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Genetic algorithm-based meta-heuristic for target coverage problem

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Manju[1] ✉, Satish Chand[2], Bijendra Kumar[1]
[1]*Netaji Subhash Institute of Technology, Sector-3, Dwarka, New Delhi 110078, India*
[2]*School of Computer and System Sciences, Jawaharlal Nehru University, New Delhi 110067, India*
✉ *E-mail: manju.nunia@gmail.com*

Abstract: In wireless sensor networks (WSNs), network lifetime and energy consumption are two important parameters which directly impacts each other. In order to enhance the global network lifetime, one should need to utilise the available sensors' energy in an optimise way. There are several approaches discussed in the literature to maximise the network lifetime for well-known target coverage problem in WSN. The target coverage problem is presented as a maximum network lifetime problem (MLP) and solved heuristically using various approaches. In this study, the authors propose a genetic algorithm (GA)-based meta-heuristic to solve the above said MLP. The GA is a non-linear optimisation solution method which is proven to be better as compared to the column generation or approximation schemes.

1 Introduction

The wireless sensor networks (WSNs) consist of small sensing devices called sensors. These sensor nodes are designed for application specific requirements. The applications are broadly categorised into commercial, military and medical [1]. The commercial applications include vehicle tracking, security systems, traffic control system, fire safety systems, supervising systems, environment monitor systems (includes nuclear, chemical and microbial pollutions) and natural disasters like flood earthquakes and hill sliding. The military applications include surveillance and intelligence defence networks. Moreover, the health care applications include a smart system in remote areas for disables, patient surveillance systems, smart environment for the elderly patients, better communication networks for physicians and medical staff. This wide range of applications led to a variety of protocols. There are certain parameters which affect these protocols' functionality. The most important parameter is available to network energy. Since sensor nodes are equipped with limited energy resources which are non-rechargeable and most of the times not replaceable, one should optimise sensors available energy in an optimised way.

Due to energy constraint, there is an intense research issue which has been widely studied is how to optimise the battery consumption. In particular, the problem of maximising the coverage duration of specific points of interests, called targets by appropriately using the sensors for the longest possible time (named target coverage) has been studied in the past few decades. The target coverage problem is usually represented as a maximum network lifetime problem (MLP). In order to solve the MLP, various heuristic approaches have been discussed [2–14]. As the sensors are deployed densely; therefore, to monitor all the targets, a subset of sensor called ***cover set***, is enough instead of activating all the sensors at once. By activating only a subset of sensors, one can save unnecessary battery uses when compared with the scenario when all the sensors are activated. The basic idea adopted by most of the protocols [2–14] is to find maximum possible cover sets. These covers are activated for a fixed duration called ***working time***. The network is called functional till each target is covered by at least one active sensor. This operational duration of the network is called ***network lifetime***. Thus, the network lifetime is the sum of all the cover set's working time.

The remaining of the paper is organised as follows: In Section 2, we give detailed work done on the target coverage problem and few of its variants. Section 3 defines the target coverage problem and gives its mathematical formulation. Section 4 discusses the proposed methods to solve the target coverage problem. In Section 5, we give simulation results to claim the superiority of the proposed work. In Section 6, we conclude the work and give future directions on the proposal.

