sensor nodes are placed randomly or in a predetermined fashion in the network field. We have also considered that the deployed targets and sensor nodes are stationary. A sensor node can sense one or more target points that are within its coverage area. The sensor nodes that are within the communication range can only communicate with each other. The data aggregation is similar to the LEACH (Heinzelman et al. 2002) where the operation is performed in rounds. Sensed data from sensor nodes is sent directly or via multihop transmission to the base station in each round with sensor that are within communication range.

### 3.2 Problem statement

In the energy-efficient active/sleep scheduling, only a subset of the sensor nodes is active out of all the deployed nodes to monitor the targets and the remaining sensor nodes are in sleep mode. The subset of nodes continuously monitors the targets which are present within their sensing range and transmits the sensed data directly or by multihop transmission to the base station till the energy of one or more nodes is drained. Then, from the remaining set of nodes, it activates a new subset of nodes. This process is repeated until no more subsets can be produced to provide coverage to all target points as well as communication among sensor nodes and the BS. Thus, active and sleep mode scheduling of the sensor nodes leads to improvement in the network lifetime.

Here we addressed the problem as follows. For the given number of deployed sensor nodes and targets, only the fewest nodes have been activated that cover all the targets and provide communication between sensor nodes and base stations. The target is covered by the sensor node, if it is in the sensing range of node. Similarly, the sensor nodes can

communicate with one another if they are in the communication range.

For example, a target-based network consists of 8 target points  $\{T_1, T_2, T_3, \dots, T_8\}$  and 12 sensors  $\{S_1, S_2, S_3, \dots, S_{12}\}$  as depicted in Fig. 1. From the figure, it is found that out of 12 deployed sensor nodes, only six nodes are active while the rest are in sleep mode. Only six nodes  $\{S_3, S_4, S_6, S_8, S_9, S_{10}\}$  are monitoring the targets and transmitting the data sensed by these nodes to the sink. It is also seen that the targets covered are inside the coverage area of at least one of the active nodes and these six active nodes are in the communication range with at least one sensor node to maintain the connectivity among sensor nodes and base station.

### 3.3 Terminologies

For the certain set of N targets and M number of total deployed nodes, minimum sensor nodes with high residual energy are selected to be active and also fulfil the criteria of coverage to all targets along with the connectivity among all active sensors and BS.

The terminology used in the proposed algorithm is described as follows:

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$distance(T_n, S_m)$ denotes the distance between the sensor node $S_m$ and target $T_n$	
$K$ = Number of active nodes	
$R_{Ssens}$ = Sensing range of the sensor node	$C_{Ccom}(S_m)$ refers to the sensor nodes, which are inside the communication range of $S_m$
$R_{Ccomm}$ = Communication range of sensor node	
$S = \{S_1, S_2, S_3, \dots, S_M\}$ are the deployed nodes	

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$T = \{T_1, T_2, T_3, \dots, T_n\}$  are the targets

$C_{sens}(T_n)$  refers to the target  $T_n$  covered by a set of sensor nodes

$$C_{sens}(T_n) = \{S_m | distance(T_n, S_m) \leq R_{Ssens}, \quad \forall m, 1 \leq m \leq K\} \tag{1}$$

$$C_{Ccom}(S_m) = \{S_n | distance(S_m, S_n) \leq R_{Ccomm}(distance(S_n, BS) \geq distance(S_m, BS)) \quad \forall n, 1 \leq n \leq K, m \neq n\} \tag{2}$$

Let the Boolean variables  $a_{mn}, b_{mn}$  be defined as follows:

$$a_{mn} = \begin{cases} 1 & \text{if } S_m \text{ covers, target } T_n \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$b_{mn} = \begin{cases} 1 & \text{if sensors } S_m \text{ and } S_n \text{ in communication range} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

## 4 Genetic algorithm

### 4.1 Basics of genetic algorithm

A Genetic Algorithm is very simplest, nature-inspired, metaheuristic optimization techniques. GA begins its search with the initial population which is generated randomly, and it is considered as the possible solution for a given problem. Each solution is called the chromosome. The fitness of the solution is then assessed by evaluating each chromosome using the cost function. After this, the GA goes through mainly three operations selection, crossover, and mutation. Two random solutions are chosen as parents from the set of initial populations in the selection operation. These two selected parent chromosomes are crossover to produce the two new child chromosomes by exchanging their genes. Then both these child chromosomes have undergone the operation of mutation to find out an improved solution. In the mutation operation, the position of a gene is selected randomly and that gene is flipped. The muted chromosomes are then evaluated by the cost function. The fitness values generated by muted chromosomes are compared to the fitness of the chromosome from the previous generation. If the muted child chromosomes are more fitted in terms of fitness values than the parent chromosome, then the parent chromosomes are substituted with the child chromosomes. This process is continuing till the iterations are over or stopping criteria are met.

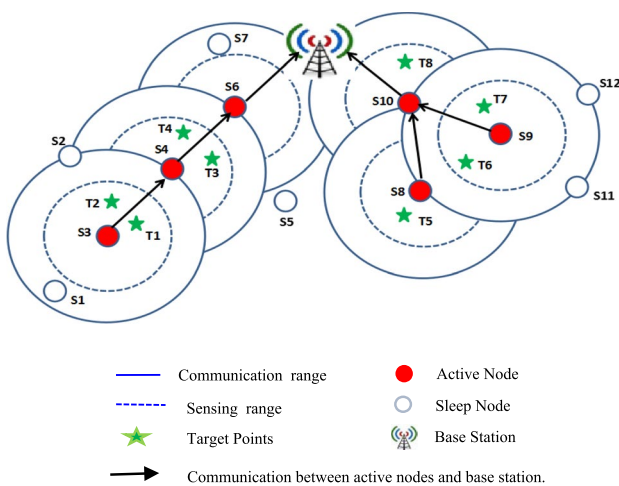


Fig. 1 An example of a network with full coverage and connectivity



### 4.2 Chromosome representation

The chromosomes are represented in the binary string of ones and zeros. The sensor nodes deployed decides the length of the chromosome. Suppose the gene value at the *i*th position is 1, it means the sensor node in *i*th position is active and if the value is 0 then the node in *i*th position is considered in sleep mode.

