Multi-Objective Optimization for Coverage Aware Sensor Node Scheduling in Directional Sensor Networks

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Abstract – The directional sensor networks (DSNs) are mainly focused to prolong the network lifetime and to optimize the energy consumption of sensors. The number of sensors deployed in an environment is much higher than those required for providing the coverage; therefore, the energy-aware methods are needed to select the sensors. Coverage is considered a major problem in DSNs and is a criterion for quality of service (QOS).In this regard, the sensor scheduling method has been discussed by researchers to prolong the sensor lifetime in a network. The present paper proposes an NSGAII-based algorithm to solve the sensors 'scheduling. This paper aimed at finding a practical solution in solving the multi-objective problems by using the multi-objective evolutionary algorithm method. There are two parameters presented for evaluating the solutions, including the number of sensors, the target coverage. To confirm the high performance of the proposed algorithm, it was compared with the recently presented algorithm. According to the simulation findings, the algorithm had better results in the comparison parameters.

Keywords: Multi-Objective Optimization, Directional sensor network, Sensor node scheduling

1. Introduction

The DSNs are composed of a large number of wireless sensors that are randomly deployed in an environment. The sensors can monitor the environment, process data, communicate with other sensors, and transmit the processed data to the sink. The WSNs are used for battlefield security monitoring, wildlife habitat monitoring, etc. [1,2]. Batteries are a sensor's power source and it is practically impossible to charge or replace them. The energy consumption in sensors is regarded as a serious challenge when the network needs to operate for a long time, it is required to take more measures for optimizing battery's energy consumption [5]. The algorithm efficiency for a DSN is often analyzed in terms of energy consumption. Sensors must be programmed in a way that the network lifetime be lengthened [3,4].

Sensors are generally classified into two categories: traditional omnidirectional sensors and directional sensors. The traditional sensors are able to sense a full 360-degree view of their surroundings. In the directional sensors, the sensing angle of the sensor node is limited in one direction and at a sector. A directional sensor can measure in several directions; however, it can only be active in one direction and at a given angle within a time unit. The directional sensors are typically ultrasonic, infrared, and video sensors and they differ from traditional sensors in characteristics, such as angle of view, working direction, and line of sight. Regarding the limited angle of directional sensors, the algorithms proposed for WSNs cannot be applied to DSNs and introducing new methods is needed [7,8].

The coverage is regarded as a critical problem in DSNs. The concept of coverage explains how the targets are covered by the sensors [10,11]. This concept defines how an object- an area or a target- is controlled or tracked by the directional sensor nodes. The quality of service (QOS) is a parameter measured by this concept [9]. As a general rule, the coverage is categorized into three groups, including target coverage, area coverage, and barrier coverage. The target coverage focuses on how to observe and to cover a series of targets or points located in the sensing range. For the most part, the target coverage is also referred to as point coverage. In the area coverage, it is aimed to observe or cover all or part of the area by a number of sensors deployed in it. According to barrier coverage, it is intended to create a barrier by using a sensor chain to detect the possibility of transgression outside the Region of Interest (ROI). This paper studies the target coverage. For more detailed information on the coverage problem in sensor networks, it is suggested to refer to papers [12,13,14].

The network's lifetime maximization is considered to be another research topic in sensor networks. Network lifetime

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is the continuous time duration when all the targets in a given area are observed by the deployed sensors [13,15]. With the aim of reducing and managing the energy consumption in the sensor networks, some nodes that share a common coverage area can be removed using a coverage optimization protocol [16]. In this regard, among several methods proposed by researchers, in the Activity Scheduling Problem (ASP) method, only a set of sensors is activated at any given time to prolong the network lifetime [17] and it has proven to be NP-hard.

Identifying the optimal solution for an NP-hard problem is computationally expensive and it is not practical even in limited time. Multi-objective evolutionary algorithms are capable of achieving the potential solutions in the multidimensional space of multi-objective problems. Accordingly, this paper aimed at finding a practical solution in solving the multi-objective problems by using the multi-objective evolutionary algorithm method.

The remainder of this paper is organized as follows. Section 2 briefly reviews the researches previously carried out on solving target coverage problem. Section 3 illustrates the problem with an example. Section 4 overviews the genetic algorithm. Section 5 presents the proposed algorithm for finding the optimal or near-optimal solution. Section 6 provides the simulation results of the algorithm and finally section 7 dedicates to the conclusion.