2 Related work

Before MLP representation, the target coverage problem was solved by Slijepcevic and Potkonjak [2] by finding maximum possible cover sets. These cover sets were disjointed where a sensor can be part of the only single cover set. Due to this restricted participation of a sensor, the obtained network lifetime was far from optimal upper bound. Further, to improve the total gain in network lifetime over [2], Cardei *et al.* [3] were first to show that MLP is more promising over [2]. In order to solve the MLP, Cardei *et al.* [3] proposed an approximation algorithm which generated non-disjoint cover sets where a sensor can be part of more than one cover set provided it cannot be used beyond its total energy assigned. In the same work, they also proved that the target coverage problem is NP-complete. The network lifetime achieved by Cardei *et al.* [3] is also less than the optimal upper bound. This is due to the fact that the cover set generation process in [3] always gives priority to those sensors which have maximum coverage. Due to this, the network will form early coverage holes which in turn exhaust the network. Further, Mini *et al.* [4] discussed another energy efficient heuristic which is an improvement over [3]. The addressed heuristic in [4] forms cover sets by giving priority to those sensors which have highest remaining energy. Since the cover sets formed this way may have coverage redundancy, they further minimalised the generated cover set to extend the network lifetime. The disadvantage of this approach is that network will exhaust soon due to early energy holes formed in the networks. Since, network dynamics getting changed over the time due to frequent node failure, learning automata-based energy-based heuristics [5–7] are proven to be better than many existing column generations and approximation-based schemes. Further, Pujari *et al.* [8] proposed another heuristic based on a polyhedral approach to maximise the total network lifetime for the target coverage problem. None of the work discussed above [2–8] considers the coverage of least covered targets with the highest priority. Since the least covered targets (called critical targets) are the one which becomes uncovered first in the network, the network lifetime can be extended by extending the coverage duration of such targets. The only work which gives priority to such poorly covered targets is discussed in [9]. The addressed heuristic in [9] tries to keep alive those sensors which are covering critical targets by selecting the minimum number of sensors from the sensors set covering critical targets.

Later, several variants of the classical target coverage problem are discussed in the literature. Among them, target Q-coverage [4, 11], connected coverage [12, 15–17], partial coverage [5, 14, 16, 18] are popular. Over the years of study, it has been shown in the works [15–20] that genetic algorithms (GAs) are more suitable than other regular methods [2–8] to solve the target coverage problem. This is due to the fact that to solve non-linear optimisation problem, GA-based approaches have been best suitable as compared to the other methods [15].

In this paper, we study the target coverage problem and propose a new meta-heuristic-based on the GA. We also compared the performance of the proposed heuristic with some existing methods [2, 3, 15].

3 Problem's mathematical formulation

Let WSN = $\{S, T\}$, be a wireless sensor network in which $S = \{s_1, \ldots, s_m\}$ be the set of $\boldsymbol{m}$ sensors and $T = \{t_1, \ldots, t_n\}$ be the set of $\boldsymbol{n}$ targets. Both sensors and targets are scattered randomly. In this work, we consider a homogenous network where all the sensors have a same sensing range and energy level equals 1 unit. During coverage, a target $t_j(1 \leq j \leq \boldsymbol{n})$, is covered if it is falling within the sensing range of one or more sensor s_i, $(1 \leq i \leq \boldsymbol{m})$. We define $\boldsymbol{SC}$, a feasible cover set where $SC \subseteq S$. We assume that each cover set SC is activated for a fixed duration (***working time***) $\boldsymbol{t}$. Hence, the total network lifetime is the summation of all the cover sets ***working time*** which is generated in the given network. Therefore, the network lifetime (L) can be represented as follows:

$$L = \sum_{i=1}^{|SC|} t(i) \tag{1}$$

Now, we present the target coverage problem with the help of MLP, which finds a collection of pairs (SC, t) where each $SC \subseteq S$ is a feasible cover set and each $t \geq 0$ is its ***working time***. The objective of this MLP is to maximise the sum of the activation times (t) and ensure that none of the sensors is used beyond its initial battery duration (b_i). With an assumption of computing the full set of all the feasible cover sets $SC_1, \ldots, SC_P$ in advance, the MLP could then be represented using the linear programming formulation as given below.