Illustration 1: Consider the network with nine targets  $T = \{T_1, T_2, T_3, \dots, T_9\}$  and 12 sensor nodes  $S = \{S_1, S_2, S_3, \dots, S_{12}\}$  deployed randomly as shown in Fig. 2a. The chromosome length is equal to the number of nodes deployed, that is 12.

From Fig. 2b, it is observed that the gene values at positions  $S_1, S_2, S_5, S_6, S_8, S_9$  are 1 as these nodes are active and the gene values at the positions  $S_3, S_4, S_7, S_{10}, S_{11}, S_{12}$  are 0 as the nodes are inactive or in sleep mode.

### 4.3 Fitness function derivation

Four objectives are considered for the fitness function as follows.

1. Select less number of active nodes.  
Suppose if *K* is the active sensor nodes out of *M* deployed nodes. Hence, the first objective will be.

Objective 1: Out of the total *M* number of deployed nodes only a few nodes are active.

$$\text{Minimize } F1 = \frac{K}{M} \tag{5}$$

2. Coverage of all the targets  
To provide full coverage, every target must be covered by at least one node. A sensor node can cover one or more target points.

Objective 2: Coverage of all targets.

As stated in Eq. (1) before,  $C_{sens}(T_n)$  is the sensor node set that covers the target  $T_n$  inside the sensing range.

The coverage cost of a target  $T_n$  is written as

$$C_{sensCost}(T_n) = \begin{cases} +1 & \text{if } |C_{sens}(T_n)| \geq 1 \\ -1 & \text{otherwise} \end{cases} \tag{6}$$

Therefore, the second objective is written as

$$\text{Maximize } F2 = \frac{1}{N} \sum_{n=1}^N C_{sensCost}(T_n) \tag{7}$$

3. Connectivity  
To provide full connectivity, all the active sensor nodes must be able to communicate with each other as well as with the base station for transmitting the data acquired from targets to the base station. It means that every sensor node should be within the communication range of at least one sensor node to retain connectivity.

Objective 3: The active nodes and base station connectivity.

As declared in Eq. (2) before,  $C_{com}(S_m)$  refers to the sensor nodes set that are inside the communication range of  $S_m$ .

Hence, the connectivity cost  $C_{comCost}(S_m)$  of a sensor node  $S_m$  will be

$$C_{comCost}(S_m) = \begin{cases} +1, & \text{if } |C_{com}(S_m)| \geq 1 \\ -1, & \text{otherwise} \end{cases} \tag{8}$$

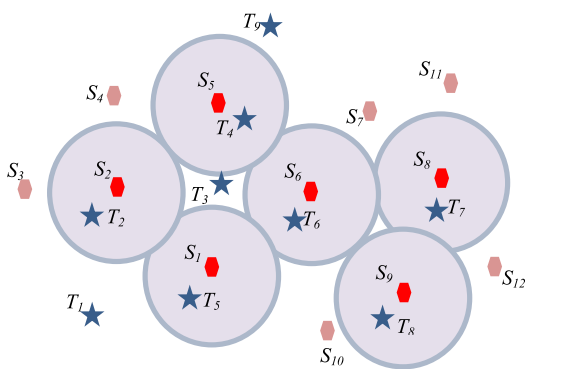
$$\text{Maximize } F3 = \frac{1}{M} \sum_{m=1}^M C_{comCost}(S_m) \tag{9}$$

4. Highest residual energy node selection  
Selecting nodes with higher residual energy avoids the frequent formation of scheduling and which in turn it will avoid the network overhead.

Objective 4: Maximum residual energy of the minimum selected active nodes is always better.

$$\text{Maximize } F4 = \{ER(S_n) \forall n, 1 \leq n \leq K\} \tag{10}$$

The weight sum technique is utilized to build the multi-objective fitness function. To create a single objec-



★ Target      ● Active node      ● sleeping sensor node

(a) WSN With twelve sensor nodes and eight targets

$S_1$	$S_2$	$S_3$	$S_4$	$S_5$	$S_6$	$S_7$	$S_8$	$S_9$	$S_{10}$	$S_{11}$	$S_{12}$
1	1	0	0	1	1	0	1	1	0	0	0

(b) Chromosome representation

Fig. 2 a WSN with twelve sensor nodes and eight targets. b Chromosome representation

tive function, a weight value is multiplied with every objective before being combined, as illustrated below.

$$\text{Fitness} = W1 \times (1.0 - F1) + W2 \times F2 + W3 \times F3 + W4 \times F4 \quad (11)$$

$$\text{Fitness} = W1 \times (1.0 - \frac{K}{M}) + W2 \times \frac{1}{N} \sum_{n=1}^N C_{sensCost}(T_n) + W3 \times \frac{1}{M} \sum_{n=1}^M C_{comCost}(S_m) + W4 \times \frac{ER}{E_{max}}$$

$E_{max}$  Is the summation of the energy of all sensor nodes.