2. Related Works

The coverage and maximum network lifetime (MLP) in DSNs is a matter of great importance for researchers. The quality of coverage is closely associated with the strategy of deploying the sensors in the network. There are two types of sensor deployment in the sensor networks: controlled or random deployment. According to the controlled method, the coverage is maximized with a minimum number of sensors and there is no occlusion and overlapping problem. The random method is the only option in remote or dangerous environments and occlusion and overlapping are inevitable [14]. Setting up active and sleep modes for sensors is regarded as a major method proposed for scheduling. All solutions are looking for a method for selecting active and sleep sensors to prolong the lifetime of the sensor network. Some of them are intended to suggest a method for creating a cover set based on which a cover set is created in each round step. The cover set must be capable of satisfying the network coverage requirements at runtime. While a cover set runs, only the sensors of that cover set are activated and the rest goes to inactive mode.

In [22], the authors proposed a new high-performance, centralized greedy algorithm to solve the coverage problem in sensor networks that are capable of generating both disjoint and non-disjoint cover sets. So as to select the best node to be deployed in the cover set at each step, the Critical Control Factor (CCF) function was used, in which parameters such as sensors' observing capability, its relationship to the critical targets that observe their quantitative sensors, and also the remaining amount of sensor energy. In [16], sensor nodes were allowed to be shared in cover sets, and the Maximum Set Cover (MSC) was introduced accordingly. Then, an algorithm based on Linear Programming (LP) was proposed to solve the target coverage problem and non-disjoint cover sets creation. Due to its high time complexity and inapplicability in the large-scale problems, a greedy algorithm was used. In [3], an algorithm was proposed to cover the targets in the sensor networks, which can create both disjoint and non-disjoint connected cover sets. In addition to creating cover sets for target coverage, the solution was intended to reduce the generated traffic and it was then saved the energy by using the greedy approach as the basic method. In [27], a memetic algorithm was proposed to solve the Q-coverage problem, in which each target was covered by one or more sensors. It was mainly aimed to maximize the network lifetime while satisfying the coverage requirements of each target through creating the maximum number of cover sets. In [28], an algorithm for scheduling sensors and creating a disjoint cover set called HDSC using the heterogeneity level of nodes' batteries was suggested. To this end, the new complex Mixed Integer Linear Programming (MILP) formula was proposed to optimally solve the HDSC problem, then a genetic algorithm (GA) based method was suggested to find the approximate solutions.

With respect to the difference between the traditional and directional sensor networks, the algorithms of such networks are also mutually distinct and a different algorithm was proposed for DSNs regarding the direction and angle restrictions.

In [29], the authors first proposed the Maximum Coverage with Minimum Sensors (MCMS) theory for sensor networks with adjustable direction nodes, and the Centralized Greedy Algorithm (CGA) and Distributed Greedy Algorithm (DGA) were suggested for solving the problem. It was then proved that the problem presented in directional sensor networks was in the category of NP-complete algorithms. In [30,31], the authors first proposed a greedy algorithm to solve the Maximum Set Covers for DSNs (MSCD) problem by creating the maximum number of cover sets in directional sensor networks. Due to the fact that the greedy algorithms may be held onto the local minimum consequently, they will not achieve the global optimal or approximate to it, a genetic algorithm was then suggested to reach the global optimal. In [32], the authors proposed a genetic-based algorithm to solve the problem of Maximum Network Lifetime with Adjustable Ranges (MNLAR) to create the maximum number of covers and maximize the network lifetime. In this respect, both network energy saving techniques, namely the sensor scheduling and the sensing range adjusting were used for creating the cover sets.

DSNs are commonly applied in remote and harsh environments. Sensors that for any matter are not capable of performing well are eliminated from the network. Therefore, if the number of sensors is less than the threshold, the coverage may not be available for all targets, i.e. full coverage may not be provided, and the network may go to the under-provisioned state. There are some factors decreasing the number of sensors, including discharge of energy from a number of sensors, an increase in the number of targets while keeping constant the number of sensors, and loss of sensors due to natural reasons in such networks. In [43], some methods were presented for balancing the network coverage when sufficient directional sensor nodes were not provided and each target required at least k sensor for coverage. In [43], a learning automata-based algorithm was proposed to solve the k-coverage in under-provisioned networks to achieve a balanced coverage in the network. The algorithm was designed to select the minimum number of sensors for each cover set while maintaining the coverage balance for all targets.