Here

x_{ij} is a Boolean variable for $i = 1, \ldots, m$ and $j = 1, \ldots, p$. $x_{ij} = 1$ if sensor s_i is in sensor cover SC$_j$, otherwise $x_{ij} = 0$. And $S_k = \{i|$ sensor s_i covers target $t_k\}$

$$\text{Max} \sum_{j=1}^{p} t(j) \tag{2}$$

$$\text{s.t.} \quad \sum_{j=1}^{P} x_{ij} t(j) \leq b_i \quad \forall s_i \epsilon S \tag{3}$$

$$\sum_{i \in S_k} x_{ij} \geq 1 \quad \forall t_k \epsilon T, j = 1, \ldots, p \tag{4}$$

$$\text{where } t(j) \geq 0 \quad \forall j = 1, \ldots, P \tag{5}$$

Here, the objective function (2) is to maximise the sum of the activation times for all the cover sets and (3) ensure that none of the sensors is used beyond its initial energy level (b_i) assigned. Similarly, (4) ensures that each target should be covered by at least one sensor in each cover set. Equations (5) and (6) ensure that all the cover sets are feasible.

As discussed in Section 1, many researchers solve this MLP either using column generation techniques or approximation algorithms. Recently, it has been observed that GAs are far better than that column generation and approximation techniques. It has been shown that GAs are meta-heuristics which are best suitable for the optimisation problems, which in turn fulfils the requirement of the objective function (2). GA initiates with an initial population of possible solutions. These solutions are randomly generated and each solution is individually represented with the help of a simple binary string of genes called chromosomes. Each chromosome contains a fixed number of elements (genes) depending on the application. To determine the quality of a chromosome, a fitness function is designed. Here, in the case of target coverage in sensor networks, a chromosome can have a number of elements equal to a number of sensor nodes in the given network. During target coverage, a chromosome represents a cover set, therefore, each gene i, $1 \leq i \leq m$, equal to 1 if the corresponding sensor s_i belongs to the cover set (hence, the sensor s_i is active), and 0 otherwise. A chromosome is said to be redundant if the sensors are activated in such a way that even if switching off some of the sensors, a cover set still exists. An optimal solution can be achieved by only considering non-redundant covers; therefore, we define the population of GA which only consists of non-redundant chromosomes. The GA operation starts with the generation of the initial population. Once the initial population is generated, the GA undergoes to three operations, called selection phase, crossover and mutation operations. During the selection phase, two chromosomes (parents) are randomly selected to produce two child chromosomes doing a crossover operation. In the crossover operation, the parent chromosomes exchange their genetic information to produce child chromosomes. Then, the child chromosomes undergo the mutation operation. The mutation operation used to produce a better solution as compared to the parent. Once the mutation operation is over, the child chromosomes are examined using the fitness function and their newly calculated values are compared with the fitness values of all the previously generated chromosomes. If these present children have better fitness values as compared to the previous chromosomes, then, these parent chromosomes are replaced by the child chromosome.

There are some existing works [15–17, 19, 20] which solves the target coverage MLP using GA. Yoon and Kim [19] proposed a GA-based heuristic to deploy the sensor nodes so that the maximum coverage can be provided in the given network. Gupta *et al.* [15] proposed a GA-based scheme to solve the target coverage problem. First, the formulated the given problem as linear programming and then solve it heuristically using GA. In order to maximise the network lifetime, the proposed heuristic minimises the number of selected positions to place the sensor nodes in the target-based sensor networks. They not only aim to maximise network lifetime for target coverage but, also fulfil the k-coverage and m-connectivity requirements of the sensor nodes. Carrabs *et al.* [16] proposed another GA-based meta-heuristic in which they aim to provide full coverage as well as partial coverage. The fitness function followed by this heuristic basically minimises the number of sensors in a cover set. Thus, the proposed heuristic keep generating new cover sets (child) till fitness functions are maximised. Rebai *et al.* [20] presented a novel GA which finds various locations to place sensor nodes in such a way that the minimum number of such locations is required. The selected set of sensor nodes not only provides full coverage to the given area but it also ensures that the individual sensor nodes are connected too with the network.