We considered  $W1 + W2 + W3 + W4 = 1$ .

$0 \leq Wn \leq 1, \forall n, 1 \leq n \leq 4$ .

Maximizing the Fitness value is the objective.

Objective : Maximize Fitness (12)

This means that maximum is the fitness function better is than the solution. Concerning the above individual objective functions following are the observations.

**Comment 1:** It is observed from Eq. (11) that  $F1, F2, F3,$  and  $F4$  are four individual objective functions that signify the active nodes count, coverage to all targets, connectivity among active sensor nodes, and energy level of nodes. Each objective functions have different ranges of scale values. Therefore, to bring the range of all the objective function values to the same scale, their values are adjusted in a manner such that the values are normalized between 0 and 1 for all the objective functions in Eq. (11).

**Comment 2:** The above four objective functions are contradictory, which means trying to optimize one objective function hinders on optimization of another objective function. Ex. Attempting to maximize the objective function with fewer active nodes may impede other objective functions  $F2$  and  $F3$  because with the fewer nodes it has become very difficult to manage the guaranteed full coverage and connectivity. Similarly trying to optimize objective function  $F4$  by choosing sensor nodes with maximum residual energy may not provide guaranteed coverage and connectivity. Sometimes low energy level sensor nodes may have been selected for providing coverage and connectivity.

**Comment 3:** Sometimes there may be some redundant nodes are activated to provide coverage or connectivity. Redundant selection of nodes for coverage or connectivity will not affect objective functions  $F2$  and  $F3$ , but it will hamper the objective function  $F1$ . Thus derived fitness function will not encourage the selection of unnecessary and redundant activation of the nodes.

## 5 Proposed work

In the proposed algorithm we have used GA with the Dither Creeping mutation rather than the traditional mutation to find out the better chromosomes. Dither Creeping mutation (DCM) replaces the popularly used bitwise mutation operator in classical GA. Rather than being a fixed mutation rate, the mutation rate in the DCM is generated randomly throughout the GA run.

In the dither creeping mutation mechanism, each mutant is assigned with probability  $P_{idcm}$  where  $P_{idcm} \in [P_{min}, P_{max}]$  is a uniform random variable. The range of  $P_{idcm} \in [0.03, 0.07]$  is used for the proposed algorithm.

Each gene of each chromosome is selected with the probability of  $P_{idcm}$  being mutated. The chromosome is selected as a probability  $P_d$  of being muted. In exploring the search space for the extremely constrained problem, Dither Creeping Mutation is more efficient than bitwise mutation. Dither Creeping Mutation Algorithm and flow chart is as follows (Fig. 3).

P: Population Individual member (chromosomes).

Rand: Any random number between 0 and 1.

$P_d$ : Probability of being mutated.

$P_{idcm}$ : Probability to be mutated.

N: length (P).

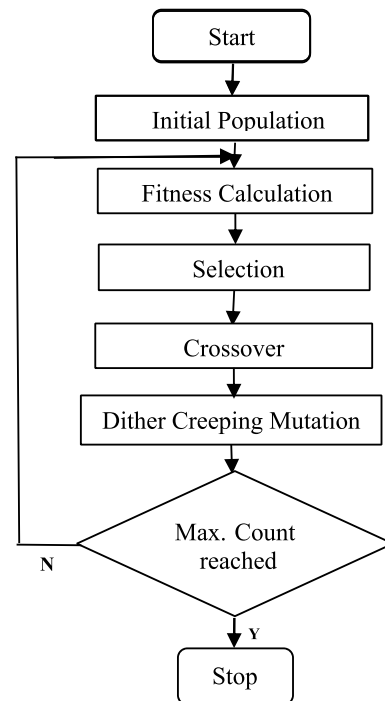
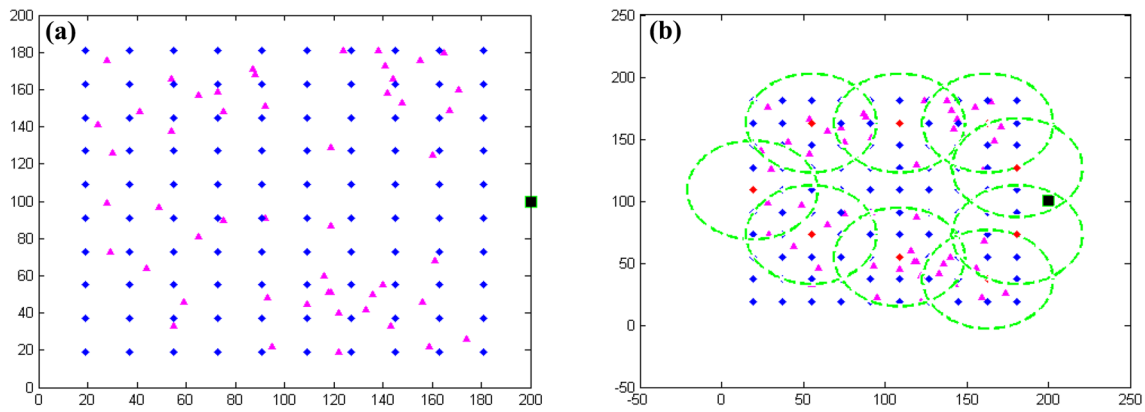


Fig. 3 Flow diagram of GA with DCM



**Fig. 4** **a** 100 sensor nodes placed in  $10 \times 10$  grid and 50. **b** Nine active sensor nodes selected out of 100 targets are deployed randomly sensor nodes