The sensor scheduling problem is regarded as a multi-objective problem with conflicting objectives; accordingly the algorithm NSGA2 were used in some methods to solve the problem. In line with these methods, a number of contradictory parameters are regarded, based on which the sensors are selected.

In [37], the multi-objective coverage optimization memetic algorithm (MOCOMA) was proposed to solve the coverage problem in DSNs. The method suggested a new structure for the chromosomes, which could include a number of cover sets. The parameters involve the number of cover sets on each chromosome, the variance of the residual energy of the sensors on the chromosome, and finally the number of unused sensors. In [38], the algorithm presented in this study was aimed to cover all targets and establish a connection between the sensors. In this regard, the contradictory parameters of the minimum number of sensors, the guarantee of coverage of all targets in the network, the guarantee of establishing connection between the sensors that will be active, and finally the maximum average energy between the selected sensors in NSGA were discussed by the authors. In [39], the visual coverage in the visual sensor network (VSNs) was studied and three metrics were used for evaluation, including visual coverage ratio, number of selected sensors, and overlapping coverage ratio. The metrics represented, respectively, the percentage of the environment that was totally covered, the number of selected sensors, and finally the percentage of the environment that was covered by more than one sensor. In [40], the authors proposed an NSGA-based algorithm to solve the redundant coverage maximum problem. The first metric was the percentage of targets observed by at least one visual sensor, the second metric was the percentage of targets covered by at least two sensors, and the third metric involved the average number of repetitive coverage of targets. In [41], the coverage problem was modeled as a multi-objective optimization problem. The study was aimed to lengthen the network lifetime while reducing the energy consumption. The parameter used in [41] is the reduction of energy consumption of sensors when measuring the energy consumed by sensing and communication.

3. Problem Definition

This section studies the maximization lifetime problem in the DSNs. It was assumed that a number of directional sensors and targets are randomly distributed in an environment, which was supposed to a Euclidean plane. It was also presumed that targets and sensors were aware of their spatial information. Each directional sensor has an ωsector, but it can only work in one direction (known as working direction).The sensors cover targets that are simultaneously in the sensing range and working direction. The directional sensors were considered to be homogeneous, have an energy level of b_i, and the energy consumed to change the sector is assumed to be negligible. Each sensor is characterized by three modes: active, sleep, idle. The parameters used here are given in the table 1.

Table 1. Notations

Notation	Definition
n	Number of sensors
m	Number of targets
s_i	The ith sensor $1 \leq i \leq n$
S	Set of sensors $\{s_1, s_2, \dots s_n\}$
T	Set of targets $\{t_1, t_2, \dots t_m\}$
$d_{i,j}$	jth direction of ith sensor
b_i	Energy level of ith sensor

Problem: How to select and activate a number of sensors in the network based on defined objectives to cover more targets and to prolong the network lifetime?

4. The Proposed Algorithm

4.1. Multi-Objective Optimization Problem

The multi-objective optimization methods are used to solve a problem, in which there is more than one objective function and in most cases these targets are contradicting. In multi-objective problems, improving a target has an adverse effect on another, and improving just a target has an adverse effect on the solution for the whole problem. In solving such problems, it is not possible to find a solution that improves all the targets at the same time, but it can improve all the targets to an acceptable degree and in a balanced way. To this end, Parteo optimization should be studied. The multi-objective optimization problems generally seek to maximize or minimize the outcomes of the problem. An overview of a multi-objective optimization problem is presented in Eq.1

$$\min/max \; f(x) = (f_1(x), f_2(x), \dots, f_p(x)) \quad (1)$$

$g_i(x) \leq 0, j = 1,2,\dots,r$

$h_k(x) \leq 0, k = 1,2,\dots,q$

$x \in \Omega \subset \mathbb{R}^n$

Where $X = (x_1, x_2, \dots, x_n)^T$ is the decision variable vector.

Each $g_i(x) \leq 0, j = 1,2,\dots,r$ indicates unequality constraints and for each

$h_k(x) \leq 0, k = 1,2,\dots,q$ represents the equality constraints.

Also, for each $f_i : \Omega \subset \mathbb{R}^n \rightarrow \mathbb{R}, i = 1,2,\dots,p$, implies the objective function p. In the case of $p = 1$, the multi-objective problem becomes a single-objective problem, thus in multi-objective optimization, it is also assumed that $p \geq 2$.