In the following section, we proposed a new meta-heuristic based on the GA paradigm. Generally, all of the above discussed GA-based approaches [15–17, 19, 20] only consider the number of sensors used by a cover set while calculating the fitness function to prolong the network lifetime. As we also know that the network lifetime directly depends on the coverage of poorly covered targets (***critical*** targets). If one can ensure the extended coverage for such targets, then, certainly network lifetime can be maximised. In our work, to derive the fitness function, we select a minimum number of sensors which are covering critical targets and for the remaining targets, we too minimises the number of selected sensors in each

Table 1 Target Coverage Relationship Matrix

s	t				
	t_1	t_2	t_3	t_4	t_5
s_1	0	0	0	1	0
s_2	0	0	0	1	0
s_3	1	0	0	1	0
s_4	0	1	0	0	0
s_5	1	1	0	0	0
s_6	0	1	1	1	0
s_7	1	1	1	0	0
s_8	1	1	1	0	0
s_9	0	1	1	0	1

Sensors	1	2	3	4	5	6	7	8	9
Gene value	0	0	1	1	0	1	0	0	1

Fig. 1 *Chromosome representation*

Input: number of sensors (S), size of initial population (K)
Output: initial population consists of K number of chromosomes

```
Boolean STR[K];
initialize P = {};
for i =1 to K
    for j=1 to S
        STR [j] = random( ) %2
    end for
    P=P ∪ STR
end for
```

Fig. 2 *Algorithm 1: initial population (P) generation*

cover set. Thus, we try to maximise the total network lifetime. The major parts of our heuristics are mainly included chromosome representation, fitness function derivation and initial population generation.

4 Proposed meta-heuristic

Like other approaches which follow GA concept, our proposed heuristic also consists of all the basic steps followed by GA like, chromosome representation, initial population generation, fitness function calculation and the crossover, mutation operations. In the following section, we discuss how the initial population is generated in our proposed meta-heuristic, the fitness function, selection, crossover and mutation operations to address *target* coverage using GA.

4.1 Chromosome representation

In our proposed heuristic, the chromosome is presented as a string of zeros and ones where the length of each chromosome is equaled to a number of sensor nodes (i.e. $|S|$) in the network. In this string (chromosome), if the value of an ith gene is 1 then we say that the ith sensor node is active in the current cover set. Similarly, the gene value 0 indicates that the respective sensor is not active. For illustration, consider a homogenous wireless sensor network with five targets $T = \{t_1, t_2, \ldots, t_5\}$ and nine sensor nodes $S = \{s_1, s_2, \ldots, s_9\}$ as shown in Table 1. All the sensors are having same sensing range (70 M) and equal initial energy level (1 unit). Here in Table 1, if a sensor covers target, then in this table, the entry is 1 otherwise 0.

As discussed above, the length of the chromosome will be 9 as same as the number of sensors in the given WSNs. In the given chromosome (Fig. 1), some gene values are 1 and others are 0. At position 3, the gene value is 1 which indicates that the sensor s_3 is active in the cover set, whereas the sensor s_2 is not active as the gene value at position 2 is 0. Similarly, s_4, s_6 and s_9 are active sensors in the cover set whereas s_1, s_5, s_7, s_8 are not active.

4.1.1 Initial population generation: The initial population is a set of chromosomes, which are chosen by the selection process. These chromosomes are randomly generated. As we know that each chromosome is a binary string of 0 and 1. In order to generate this binary string, we have given in Algorithm 1 (see Fig. 2).

4.1.2 Fitness function: The quality of a newly created chromosome depended upon the fitness function used. There are certain objectives which collectively constitutes the fitness function. In order to fulfil these objectives, the fitness function is derived to pursue all the defined objectives. In the proposed meta-heuristic, we aim to select the minimum number of sensors covering least covered targets (***critical targets***) and select the minimum number of sensors in total. In order to fulfil all the above said objectives, our proposed fitness function is depending on the following parameters.