**Algorithm 1** Dither creeping mutation.

**Input:** A chromosome,

**Output:** Mutated chromosome

```

1      Initialize Chromosome  $P$ 
2      for  $i = 1$  to  $N$ 
3           $P_{idcm} = P_{min} + \text{Rand}(1) \times (P_{max} - P_{min})$ 
4           $P_d = 0.5$ 
5          if  $\text{Rand}(1) < P_{idcm}$ 
6              if  $\text{Rand}(1) \leq P_d$ 
7                   $popm(i) = \text{Min}(0, P(i))$ 
8              else
9                   $popm(i) = \text{Max}(1, P(i))$ 
10             end if
11         end if
12     end for

```

## 5.1 Energy model

The energy model employed in the experimentation is similar to the energy model employed in Heinzelman et al. (2002). Energy from the transmitter is used to power both the amplifier and radio electronics. The energy from the receiver powers the radio electronics. The number of bits to be transferred over the distance determines the amount of energy dissipated by the sensor nodes. If the propagation distance  $d$  is less than the threshold distance  $d_0$ , the amount of energy that the sensor node consumed is proportional  $d^2$  else it is  $d^4$ . The amount of energy expended by each sensor node in the network to transmit  $n$  bits over a distance is stated using the equations below.

$$E_{TX}(n, d) = nE_{elect} + nE_{fs} \times d^2 \quad (d < d_0) \quad (13)$$

$$E_{TX}(n, d) = nE_{elect} + nE_{fs} \times d^4 \quad (d > d_0) \quad (14)$$

where,  $E_{elect}$  is the amount of energy used to operate the transmitter or receiver and reliant on different parameters like digital coding, filtering, signal spreading, and modulation.

The receiver circuit's energy consumption for receiving  $n$  bits of data is represented as

$$E_{RX}(n) = n \times E_{elect} \quad (15)$$

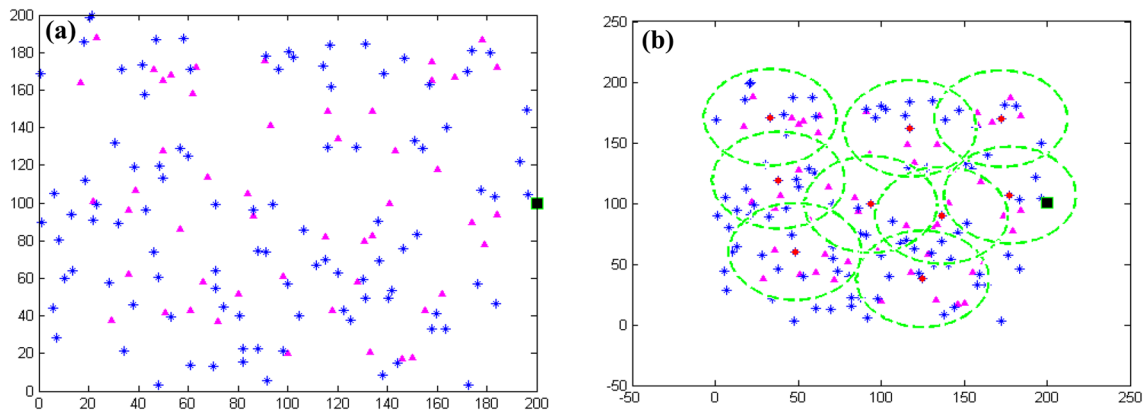
## 6 Experimental setup and result

The implementation of the proposed algorithm is carried out on a system with a 2.4 GHz CPU, an Intel i5 processor, 4 GB RAM, Microsoft Windows 10 platform, and MATLAB R2013a.

To perform the extensive simulation, the experimentation is done on two distinct scenarios #WSN1 and #WSN2 as shown in Figs. 4a, 5a. The area of the sensor network for both the scenarios is considered as  $200 \times 200$  m and the base station is considered at (200, 100). The #WSN1 is considered a grid-based scenario in which at each grid cross point a sensor node is placed and targets are placed randomly. Whereas in #WSN2, both sensors and targets are placed randomly. Table 1 lists the radio model and Network parameters that were used to run the simulation.

The weight factors  $W_1$ ,  $W_2$ ,  $W_3$ , and  $W_4$  are tested for the different combinations of weight values. It is find that the performance of proposed algorithm substantially better





**Fig. 5** **a** 100 sensor nodes and 50 targets. **b** Nine active sensor nodes selected out of 100 deployed sensor nodes randomly

**Table 1** Radio model parameters and network parameters

Parameter	Value
<i>Radio model parameters</i>	
<i>E<sub>elect</sub></i>	50 nJ/bit
<i>E<sub>fs</sub></i>	10 pJ/bi/m <sup>2</sup>
<i>E<sub>mp</sub></i>	0.0013 pJ/bi/m <sup>4</sup>
Length of packet	4000 bits
Size of message	500 bit
<i>Network parameters</i>	
Simulation area	200 × 200 m, 300 × 300 m, 400 × 400 m
Base station	200 × 100 m, 300 × 150 m, 400 × 200 m
Sensor node	100–300
Sensor position	Scenario 1 (#WSN1): grid based Scenario 2 (#WSN2): random based
Targets	50–100
Range of communication	70 m
Coverage range	40 m

in random and grid based scenarios for  $W_1 = 0.3$ ,  $W_2 = 0.2$ ,  $W_3 = 0.2$  and  $W_4 = 0.3$ .

For the performance comparison purpose, we have also implemented active/sleep scheduling of sensor nodes with Noncrossover dither creeping mutation-based GA (GANCDM), traditional GA, NSGA-II (Deb et al. 2002), and scheduling of sensor nodes with improved GA (Harizan and Kuila 2019) and compared the performance parameters of these algorithms with the proposed algorithm i.e. active/sleep scheduling of sensor nodes with Crossover dither creeping mutation-based GA (GACDCM).