In a multi-objective optimization problem with the objective function p, a solution $x_1 \in X$ dominates potentially another solution (for example $x_2 \in X$) in this set, if and only if $f_i(x_1) \leq f_i(x_2) \quad \forall i \in \{1,2,\dots,k\}$.

If a solution $x_1 \in X$ weakly dominates the solution $x_2 \in X$, if and only if

$f_i(x_1) \leq f_i(x_2) \quad \forall i \in \{1,2,\dots,k\}$, $f_i(x_1) < f_i(x_2) \quad \exists i \in \{1,2,\dots,k\}$

For example, the non-dominated sorting of a problem with two objective function is given in the following table. As it is indicated in Fig.1, *f1* dominates*f2*,*f3*, and *f2* dominates *f3*.

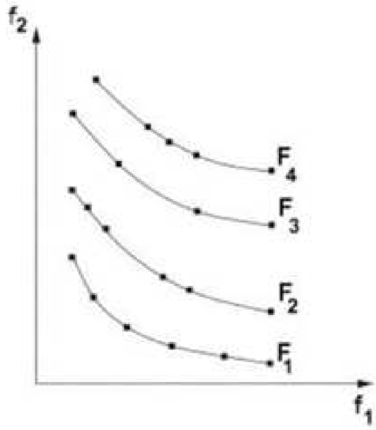

Fig 1.Non-dominated sorting

A solution that is not dominated by other solutions is called Pareto optimal. The set of Pareto optimal results is often known as the Pareto frontier.

4.2 An Overview of a Fast Non-Dominated Sorting Approach (NSGA II)

NSGA-II is a multi-objective evolutionary algorithm (MOEA) that optimizes multiple targets simultaneously and follows the basic steps of genetic algorithm (GA) [24].In NSGA-II, the initial population is generated and the population is quickly classified based on a sorting method based on the non-domination. The fitness value of each chromosome in each class is equal to the unclassified value. When the non-dominated sorting is complete, the crowding distance is also determined. The crowding distance is a criterion for determining the close proximity of each chromosome to its neighbors. A large number of average crowding distance will create better diversity in the population. Parents can be selected from the population using a method-for example, binary tournament selection-based on rank and distance. Offsprings are generated by applying crossover and mutation operators to parents, and the generated offsprings are added to the previous population. Since all previous and current superior chromosomes are added to the population, the presence of superior chromosomes in NSGA-II is guaranteed.

4.3 The Proposed NSGA-II Base Algorithm

This section presents a proposed NSGA-base algorithm to solve the coverage problem in the DSN. An algorithm inspired by a multi-objective genetic algorithm was proposed to simultaneously lengthen the network lifetime and provide the maximum coverage for the targets deployed in the environment through selecting the least number of sensors. The proposed algorithms involves the following steps: representation of chromosome, generation of the initial population, creation of multiple fitness functions, common operations with the genetic algorithm, including selection, crossing, and mutation. Then, the nextoffsprings were generated by using the quick non-dominated sorting and crowding distance. All of the aforementioned steps are summarized in the following sections.

4.3.1Chromosome Representation

A chromosome represents how to model a solution to a problem. In this regard, am integer-based numerical representation was used to represent the chromosome. According to the proposed model, each chromosome represented a set of sensors. The number of genes on each chromosome was equal to the number of targets in the environment. Each gene indicated each target was covered by which sensor and sector. So as to generate the chromosomes, the algorithm assigned priority to the critical targets (those targets that were covered by the minimum number of sensors). Accordingly, those genes associated with the critical targets were first quantified. It should be noted that each sensor of a set can be presented with just one sector. Figure 2 illustrates a sample of a valid chromosome.

Target number	t_1	t_2	t_3	t_4	t_5
Gene Value	$S_{5,2}$	$S_{8,3}$	$S_{1,2}$	$S_{2,3}$	$S_{7,4}$

Fig.2 A valid chromosome in the network

4.3.2 Initial Population

In order to generate the initial population, a number of chromosomes were randomly selected. The value of each gene was selected from the values covered by the target. As previously stated, each sensor can only be presented in a cover set by one of its sectors.