Objective 1: Select minimum sensors covering critical targets: The network is called functional till all the targets are covered by at least one sensor. The least covered target(s) (***critical targets***) are one which is left uncovered first in the networks. Thus, network lifetime directly depends on such least covered targets. In order to maximise the network lifetime, we need to keep alive sensors those covering ***critical targets*** for maximum possible time. We denote these sensors covering ***critical targets*** as S_{critical}. Thus, the first objective can be written as below:

$$\text{Minimise } \boldsymbol{F}_1 = \frac{S_{\text{critical}}}{S} \tag{6}$$

Objective 2: Select the minimum number of sensors for the rest of the targets (except critical targets): For the rest of the targets, we should select the minimum number of sensors to say, M, therefore, we need to minimise the selected sensors in each cover set. Thus, our second objective is as given below:

$$\text{Minimise } \boldsymbol{F}_2 = \frac{M}{S} \tag{7}$$

Here we have two objectives (F_1, F_2) to be fulfilled at once. To constructing a multi-objective fitness function, weight sum approach (WSA) [21] is discussed. In the literature, the WSA proved to be best suitable to solve a multi-objective optimisation problem. In WSA, each objective is multiplied by a weight value W_i. Then, all the multiplied values are added to get a single scalar objective function called fitness. Thus, the fitness value for the two proposed objective functions F_1, F_2 can be written as follows:

$$\begin{aligned}\textbf{Fitness} &= W_1 \times (1 - F_1) + W_2 \times (1 - F_2)\\ \textbf{Fitness} &= W_1 \times \left(1 - \frac{S_{\text{critical}}}{S}\right) + W_2 \times \left(1 - \frac{M}{S}\right)\end{aligned} \tag{8}$$

4.2 Objective: maximise fitness

In our proposed meta-heuristic, we take $W_1 + W_2 = 1$ and $0 \le W_i \le 1$, $\forall i$, $1 \le i \le 2$. Our aim here is to maximise the ***fitness*** value given in

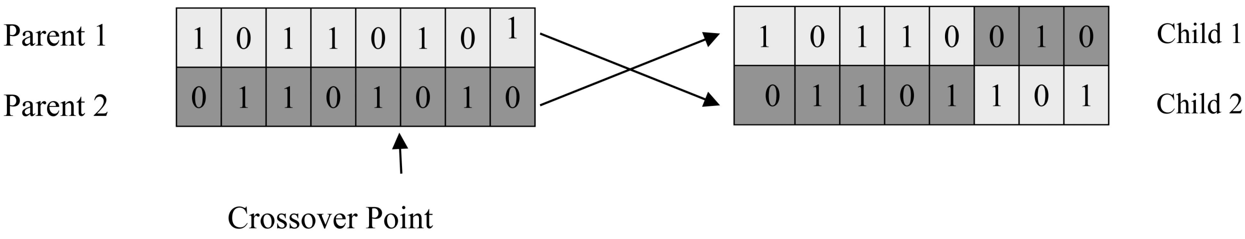


Fig. 3 *Crossover operation*

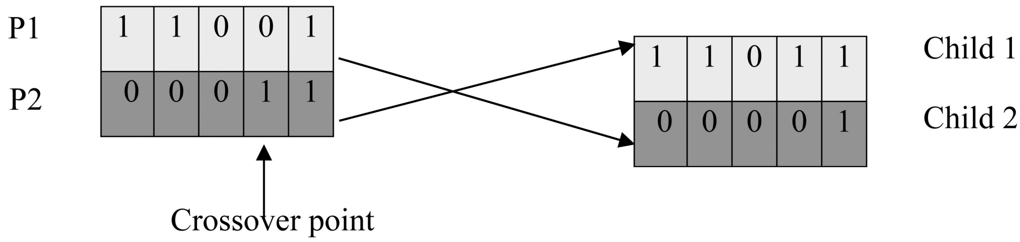


Fig. 4 *Mutation operation*

(8). Therefore, higher fitness value results in the better chromosome. Here, in the WSA, one can test various values of the weight factors, W_1 and W_2.

4.2.1 Selection: Once the initial population is generated, then, only valid chromosomes are selected by using various methods like Roulette-wheel selection, tournament selection and rank selection. The chromosomes which have better fitness value will have more chance to be selected. Our proposed meta-heuristic uses Roulette-wheel selection method. Thereafter, selected chromosomes are used to produce new chromosomes called child chromosome using the crossover operation as given below.

