An Improved Genetic Algorithm for Scheduling Sensor Nodes in WSN

Sami Qawasmeh*

[1]Department of Computer Science Jadara University Irbid, Jordan E-mail: sqawasmeh@jadara.edu

Abstracts: The extended lifetime of Wireless Sensor Networks (WSN) is an attractive goal for various types of research. This can be achieved if not all sensor nodes in the network consume their energy; this is because the energy consumption of every sensor node is a vital resource for a WSN. The scheduling techniques have recently enticed the interest of the researchers' community, as they provide the ability to adjust a set of nodes in sleep mode instead of activating all sensor nodes. However, we consider the sensors that were selected to be in sleep mode, which will not affect network coverage for any target or full connectivity. In this paper, the genetic algorithm has been used to build efficient scheduling for the sensor nodes, which were based on multiple objectives in the fitness function, and we have proposed improved mutation and crossover operations. Then, we evaluate our approaches in a target tracking application compared with previous GA approaches. Our simulations show that we have an optimal chromosome that contains a minimum number of active sensor nodes for scheduling within 3-5 iterations.

Keywords: Wireless Sensor Network, Genetic Algorithm, Scheduling, Coverage And Connectivity, Routing, Optimization.

1. INTRODUCTION

The last few years have witnessed rapid and important developments in every field of technology, such as smart spaces, IOT, and home security. Wireless sensor networks WSN became widely used in many fields of applications, such as environmental or place monitoring, fire forecasting, irrigation systems, and biological detection.[1]. WSN is a collection of thousands of tiny sensor nodes that are deployed randomly or manually in a specific area to sense data and then send this collected data to the base station directly or through other sensor nodes. Data routing to reach the sink node occurs through many types of routing protocols. There are many classifications of routing protocols that determine the use of any of them depending on the application, such as flat protocols, hierarchical protocols, and location-based protocols. In the sink node or base station there are performing a process, analyzing the data, and taking actions based on the collected data, WSN as shown figure 1.

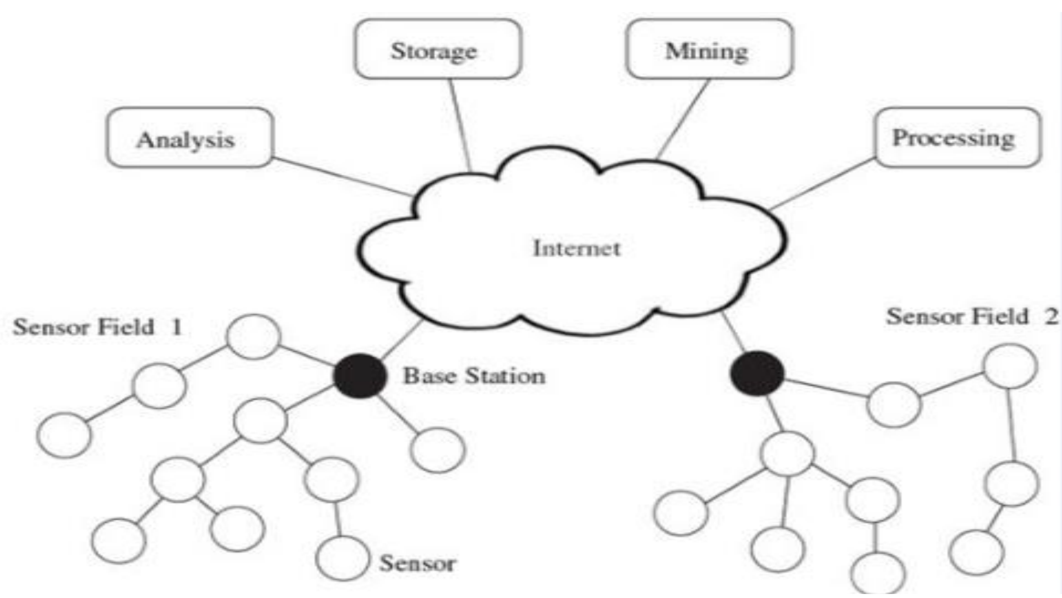


Figure 1 Wireless Sensor Network

Sensor nodes are small devices with low costs, but with limitations in energy and storage, sensing and forwarding data between sensor nodes leads to a lot of energy consumption, minimizing the lifetime of the WSN. On the other hand, recharging the batteries in the sensor nodes is impossible in some applications, especially in difficult-to-reach environments. So, the extended lifetime of the network is a major challenge in WSN, and there is a lot of research on this issue. There are several challenges faced by WSN, which are given below:

1) Battery power is limited.

2) Limited capability for storage.

3) Low band width.

4) Ensure complete coverage and full connectivity.

5) High error rate and security issue, due to wireless connection.