4.3.3 Evaluation of the Multiple Fitness Values

The quality of chromosomes in a population is measured by fitness values. This section was intended to find a set of minimum number of sensors in the environment and activate them to cover the targets deployed in the environment. It should be drawn particular attention to the value of energy in the sensor while selecting them. If a sensor loses its energy, the sensor will be destroyed and the targets covered by which will remain uncovered. In this case, the sensor selection operation must be performed once more. The proposed multi-objective functions in this paper are as follows:

***Objective 1 (Selecting the minimum number of sensors)*:** Selecting a minimal number of sensors causes a smaller number of sensors to be selected and as a result lose their energy, and it would then be possible to select more sensors in the subsequent steps. According to the proposed chromosome model, it should be noted to select sensors capable of covering a larger number of targets so that to have fewer sensors. This section was aimed to minimize Eq.2. Assuming that if there are N sensors in the network and N'sensors are selected.

$$n = \frac{N'}{N} \qquad \textit{Objective 1: Minimize } n \tag{2}$$

Objective 2 (The maximum target coverage): Target coverage in the network is regarded as one of the main objectives of this study. According to equation ?, the value of C represents the percentage of targets covered by at least one sensor. In this equation, if the target is not covered, the covert$_i$ function value is *0* and if it is covered by at least one target, the value is *1*. This section was aimed to maximize Eq.3.

$$C = \frac{\sum_{i=1}^{m}(covered(t_i))}{m} \qquad \textit{Objective 2: Maximize } C \tag{3}$$

Selection: In this operation, the most suitable chromosomes are selected to generate the offsprings. In this vein, two more qualified parents must be selected. In this study, two members are selected among the population in order to find a parent. If their rank is not equal (not to be on the same frontier), the chromosome with the lowest rank is selected. If they have the same rank, the chromosomes that have the most crowding distance is selected. Likewise, the second parent is selected.

Crossover and Mutation: With the aim of generating the next offsprings, the crossover operation was applied to two chromosomes that were randomly selected from the population. There are several crossover methods such as single-point, two-point, etc. This paper applies a single-point crossover operator to generate a pair of offspring chromosomes of the parent chromosomes. In this respect, the crossover point was randomly selected, then the parent chromosomes exchange their information. Fig.3 indicates the two chromosomes selected as the parent. Moreover, the crossover point is specified. The offsprings of the crossover process are also shown. As indicated by the Fig.3, one or both offsprings may have invalid values after the crossover, so a repair operator is needed, which is described in the following.

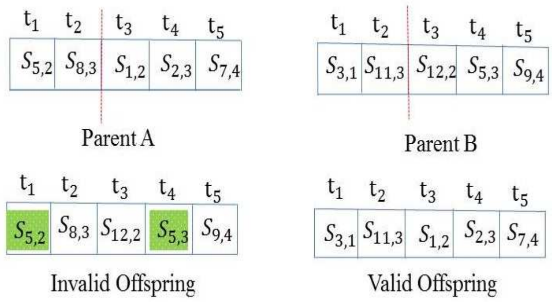

Figure 3. An Example of a Crossover operator

Once the optimal chromosome generated, the mutation process begins, according which a chromosomal gene is randomly selected and its value is changed. Thus, among the sensors covering the target, a value is randomly selected and replaced by the current value or the null value. During the mutation, it must be taken not to have a sensor with two sectors in a cover set.

Algorithm 1. The NSGA-II general framework

```
Input:
  Multi-Objective Problem (MOP)
  The number of individuals ;Npop
  The maximum number of generations ;MaxIt
Output:
  Pareto Front (PF)
Initialization:
pop = Initialization population ()
pop = Non_Dominated_Sorting (pop)
pop = Calculate_Crowding_Distance (pop)
pop = Sort_Population (pop)
            % NSGA-II Main
for it = 1: MaxIt
begin
pc = Crossover(pop)
pm = mutation(pop)
pop = [ pop
popc
popm ];
pop = Non_Dominated_Sorting (pop)
pop = Calculate_Crowding_Distance (pop)
pop = Sort_Population (pop)
pop = pop(1:Npop)
pop = Non_Dominated_Sorting (pop)
pop = Calculate_Crowding_Distance (pop)
pop = Sort_Population (pop)
                    % Stopping criteria met?
            If (Stopping criteria met) then
Return Pareto Front (PF)
else
MaxIt = MaxIt+1
end for
end program
```

Repair Operator: Once the crossover process is performed, one or both chromosomes may have invalid values. If there is a sensor with two sectors in a cover set, the chromosome is invalid and the value of that gene must be replaced by a valid value. Algorithm 1. gives the pseudo-code of the NSGA2 algorithm.