4.2.2 Crossover: New chromosomes are produced by selecting two chromosomes randomly and then apply the crossover operation. In the literature, there are various types of crossover operations such as one-point crossover, uniform crossover, two-point crossover and so on [21]. Our proposed meta-heuristic apply one-point crossover where a single crossover point is chosen at random. Then, the two selected parent chromosomes do exchange their information after that point (as shown in Fig. 3).

4.2.3 Mutation: As we know that crossover operation is performed to produce child chromosomes and further, these child chromosomes are tested on the basis of fitness values. If the child chromosomes have better fitness value as compared to the parent chromosome then, the parent chromosome is replaced by that newly produced child chromosome. However, in some cases, the child chromosome may not be valid (i.e. not a cover set), then, the mutation operation is required. In the mutation operation, a gene position is randomly selected and then its value is changed to 0 to 1. In order to understand the need for the mutation operation, consider the following scenario where there are five sensors and four targets. Here, in the figure, if a sensor covers target, then in Table 2, the entry is 1 otherwise 0.

During crossover operation, suppose we take two parent chromosomes (cover sets) as follows:

Table 2 Target Coverage Relationship Matrix

s	*t*			
	t_1	t_2	t_3	t_4
s_1	0	1	0	0
s_2	1	0	1	0
s_3	1	0	1	1
s_4	0	0	1	0
s_5	1	1	0	1

$$\mathbf{P1}: 11001 \text{ and } \mathbf{P2}: 00011$$

After one point crossover operation, we found two child chromosomes (cover sets) namely Child 1 and Child 2 (Fig. 4).

Since chromosome represents a cover set in the case of the target coverage problem, Child 2 is not a cover set here. Therefore, Child 2 is not a valid chromosome as it's not covering all the targets (only sensor s_5 is active which do not cover t_3). So here, we need a mutation operation to make it valid by turning on either sensors s_2 or s_3 or sensor s_4 by flipping one bit from 0 to 1 in Child 2 chromosome. Therefore, we need a mutation operation in such situation to generate valid chromosomes.

In the next section, we discuss the performance of proposed meta-heuristic for solving target coverage problem using the above said GA-based meta- heuristic

5 Simulation results

In this section, we perform an extensive simulation to claim the superiority of the proposed meta-heuristic. For all the simulation scenarios, we considered two square sensing areas of sizes $200 \times 200\ \text{M}^2$ and $300 \times 300\ \text{M}^2$. We consider homogenous sensor networks where all the sensors have same initial energy level (**1** unit) and equal sensing range (70 M). We have randomly deployed sensors and targets in the given sensing fields. In order to generate their coordinated in the given areas, we have used a random number of generator functions. All the simulation values are an average of 40 problem instances which are randomly in nature. All the simulation scenarios executed on MATLAB (R2009) using a core i5 processor @ 4 GB. Table 3 shows all the simulation parameters used in the subsequent experiments.

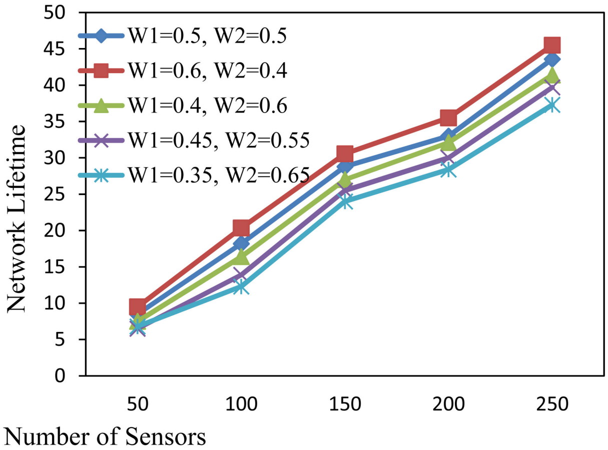
In order to execute the proposed meta-heuristic, we have considered the initial population of 60 chromosomes and mutation rate as 3%. As discussed in Section 4, both the weights W_1 and W_2 can vary between 0 and 1, therefore, we have simulated for different-different weight values. We have depicted all the simulation outcomes through ***experiment***s 1–4 as follows.