To design a WSN with limited challenges, especially the lifetime of the WSN, researchers have introduced several techniques, where scheduling sensor nodes is the most efficient technique.

This paper proposes an improved algorithm for task scheduling with the goal of maximizing WSN lifetime by not activating all sensor nodes in the network. Simply in a specific round, a set of sensor nodes out of all deployed sensor nodes in the network are in active mode, sensing and collecting data from target points, which we are monitoring and tracking, and all remaining sensor nodes are in sleep mode. In the next rounds, sensor nodes will be switched between inactive and sleep modes. This technique reduces the total power consumption of the WSN [3].

Due to the significance of the energy efficient problem in the WSN, various efforts have been made to tackle this problem. These proposed algorithms are used to schedule the sensor nodes, like natural algorithms such as Ant colony optimization, Particle swarm optimization, a Lion algorithm, and a Genetic algorithm. In this paper, we will use a genetic algorithm as an optimization technique to schedule sensor nodes in WSN.

To model the WSN with some number of nodes having different parameters, such as sensing radius, transmission radius, and resource consumption model, is a major challenge. These parameters have an impact on task scheduling. Task scheduling should meet the application’s demands. For that, careful consideration should be given to modeling the WSN and the applications.

2. OVERVIEW GENETIC ALGORITHM

The genetic algorithm (GA), as a natural network, is one of the optimization and search algorithms. It’s inspired by the natural evolution theory of Darwin. GA is widely used to solve several optimization problems and find an optimal solution. In GA, there are many solutions, and GA selects the best solution based on the proprieties of each one.

The genetic algorithm goes through five phases, as follows:

1) Initial population: this process starts with a set of individuals, or initial population. As a random process, each of these individuals is called a chromosome, and every chromosome is one possible solution to the problem [4]. So, in the first step, we generate a population that is a random set of individuals or chromosomes. Each chromosome has a string of genes; the number of genes depends on the problem to be solved. The genes may be represented as numbers or alphabets; binary values are usually used (a string of ones and zeros), as shown in figure 2.

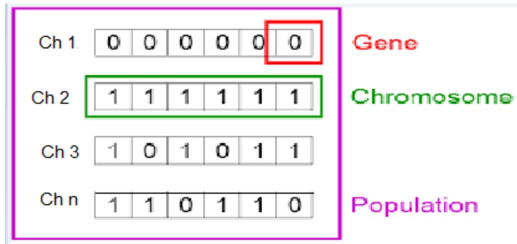


Figure 2. Set of population

2) Fitness function: Each chromosome has a fitness value that expresses its quality, and it is determined through fitness function.

3) Selection: In this phase, fit chromosomes are selected and used in the next genetic operation to create a new generation.

The chromosomes with higher fitness values have more chances to be selected for the next generation. There are several types of selection, such as rank selection, tournament selection and Roulette wheel selection, etc.

4) Crossover: In this process, a pair of random chromosomes is selected as parents, in which a set of genes is swapped to produce a new generation of children, as shown in figure 3. There are different types of crossovers, such as crossover on one-point crossover on two-point, uniform crossover, etc.

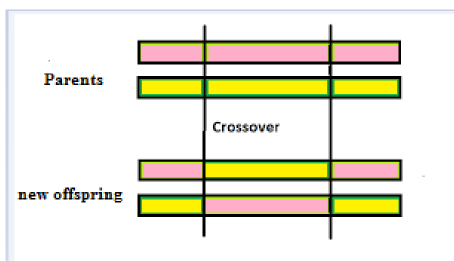


Figure 3. Crossover

5) Mutation: This process occurs in one of the genes values in the chromosome, where this value is randomly flipped to produce a new generation, as figure 4 flipped the gene value of 3 and 4.

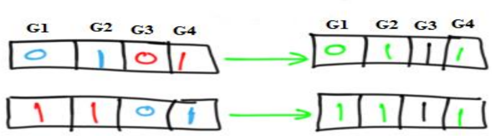


Figure 4. Mutation

After these five phases, the new generation (new offspring) will be produced, and this algorithm will terminate if the new generation is not different than the previous one [4].

3. RELATED WORK

In [5] a genetic algorithm is presented to deploy the sensor nodes in an M*N grid. The sensor nodes are placed at crossing points in the grid network to cover all targets and get full connectivity. The chromosomes in GA are represented with equal length as M+N, starting with M genes as row numbers and N genes as column numbers.

The fitness function in this paper is the minimum number of selected sensor nodes needed to provide full coverage and connectivity.

In GA operations, the new chromosomes are not valid, especially after crossover operations. To fix invalid offspring, use the new chromosome correction phase with the GA to get better offspring. The local search algorithm (LS) is also used with GA to get the optimal solution to the full coverage and connectivity problems.