5. Simulation

Simulation and comparison of the results obtained by the algorithms are considered as major methods for evaluating their performance. For this purpose, this study performed several experiments by using MATLAB software and the results are consistent with the recently proposed algorithm. The selected simulation scenario is that N sensors and T targets are randomly deployed in a $1000\text{m} \times 1000\text{m}$ environment. This section provides several experiments conducted to evaluate the performance of the proposed algorithms. The sensors are randomly distributed in the environment. The sensors include four preset sectors. There are four experiments performed in this paper. The first experiment was aimed to investigate the effect of increasing the number of targets on the network lifetime while the sensing radius and the number of sensors are constant. The second experiment was intended to investigate the effect of increasing the number of sensors on the network lifetime while the sensing radius and the number of targets are constant. The third experiment indicated the effect of changing the sensing radius on the network lifetime while the number of targets and the number of sensors are constant. The fourth experiment addressed the relationship between the number of sectors and the network lifetime. The sensors have four predefined sectors. The proposed algorithm was compared with [44]. For further adaptation of the comparison conditions, it is necessary to assume the sensing radius of the sensors at a constant value. The method presented in [44] is based on a multi-objective method that is modeled linearly and it has multiple objectives.

This paper has performed each test scenario 15 times for more certainty, and the average results are presented. For simulation, MATLAB R2014a was used on a system with RAM Intel i3 processor, 1.7GHz CPU, 4GB in Windows 7 environment.

Experiment 1. It was assumed that the number of targets was variable and the sensing radius and the number of sensors were constant. This experiment was aimed to investigate the effect of changing the number of targets during the network lifetime. In this regard, the number of targets was increased by 10 units for each step from the initial value of 50. The sensing radius and the number of sensors were fixedat 100 and 90,respectively. As indicated in Fig.4, the network lifetime decreases with increasing the number of targets. This is due to the fact that more sensors are required to cover the targets by increasing their number in the network. Considering the greater collaboration of the sensors in covering the targets, the network energy is depleted faster and the network lifetime is decreased.

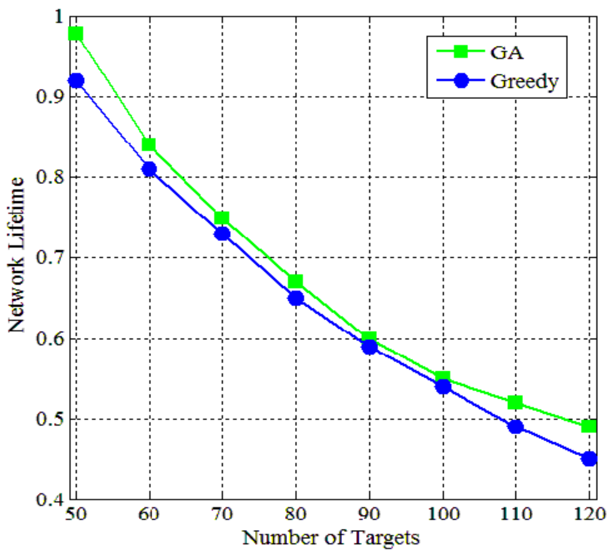

Fig. 4 Effect of the number of targets on the network lifetime.

Experiment 2. This experiment was intended to examine the effect of increasing the number of sensors on the network lifetime. The sensing radius and the number of targets were assumed to be fixed at 100 and 70, respectively. The number of sensors was increased by 20 units for each step from the initial value of 20. According to the results given in Fig.5, it is proved that the network lifetime may be prolonged by increasing the number of sensors. The fact is that more sensors lead to creating more cover sets that are capable of satisfying the coverage requirements of all targets. The increased number of cover sets and their sequential run will prolong the network lifetime.