5.1 Experiment 1

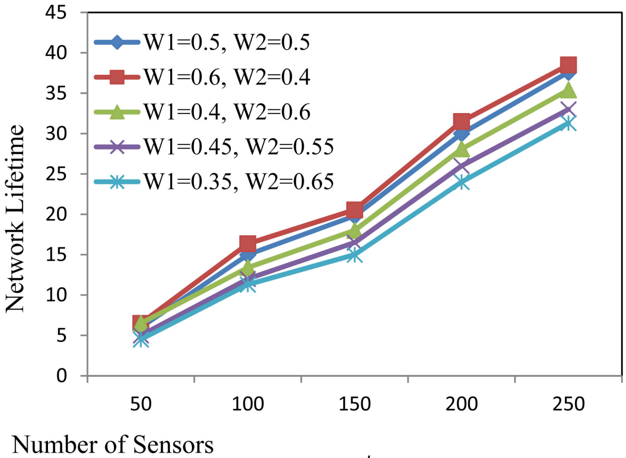
Here, we consider homogenous sensor network where targets are fixed (50) and sensors are varying (between 50 and 250). Being a homogenous sensor network, all the sensors are having same sensing range (70 M) and equal initial energy level (1 unit). In this experiment, we consider different values of W_1 and W_2 to calculate the fitness value by the proposed meta-heuristic. We simulated the proposed meta-heuristic to test on weights W_1 and W_2. Fig. 5*a* shows the network lifetime achieved by the proposed meta-heuristic with various values of weights W_1 and W_2 in the sensor network of size $200 \times 200\ \text{M}^2$ and Fig. 5*b* is on sensor network of

Table 3 Simulation parameters

Parameter	Value
network area ($M \times M$)	(200×200) M^2, (300×300) M^2
sensors	50–250
targets	50
sensing range	70 M
initial energy of sensor	1 unit
mutation rate	3%
cover set working time	0.5 time unit



a

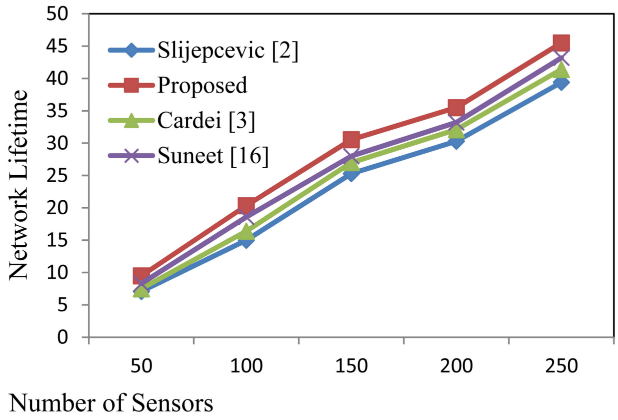


b

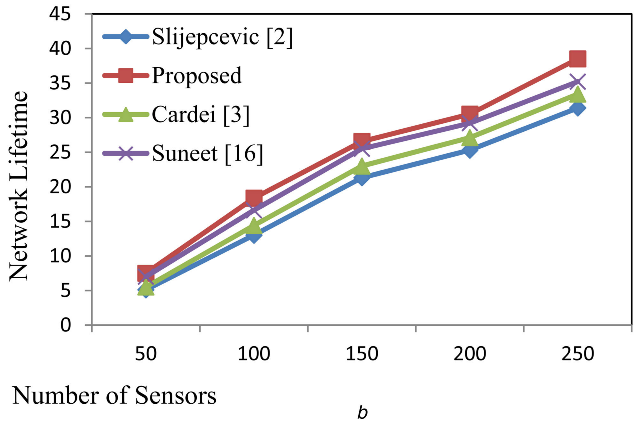
Fig. 5 *Network Lifetime vs Number of Sensors*
(a) Network lifetime achieved by proposed heuristic under various values of W_1 and W_2, ***(b)*** Network lifetime achieved by proposed heuristic under various values of W_1 and W_2

size 300×300 M^2. In both the network sizes, we have simulated the proposed meta-heuristic for around 20 combinations of both the weights W_1 and W_2. Among them, the top five weights combinations for which the achieved network lifetime is better as compared to the rest of the weights combinations are shown here.