Gupta et al.[6] propose two algorithms and a greedy approach, using GA to place a minimum number of relay nodes in predetermined places and achieve k connectivity for each sensor node with relay nodes together; the other sensor nodes are placed randomly. A greedy approach was used to structure a policy of node deployment. However, the connectivity between the relay nodes is not mentioned in this paper.

The connectivity problem between all sensor nodes is solved in [7] proposed GA approach to deploy a minimum number of sensor nodes, coverage to all targets, and m connectivity for each placed sensor node. GA operation, crossover, and mutation produced an efficient chromosome.

Sensor nodes deployment remains one of the main problems in WSN. In [8] introduces the ACO-Greedy approach to deploy sensor nodes in a grid network, each crossing point in the grid is determined as a point of interest (POI). The objective is to cover all points of interest with the minimum number of sensor nodes placed at each crossing point.

Chin and Yang [9] proposed a deployment of a minimum number of sensor nodes with an energy-neutral process. They proposed the GMILP approach to ensure coverage for sensing nodes and relaying nodes by applying two heuristics: DirectSearch and GreedySearch, which are based on direct paths to the sink node.

Chin and Yang in [10] the sensor nodes are placed in each grid point to cover all targets and determine that each grid point is an energy harvesting point. To maximize a network's lifetime, the authors propose a linear programming and Maximum Utility Algorithm (MUA) to schedule sensor nodes in WSN while ensuring all targets are covered. LP solution gives more efficient performance than other algorithms, but it is computationally very costly.

Hou and Zhang in [11] discuss the relationship between connectivity between sensor nodes and coverage for targets. That display if the radio range is smaller than twice the sensing range. Hence, full coverage also means complete connectivity.

The authors in [12] proposed a greedy approach to energy-efficient target coverage by determining the remaining energy for each sensor node and the number of targets. This approach achieves better performance than traditional algorithms without considering connectivity problems.

Rossi and Lersteau in [13] propose a scheduling approach for the sensor nodes to extend the lifetime of WSN, a scheduling approach used to maintain and balance the residual capabilities of the sensor nodes to keep tracking all moving targets. This approach is done in two steps: processing the input data to get a mathematical formula, and then a column generation algorithm.

Banerjee and Jun [14] proposed increasing lifetime with a controllable mobile cluster head. The authors here introduced an improved cluster head protocol instead of static CH by using a mobile CH. The idea is to control a CH to move near sensors with high energy and towered targets.

Elhoseny and Mohamed [15] proposed a new K-coverage model based on a genetic algorithm (GA) to extend a WSN's lifetime. Also, their proposed method improved the WSN's performance regarding the amount of energy consumed, the network lifetime, and the required time to switch between different covers.

Moh'd and Al-Ajouri (16) tried to maximize the coverage and lifetime of WSN by introducing a deployment algorithm with harmony search to select the optimal sensor nodes. They combine adaptable length encoding in all solution vectors to represent a variable number of candidate sensor nodes.

In [17], Particle Swarm Optimization (PSO) algorithm is also used to solve the k coverage and m connectivity problems with minimum cost and find the optimal deployment of sensor nodes for global search using PSO and GA for local search. Deb and Pratap [18] provide a multi-objective algorithm, using a genetic algorithm with sharing parameters on non-dominated sorting multi-objective NSGA, to create a mating pool using selection operations to collect an offspring, and parents then select the optimal solution, which is the minimum number of nodes that converging the target area.

The authors in [19] proposed to extend the lifetime of the WSN genetic algorithm based on multi-objectives to schedule sensor nodes; they have introduced improved mutation operations to discard redundant and unimportant sensor nodes; and they used Linear Programming (LP) to formulate the scheduling problem.

4. PROBLEM STATEMENT

In order to extend the lifetime of WSN instead of activating all sensor nodes in each round, a set of sensor nodes are selected to be in active mode and the remaining sensor nodes are in sleep mode. When depletion energy of one or more sensor nodes, the network will become uncovered and disconnected. So, a new set of nodes from a remaining sensor node will be set to be in active mode. The process continues until no group can be created to provide full coverage of the targets and a complete connection between the sensor nodes and the Base Station (BS). Therefore, whenever fewer sensor nodes are chosen to be in active mode, this leads to an increase in the lifetime of the network.

The problem is that when selecting a sensor node set to be in active mode, it should be considered that these sensor nodes provide coverage for all target points with full connectivity between all sensor nodes and the base station (BS) to transmit data that is sensed from targets.

5. PROPOSED APPROACH

In our approach, we will be using an improved genetic mutation and crossover algorithm based on scheduling WSN to select a minimum number of sensor nodes to be in active mode to provide full coverage and connectivity in the network.