## 6.1 Simulation result

### 6.1.1 Experiment 1

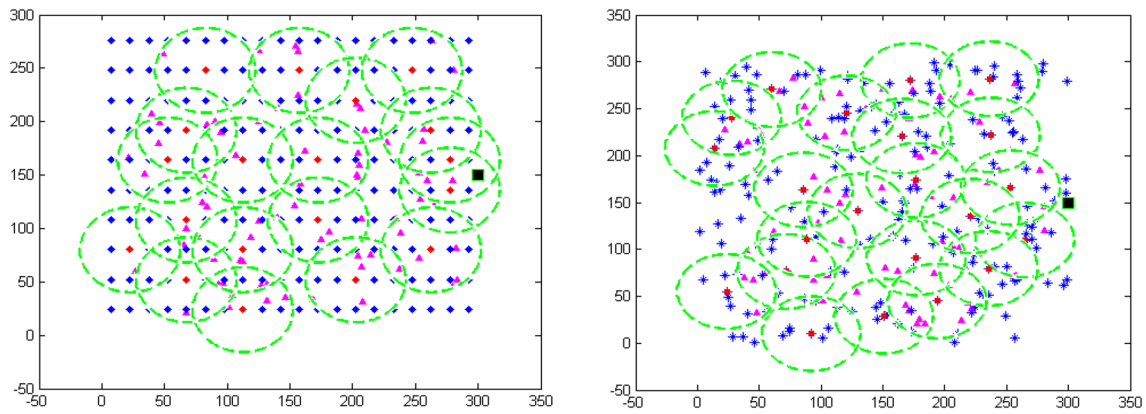
The proposed algorithm is demonstrated in random as well as in grid based scenarios, where the deployed sensor nodes are considered 100, target points are 50, and network field area is considered  $200 \times 200$  m.

In the first scenario, the 100 sensor nodes are placed in the grid of  $10 \times 10$  and randomly 50 targets are deployed whereas, in scenario two, 100 sensor nodes and 50 targets are deployed randomly. In the #WSN1 and the #WSN2 scenarios, the proposed algorithm with GACDCM only selects nine active nodes out of 100 deployed nodes in the first round.

In the same way, the experiment is carried out in both scenarios for the number of nodes 200 and 300. The number of targets are taken 75 and 100 respectively. The network area is considered as  $300 \times 300$  m and  $400 \times 400$  m respectively. The simulation results for both scenarios are shown in Figs. 6a, b, 7a, b.

### 6.1.2 Experiment 2

In this experimentation, the deployed sensor nodes count is kept same and the targets are varied in both grid and random based scenarios. Here the nodes are considered as 300 and targets are varied from 40 to 100. The parameters of all the algorithms which are mentioned above are kept the same and a comparison of algorithms is done based on the parameter like the nodes selected with guaranteed connectivity and coverage. Figure 8a, b show the comparative results of all mentioned algorithms in both the scenarios. The suggested algorithm's performance is analysed based on the active nodes selected for the given targets. From the result,



**Fig. 6** **a** 200 sensor nodes, targets 75, selected nodes 20. **b** 200 sensor nodes, targets 75, selected nodes 22

it is seen that the active node count increases, as the targets increases. The active nodes selected to cover the 40 targets are 13 and 16 which are less than other algorithms. Thus as compared to the algorithms mentioned here, the suggested GACDCM algorithm selects less active sensor nodes which in terms minimize the energy consumption and maximize the lifetime of the network.

### 6.1.3 Experiment 3

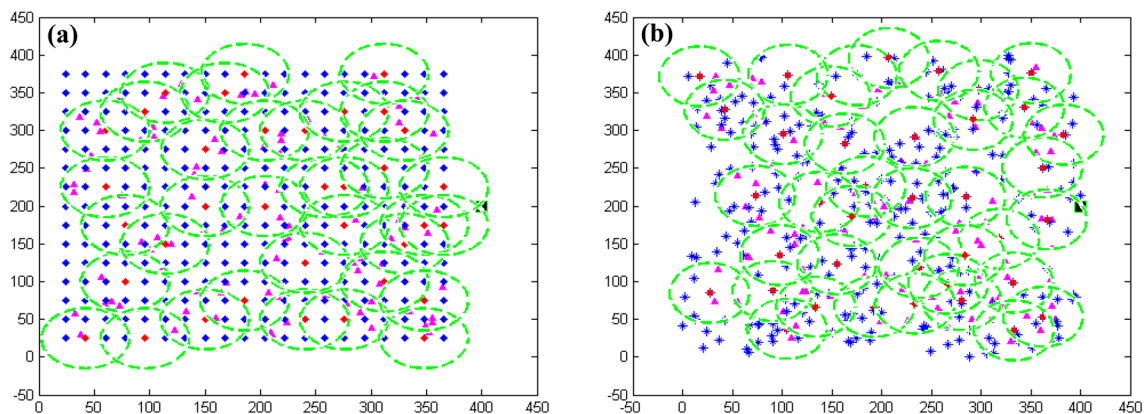
In this experimentation, the sensor nodes deployed are varied and targets are kept the same. For experimentation, the number of targets are considered 75, and the total deployed sensor nodes are varied from 200 to 400.

Figure 9a, b show the comparative results for the active sensor nodes selected for given target points and different numbers of sensors deployed. From the experimental results, it is noted the nodes selected from 300 deployed nodes are 18 and 20 in both scenarios respectively. Thus the proposed GACDCM selects less active sensor nodes than coexisting schemes.