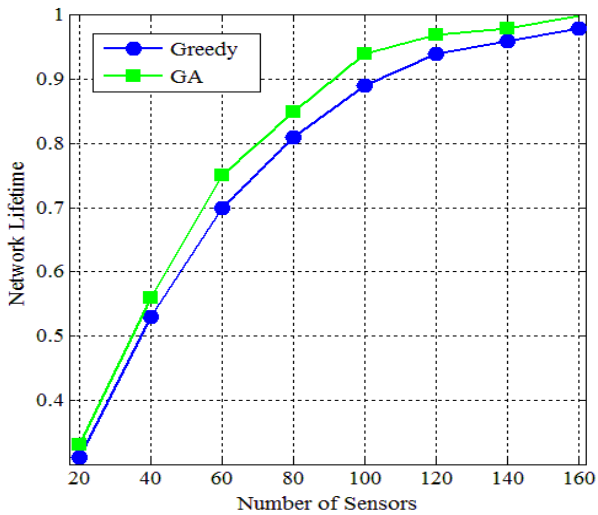

Fig.5 Effect of the number of sensors on the network lifetime.

Experiment 3. This experiment was designed to investigate the relationship between the sensing range and the network lifetime. The number of sensors and the number of targets were fix at 100 and 70, respectively. The sensing range was increased from 60 to 120 meters, by 10 meters for each step. More targets were covered by each sensor that its sensing range was extended; accordingly, the coverage requirement of targets may be satisfied by a negligible number of sensors. The Less collaboration of sensors covering the targets in the network led to reducing the energy consumption of the sensors as well as prolonging the network lifetime. As it is shown in Fig.6, the network lifetime was prolonged by extending the sensing range.

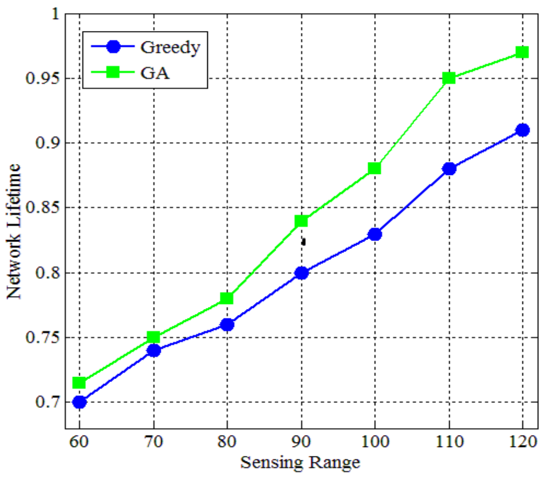

Fig.6 Effect of sensing range on the network lifetime.

Experiment 4. This experiment was aimed at detecting the relationship between the number of sectors and the network lifetime. In this respect, the number of sectors was increased from 1 to 5, by one unit each time. The number of sensors and the number of targets were fix at 100 and 70. The number of sensors was fixed at 100. The initial amount of energy was set equal to the number of sectors.

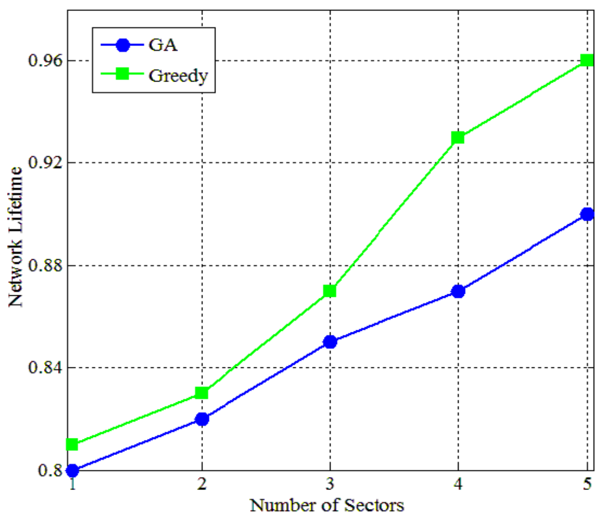

Fig.7 Effect of number of sectors on the network lifetime.

According to the results indicated in Fig.7, there is a direct relationship between the number of sectors and the network lifetime. Consequently, the network lifetime was prolonged by increasing the number of sectors.

6. Conclusion

The coverage and maximum network lifetime (MLP) are regarded as major problems in DSNS. This paper aimed to achieve the target coverage and maximum network lifetime by studying the sensor scheduling in the network. Considering that the sensor scheduling is inherently a multi-objective problem, the NSGA-II evolutionary algorithm was used to find the solution. In this regard, the fitness function with two objectives was used to evaluate the quality of chromosomes. Two metrics were used in the fitness function, including the number of sensors, target coverage.

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