Our proposal encoded the chromosome as a binary representation; all chromosomes have the same length and are randomly generated. Each chromosome has several genes equal to the number of deployed sensor nodes in the network. If the gene value g_i is 1, the sensor node in this position is active; hence, if the gene value g_i is 0, the sensor node is in sleep mode. i here $1 \le i \le N$, where N is the number of all sensor nodes, $N = \{ s_1, s_2, \ldots s_N\}$, and K is the number of targets $K = \{\lambda_1, \lambda_2, \ldots \lambda_K\}$.

The main modifications that we have proposed to the genetic algorithm are:

A. fitness function:

After generating the chromosomes, we evaluated each chromosome based on fitness function. In the [19] their proposed approach is a derived fitness function to conflicting multi objectives: selecting a lower number of active sensor nodes, full coverage, complete connectivity, and energy level of the sensor nodes that have been selected. These objectives are described as follows:

- Objective 1: Create a group with fewer sensor nodes for scheduling. The formation of a schedule with a minimum number of active sensor nodes helps extend the lifetime of the network [19], the objective 1 can be identified as: $f_1 = \sum_{i=1}^{N} g_i$ Maximize That suggests choosing the chromosome with a smaller number of ones.
- Objective 2: (Ensure full coverage for all targets), it can be stated as: $\text{Maximize } f_2 = \sum_{i=1}^{K} \gamma_{cost}(\lambda_i)$

  For each chromosome, calculate the overall target coverage cost; it is given as γ cost(λi). Not all targets are covered by a given chromosome; hence, give a positive cost for all targets that are covered and a negative amount with the same cost for uncovered targets. In other words,

$$\gamma_{cost}(\lambda_i) = \begin{cases} +1, & \text{if } |\zeta_{cov}(\lambda_i)| \geq 1 \\ -1, & \text{otherwise} \end{cases} \quad (1)$$

Where *ζcov(λi)*, is a group of active sensor nodes that are covering the target *λ(i)*, if it is within the sensing range of the sensor nodes [19].

- Objective 3: (Ensure full connectivity between selected sensor nodes that are in active mode) can be stated as: $\text{Maximize } f_3 = \sum_{i=1}^{N}(g_i \times \eta_{cost}(s_i))$

Where $\eta_{cost}(s_i)$, is the connectivity cost of a s_i, determine the positive cost for all sensor nodes within the communication range of s_i, and the same amount of cost with a negative sign as follows:

$$\eta_{cost}(s_i) = \begin{cases} +1, & \text{if } |v_{con}(s_i)| \geq 1 \\ -1, & \text{otherwise} \end{cases} \quad (2)$$

Where $v_{con}(s_i)$, is the group of active sensor nodes that are within the communication range of s_i, and closed to BS. Moreover, sensor node s_i can transmit data to any sensor node in this set [19].

- Objective 4: (pick out the maximum energy value from a set of lower energy nodes): each sensor node should have enough energy level to end a certain round [19]. The four objectives can be stated as:

$$\text{Maximize } f_4 = \text{Min } \{ \text{E}_R(s_i | g_i = 1, \forall_i, 1 \leq i \leq N \},$$

where E_R is the residual energy of sensor node s_i.

The fitness function with multiple objectives is created here using the Weight Sum Approach (WSA) [20], so each of these four objectives is multiplied by a weight value as (WSA), and then all multiplied values are compiled into one objective as this:

$$\text{Fitness} = \{ \text{W}_1 \times (1.0 - \frac{1}{N}\sum_{i=1}^{N} g_i) + W_2 \times \frac{1}{K}\sum_{i=1}^{K} \gamma_{cost}(\lambda_i) + \text{W}_3 \times \frac{1}{N}(g_i \times \eta_{cost}(s_i)) + \text{W}_4 \times \frac{E_{MIN}}{E_{MAX}} \}$$

Wi is a weight value, where $0 \leq W_i \leq 1$, $\forall_i$, $1 \leq i \leq N$, and the sum of these weight values is 1. The appropriate chromosomes have a higher fitness value.

B. Crossover operation:

For each chromosome, calculate the overall target coverage cost; it is given as $\gamma_{cost}(\lambda_i)$. Not all targets are covered by a given chromosome; hence, give a positive cost for all targets that are covered and a negative amount with the same cost for uncovered targets. In other words, in our proposed work, we have used a novel crossover operation. The pseudo-code for the proposed crossover method is given in Algorithm 1.

```
Algorithm 1 : Improved Crossover
Input : G1, G2
Output : GNEW
For i = 1 : N
α = random()
If α<a1
GNEW(i) = G1(i)
End If
If a1 <α<a2
GNEW(i) = G2(i)
End If
If α>a2
GNEW(i) = beroulli(p)
End If
End For
```

C. Mutation operation:

In our proposed work, we have used a novel mutation operation. Instead of checking coverage and connectivity as proposed in [15], we proposed an algorithm that checks the improvement by the objective function Fitness. It helps use each chromosome with greater value. In the improved algorithm, first we create a random permutation *PERM* of the vector (1, 2, . . ., N), then we check all *gPERMi* for i=1, . . ., N. In this case, all gene positions I =1, . . ., N have the same importance, so the sequence of changing genes is random, not 1,2,3, . . . N.