### 6.1.4 Experiment 4

The simulation has been carried out to check how many rounds are taken by various algorithms to die out the first node. It is observed from Fig. 10a, b, that the rounds taken to die out the first node in case of the proposed algorithm is higher than the NSGA-II, GANDCM, and GA algorithms but it is comparable with the algorithm presented by Harizan and Kuila (2019). The proposed algorithm took more round because the algorithm selects the nodes which are having maximum residual energy as per the fourth objective of the fitness function. Therefore, nodes took more time to run out of energy.

The experimentation is extended to examine the energy consumption of the proposed GACDCM. The energy model used in this experiment is the same as that is used in LEACH (Heinzelman et al. 2002). Figure 11a shows the comparison of all the algorithms in terms of residual energy per round. From Fig. 11a it is observed that the network has full coverage and connectivity till 1742 rounds for GA, 2087 rounds for GANDCM, 2358 rounds



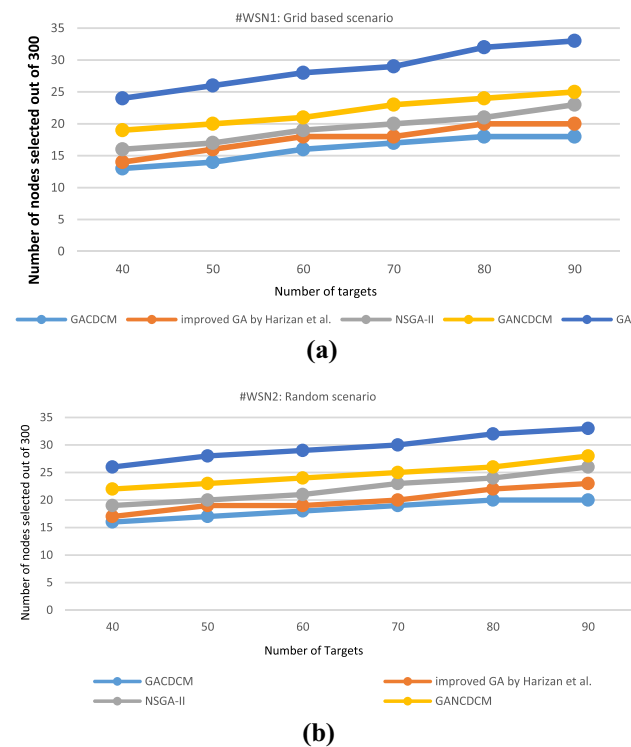
**Fig. 7** **a** 300 sensor nodes, targets 100, selected nodes 36. **b** 300 sensor nodes, targets 100, selected nodes 39

NSGA-II, 2566 for the improved GA by Harizan and Kuila (2019), and 2670 rounds for the proposed GACDCM. Thus from the results, it is clear that the lifetime of the proposed GACDCM is increased by 53.27% than traditional GA, 27.93% than GANCDM, 13.23% than NSGA-II, and 4% than algorithm proposed by Harizan and Kuila (2019). It is concluded from the result that the lifetime of the proposed GACDCM is more as compared to the other algorithms.

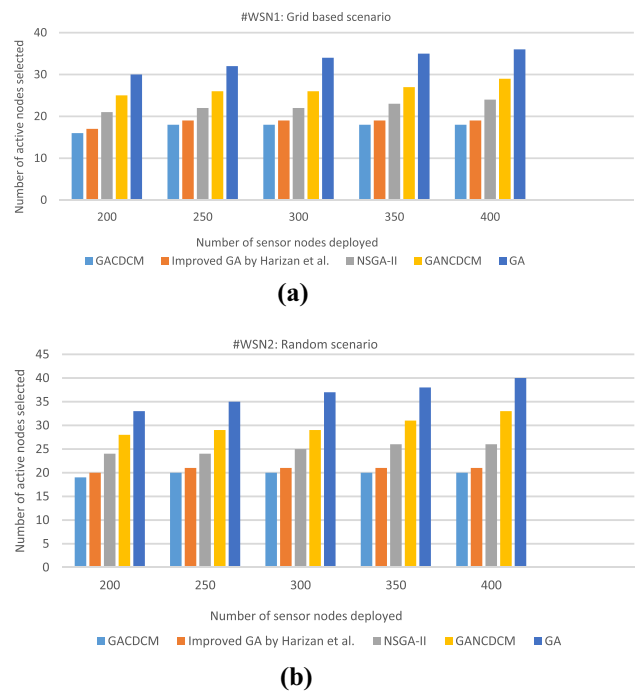
It is also observed residual energy of the proposed GACDCM algorithm is more than the other algorithm throughout all the rounds. The reason for this is as the offered algorithm is selecting the minimum number of active nodes per round, less energy per round is consumed that helps to enhance the network lifetime.