As depicted in Figs. 5*a* and *b*, the network lifetime achieved by the proposed meta-heuristic is reasonably better when we have taken $W_1 = 0.6$ and $W_2 = 0.4$. Thus, in our rest of the experiments, we will take the weight values as $W_1 = 0.6$ and $W_2 = 0.4$. We can also observe while comparing Figs. 5*a* and *b* that the network lifetime decreases when we increase the size of the sensing area with the same number of sensor nodes. This happened so because, with the larger area, the sensor will have more space to be dispersed. Due to that, to form a cover set, we need more sensors which in turn results in decreased network lifetime.



a



b

Fig. 6 *Network lifetime achieved in*
(a) Area 200 × 200 with $W_1 = 0.6$ and $W_2 = 0.4$, ***(b)*** Area 300 × 300 with $W_1 = 0.6$ and $W_2 = 0.4$

5.2 Experiment 2

In this experiment, we compared the performance of the proposed meta-heuristic with the existing algorithms in [2, 3, 15]. The algorithm by Slijepcevic and Potkonjak [2] and Cardei *et al.* [3] is greedy heuristics which generate sensor cover by greedily giving some priority to the sensors based on the number of target coverage or remaining energy. The algorithm proposed by Gupta *et al.* [15] is based on GA. This heuristic basically provides ***k***-coverage (each target should be covered by ***K*** number of sensors) and ***m***-connectivity (each sensor should be connected to ***m*** number of other sensors). In order to compare the performance of this heuristic [15] with our proposed meta-heuristic, we set ***k*** = 1 and ***m*** = 1. Figs. 6*a* and *b* show the achieved network lifetime by methods in [2, 3, 15] and the proposed meta-heuristic. As shown in experiment 1, we take 50 targets, $W_1 = 0.6$ and $W_2 = 0.4$ with which network lifetime is better as compared to other weight combinations.

As depicted in Figs. 6*a* and *b*, the network lifetime achieved by the proposed meta-heuristic is better than those achieved by the heuristics in [2, 3]. The methods of providing target coverage in [2, 3] are simply following incremental algorithm. Hence, it can be seen that the GA-based meta-heuristic is more suitable for solving the target coverage problem. Further, the proposed meta-heuristic is also performing better than the existing GA-based heuristic by Gupta *et al.* [15]. This happened so; because, the fitness function in heuristic [15] is having three fold objectives ensuring a minimum number of sensor selections, provide ***k***-coverage and ***m***-connectivity. In order to compare its performance with our proposed meta-heuristic, we set ***k*** = 1 and ***m*** = 1, which in turn results in single objective fitness function of selecting the minimum number of sensors by each cover set. Thus, the heuristic [15] does not consider the coverage of critical targets whereas our meta-heuristic first try to prolong the coverage of critical targets by selecting only the minimum number of sensors which are covering such targets. Hence, we can say that the proposed meta-heuristic is better than the heuristic in [15].

6 Conclusion

In this paper, a GA-based meta-heuristic is proposed for finding the minimum number of sensors in each cover set to maximise the total network lifetime. In order to do that, first, we have formulated the target coverage problem as MLP and represent it using the linear programming. Then, to solve this MLP, we have proposed a GA-based heuristic. In this meta-heuristic, all the basic operations such as chromosome representation, calculation of fitness function, selection, crossover and mutation has been presented with suitable examples. Our extensive simulations results have shown that the proposed meta-heuristic has achieved better network lifetime as compared to other existing GA-based approach as well as non-GA approaches.

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