The pseudo-code for the proposed mutation method is shown in Algorithm 2.

Algorithm 2 : Improved Mutation

Input : G , N
Output : G^{new}

$G^{new} = G$
Randperm(N)
For i = 1:N
$G^{temp} = G^{new}$
$G^{temp}(i) = 1 - G^{temp}(i)$
If fitness(G^{temp})>(G^{new})
$G^{new}(i) = G^{temp}(i)$
End If
End For

6. SIMULATION EXPERIMENTS

A. Simulation environment and parameters

This experiment was conducted to modify the genetic algorithm, make scheduling of the sensor nodes, and choosing a smaller number of nodes to be in active mode, considering covering all targets, achieving full network connectivity, and having enough energy. This experiment was executed on two network scenarios. The first scenario, WSN 1, is the deployment of random sensor nodes and random targets in different network areas. The second scenario, WSN 2, is a network-based 15*15 grid, where the sensor nodes are located at the crossing point for the grid and target points are placed randomly in the network. The base station in both scenarios is placed as follows: (Area, Area/2).

In our experiment, we used 60 chromosomes as the initial population, with different gene numbers (deployed sensor nodes).

B. Simulation results

To evaluate the performance of our improved GA, we simulated the experiment using MATLAB. In our simulation environment, we utilized random deployment and grid-based deployment scenarios to execute our improved genetic algorithm on the network. The result after executing our improved GA in WSN#1 is to select 17 active sensor nodes, as shown in figure 5, and 18 active sensor nodes in WSN#2 out of 255 sensor nodes, as shown in figure 6. Similarly, we execute our improved GA in both scenarios WSN#1 and WSN#2 on different areas of 400*400 and 500*500 square meters, whereas when we execute our improved genetic algorithm in WSN1, on areas 400*400 and 500*500, we select 23 and 35 active sensor nodes, respectively, out of 255 sensor nodes. When we execute it in WSN2, on 400*400 and 500*500 square meters, we select 24 and 30 active sensor nodes, respectively, out of 255 sensor nodes. It can be seen in figure 7.

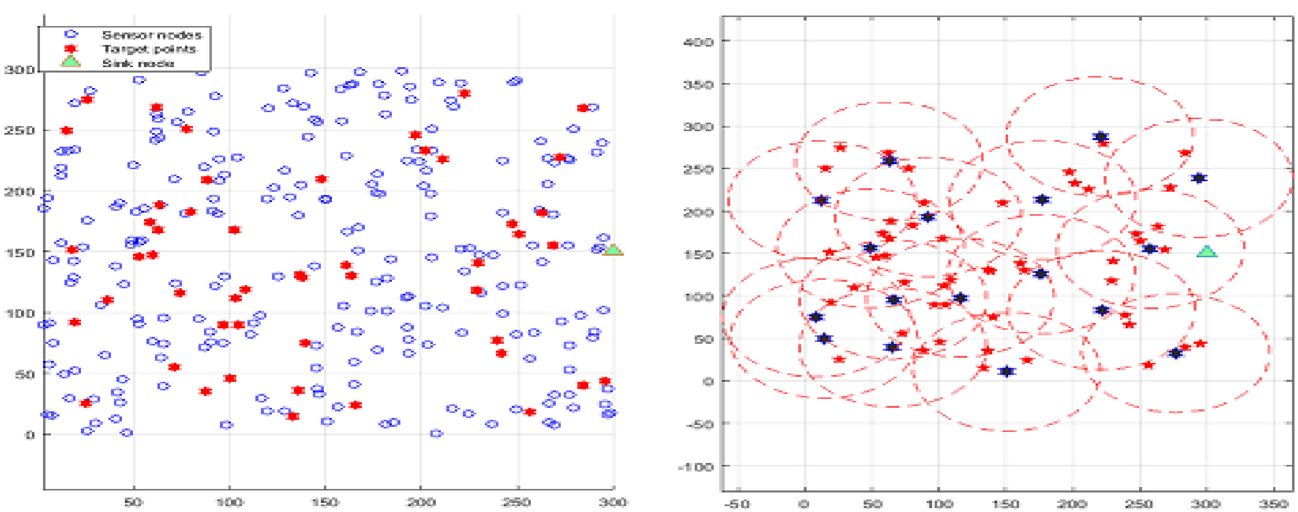


Figure 5. WSN#1: 17 active sensor nodes out of 225 have been selected by our improved GA