### 6.1.5 Experiment 5

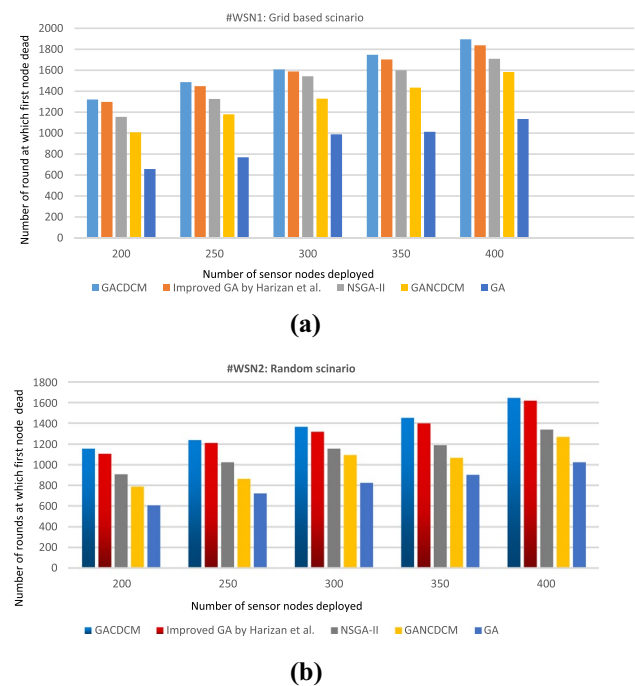
Further, the research is extended to furnish the requirement of k-coverage to every target point and m-connectivity between the sensor nodes, taking into consideration that sensor nodes are prostrate to failure. Because of this, if one of the sensor nodes failed, each target point is covered with minimum k-1 coverage similarly every sensor node is covered with m-1 connectivity.



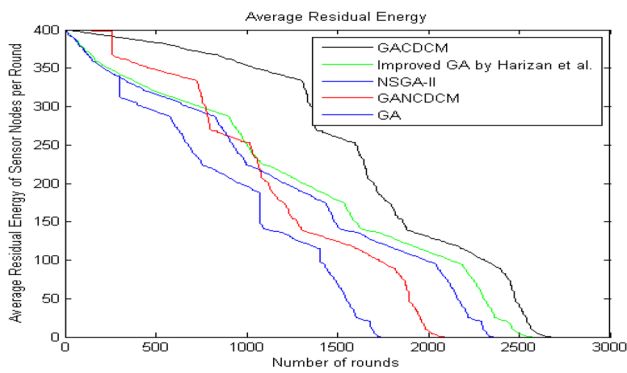
**Fig. 8** a Comparison of various algorithms according to the active nodes and targets for #WSN1 grid based scenario b Comparison of various algorithms according to the active nodes and targets for #WSN2 random scenario.



**Fig. 9** a Comparison of various algorithms according to active nodes and nodes deployed for #WSN1 grid based scenario. b Comparison of various algorithms according to active nodes and nodes deployed for #WSN2 random scenario.

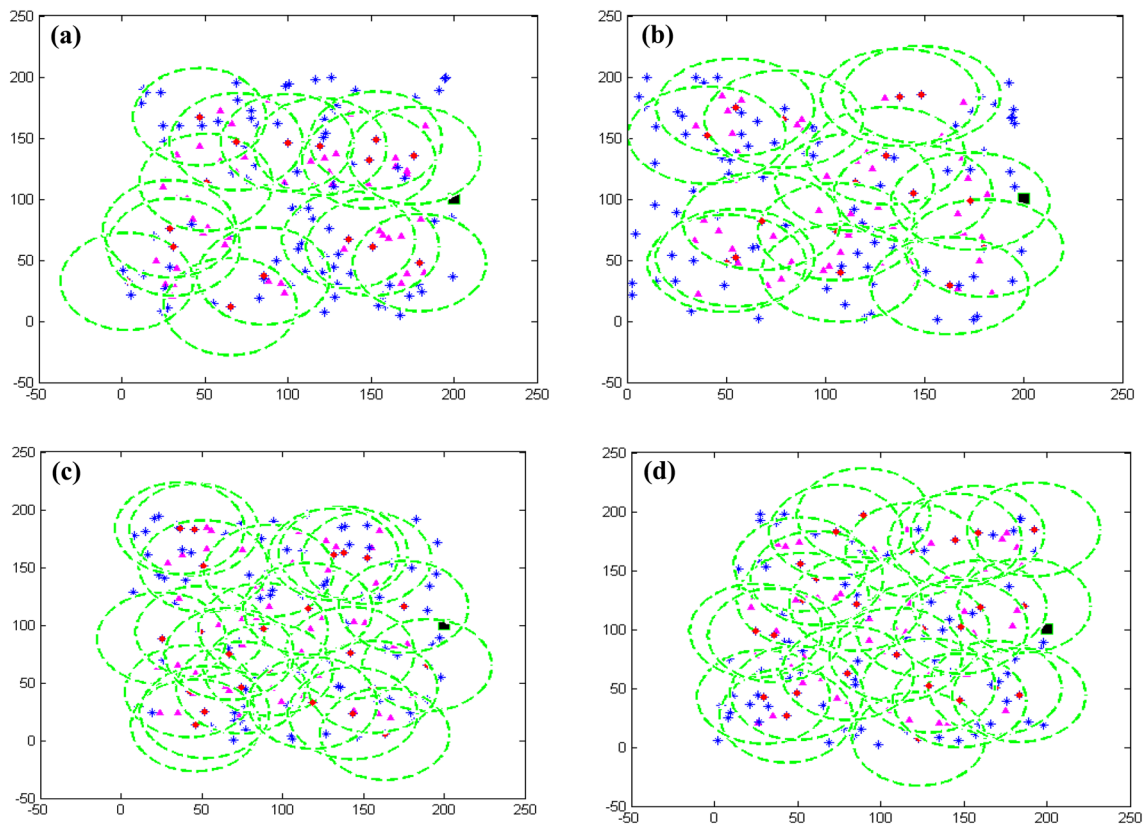


**Fig. 10** a Comparison of total nodes deployed and the round at which the first node dies b Comparison of total nodes deployed and the round at which the first node dies