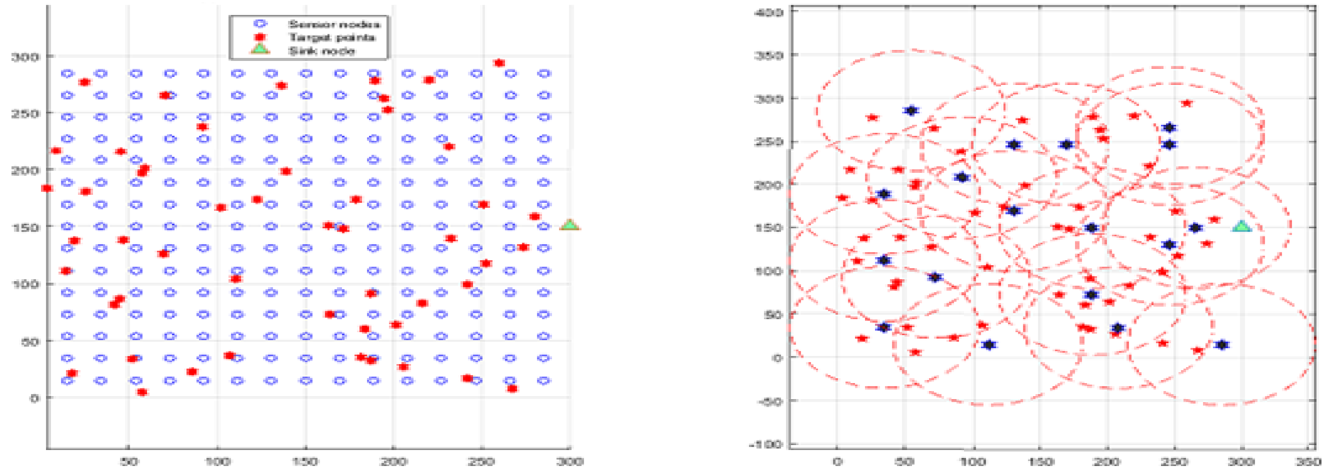
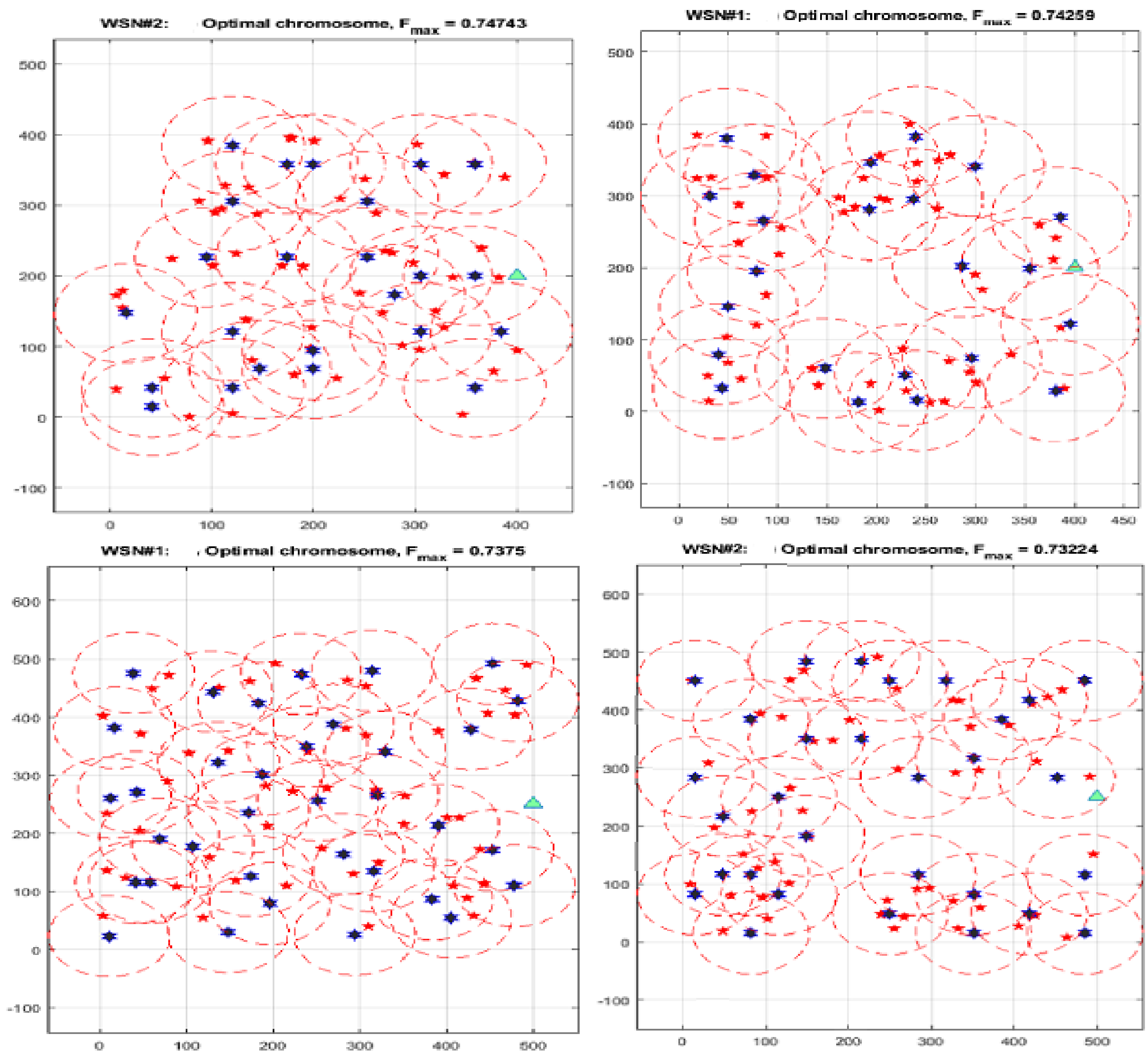


Figure 6. WSN#2: 18 active sensor nodes out of 225 have been selected by ourimproved GA



For comparison, we compare our improved genetic algorithm with a previously improved genetic algorithm [19]. The performance of our improved genetic algorithm to select a minimum number of sensor nodes is shown in the figures with 40–80 target points. The results of our improved genetic algorithm show that the higher the number of targets, the higher the number of active sensor nodes; however, in our improved GA, the number of sensor nodes that are selected in active mode is less than in the previous improved GA for various numbers of target points. As shown in figure 8, to cover 70 targets using your improved algorithm, only 20 active sensor nodes were selected. Compared to a previous improved GA, 24 active sensor nodes were selected.

We also executed our improved GA on both scenarios, WSN#1 and WSN#2, using the different number of sensor nodes for a constant number of target points of 75. The result compared with the previous improved GA [19] on WSN#1 is almost the same. However, the results of our improved GA are better than the results of the previous improved GA in WSN#2. The result of the comparison is shown in figure 9.

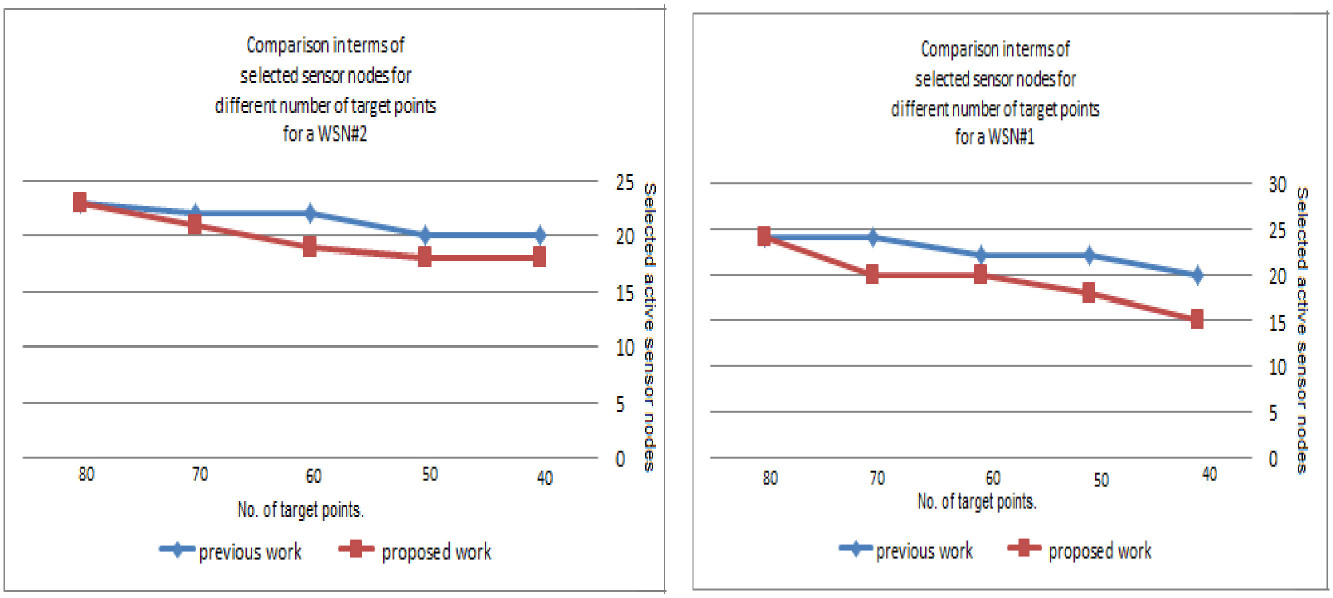


Figure 8. Comparison between two genetic algorithms of selected active sensor nodes for different numbers of target points for a WSN#1 and b WSN#2