**Fig. 11** Comparison in terms of average residual energy

of energy and prolongation network lifetime, we have presented the energy-efficient active/sleep scheduling algorithm for the sensor nodes using a GA with Dither Creeping mutation. The algorithm aims to activate less active sensor nodes from the total sensor nodes deployed in the network field which ensures maximum coverage to all targets as well as connectivity among active nodes and base station. The novelty of the proposed GA with Dither Creeping mutation is that the mutation probability is generated randomly rather than the fixed value for each string. As a result, for the same generation, the various strings of the proposed algorithm will be subjected to various creeping mutation probabilities and the same string is subjected to various creeping mutation probabilities at successive



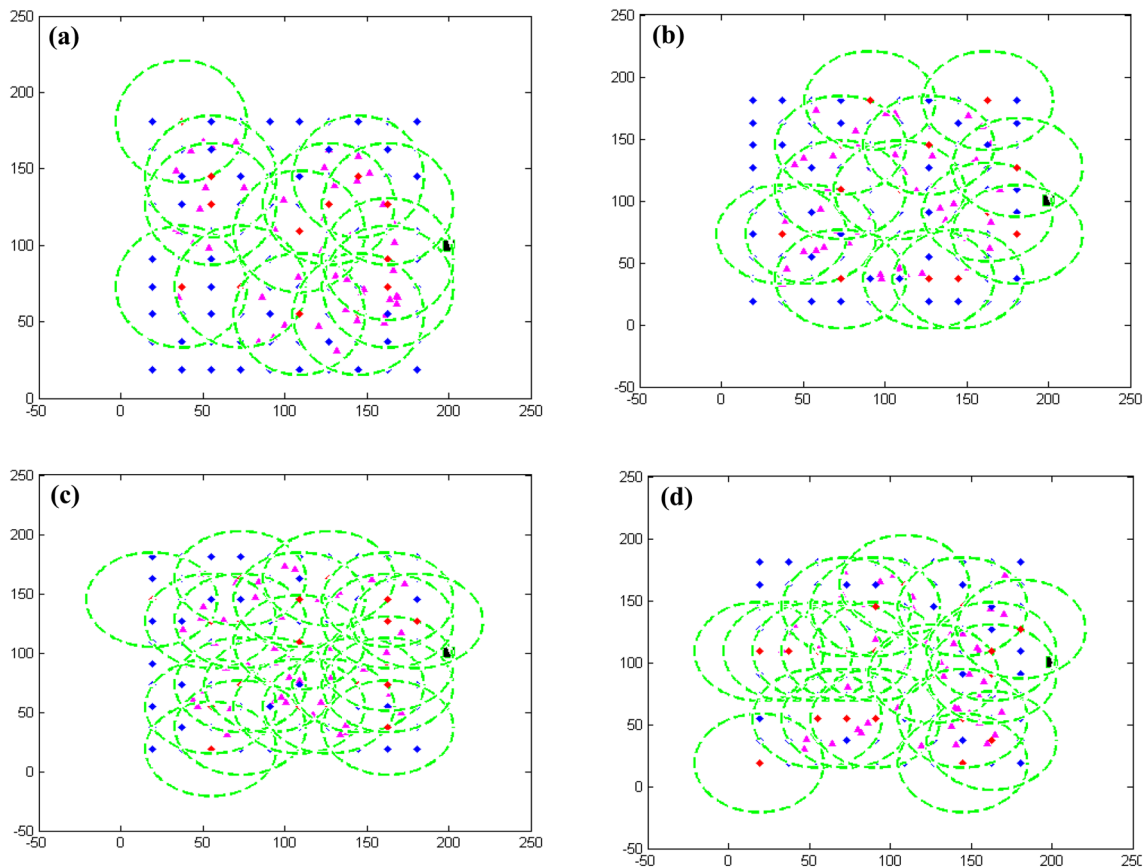
**Fig. 12** Sensor network for the various k-coverage and m-connectivity for random based scenario

Figure 12a–d and 13a–d show the sensor network for the various k-coverage and m-connectivity for random as well as grid based scenarios.

## 7 Conclusion

The two important challenges in the development of WSNs are the efficient utilization of the energy of the nodes and the network lifetime. Therefore, to reduce the consumption

generations. The proposed GA with the Dither Creeping mutation approach replaces the traditional bitwise mutation. For exploring the search space in case of extremely constrained problems, Dither Creeping Mutation is more efficient than bitwise mutation. The proposed algorithm has been thoroughly simulated under several scenarios and conditions such as a fixed number of sensor nodes and the different number of targets in the field, fixed number of targets and the different number of sensor nodes in the field,



**Fig. 13** Sensor network for the various  $k$ -coverage and  $m$ -connectivity for grid based scenario

etc. From the experimental result, it is observed that the lifetime of the proposed algorithm GACDCM is increased by 53.27% than traditional GA, 27.93% than GANCDM, 13.23% than NSGA-II, and 4% than algorithm proposed by Harizan and Kuila (2019). The experimental results demonstrated that the performance parameters of the proposed algorithm are better as compared to GA, GANCDM, NSGA-II and scheduling algorithm by Harizan and Kuila (2019) under all conditions in terms of the number of less active node selection, less consumption of energy, and lifetime of the network.

We have extended our research to furnish the requirement of  $k$ -coverage to every target point and  $m$ -connectivity between the sensor nodes, taking into consideration that sensor nodes are prostrate to failure. The result demonstrated that if one of the sensor nodes failed, each target point is covered with minimum  $k-1$  coverage similarly every sensor node is covered with  $m-1$  connectivity.

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