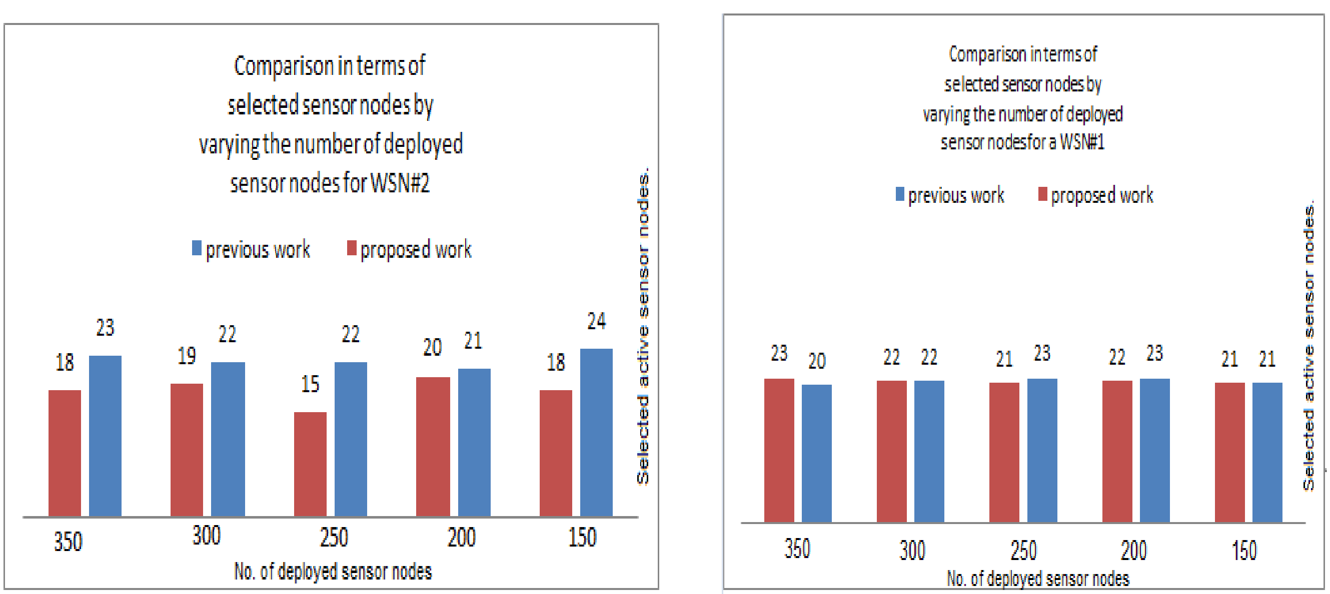


Figure 9. Comparison between our improved GA and previous improved GA, to selected active sensor nodes by different number of deployed sensor nodes for a WSN#1 and b WSN#2

7. RESULTS AND DISCUSSIONS

In this paper, we have proposed an improved genetic algorithm for scheduling sensor nodes in active and sleep modes to extend the lifetime of WSN. The key idea of the proposed algorithm is to select a minimum number of active sensor nodes in scheduling, considering full coverage for all targets, connectivity between all sensor nodes and the base station, and the maximum level of energy of sensor nodes. In this paper, we have used multiple objectives for the computation of the fitness function. These objectives are to select the fewest number of sensor nodes in active mode, full connectivity, complete coverage, and the maximum level of energy for sensor nodes. Hence, the optimal chromosome is the one with the maximum fitness value. Besides that, we have proposed modified mutation and crossover operations in genetic algorithm for better performance and more effective chromosomes. In our improved mutation operation, instead of randomly flipping the gene value on the chromosome, we used values of fitness function to compare whether the gene's flipping value gave a better fitness function value. If it does not give a better value for fitness, there is no need to flip this gene value, and so on. Also, we have introduced modifications in the crossover operation to create a new chromosome with a probability of $1 - a_1 - a_2$. The performance of our improved genetic algorithm is compared with the previous improved GA, and we have found an optimal chromosome that contains a minimum number of active sensor nodes in scheduling within 3-5 iterations.

In the future, we will extend the proposed algorithm to find the optimal routing protocol and add it as one of the objectives in the fitness function.

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