A Meta-Heuristic Based Approach with Modified Mutation Operation For Heterogeneous Networks

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Abstract

The peculiar factor of coverage called target coverage in an energy-constrained wireless sensor network is a fierce challenge nowadays. Genetic algorithm-based meta-heuristic has proven methodology while aiming to prolong the achievable network lifetime. There is a plethora of research works where maximizing the total network lifetime issue is classified as an optimization problem. In the literature, evolutionary techniques like meta-heuristics are best to use while solving an optimization problem. The task becomes more challenging due to the dense deployment of sensor nodes in the given pre-decided network. In this paper, the target coverage problem is addressed with the primary objective of maximizing the coverage of a specified set of targets with sensors with limited energy. The proposed genetic algorithm-based heuristic with modified mutation operation prolongs the network lifetime. The experimental results clearly depict that the proposed meta-heuristic performs considerably better while computing network lifetime. Besides, the performance of the proposed methodology is also compared with existing works, and it is observed that proposed algorithms perform better.

Keywords Energy-efficiency · Optimization · Network lifetime · Upper bound · Coverage · Meta-heuristic

1 Introduction

1.1 Background and Motivation

A wireless sensor network (WSN) is comprised of sensors with the perceptual ability and self-organizing capability. The prime necessity of such a network is to provide data collection via monitoring and transmission together. There is a wide range of sensor networks applications, including environmental protection, battlefield surveillance, smart home furnishing, and many more [1–6]. Due to the fierce competition among manufacturing industries to manage cost and volume, sensor nodes are equipped with a limited-capacity battery to provide energy. Based on the necessity of application severity level, sensors' energy

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cannot be replaced or recharged. Therefore, coverage and battery life both are prominent research problems in WSNs.

At present, eminent scholars have done great work to optimize the battery usages in the energy scared wireless sensor networks. Remarkably, the problem of maximizing the coverage duration of targets of interest in a given region is defined as the target coverage problem. In order to solve it, the conventional approach is to first explain the target coverage problem as MLP (maximum network lifetime problem). In literature, over the last two decades, there are various heuristic approaches addressed to solve this MLP [7–10]. The very similar approach that is progressively adapted by most of the existing heuristics is to find maximum possible cover sets so that each independent cover set solely covers all the targets deployed in the given region. By doing this until there is no scope of a new cover set, one can promisingly enhance network life cycle. Further, every cover set is assigneda pre-defined time duration (activation duration). The network lifetime is defined as the summation of this activation duration of all these cover sets.

1.2 My Contribution

In this manuscript, a novel meta-heuristic is proposed which is based on a modified mutation approach where sensors are selected for coverage in a peculiar way, which in turn maximizes the network lifetime. The overall contribution of this manuscript is as follows:

a. Formulated a linear program (LP) for the node's activation duration scheduling in a wireless sensor network.
b. Creation and representation of a valid chromosome after crossover and mutation operations.
c. An energy-efficient fitness function is derived for increasing the achievable network lifetime.
d. A novel mutation strategy is devised to optimize the usages of such sensors thatprovide coverage to critical targets (i.e., least covered targets).
e. Extensive simulation is carried out to prove the superiority of the designed meta-heuristic.

1.3 Organization of the Paper

This manuscript is organized as follows: Sect. 2 discusses the previous works done so far on the target coverage problem. In Sect. 3, the author defines the target coverage problem and models it as an optimization problem. Afterward, this paper discusses the proposed heuristic in Sect. 4, and in Sect. 5, various simulation results are discussed. Finally, Sect. 6 concludes the work and gives future directions to extend this work.

2 Work Done

There are many factors such as energy-efficiency [7], data integrity [6], and confidentially of networks [9], which are mainly judged while checking the quality of a WSNs. There are certain constraints of WSNs, which include multi-hop communication, routing in a densenetwork, coverage withscarce resources, optimal usages of energy consumption and

many more need close attention [1–3]. Among all of these, energy consumption optimization is the prime research issuein WSNs [11–15]. Consequently, effective energy optimization techniques are the main concern where the far most objective is to minimize the energy consumption [16–22].

In order to deal with target coverage in heterogeneous sensor networks, a plethora of research outcomes based methodologies is addressed in the literature [7–18].All of these works mainly focused on achieving a network lifetime near to optimal upper bound.

Initially, work in [8] addressed a heuristic which generates disjoint cover sets. A disjoint cover set does not allow the participation of any sensor across the cover sets. Due to such restricted participation of nodes, the achieved lifetime is quite lower than the upper bound on network lifetime. Further, in the same work, another greedy heuristic is addressed where cover sets are non-disjoint, which let sensors participate in multiple cover sets. To form cover set, the addressed greedy methodology prioritizes sensors based on the coverage of uncovered targets. The network lifetime achieved by this greedy method is considerably higher when compared with the previous method.

Manju et al. [9] discussed High-Energy-Small-Lifetime (HESL) heuristic, which aimed for maximizing network lifetime by constructing a cover set where a sensor with high remaining energy is chosen first to participate in the current cover set. This process iterates until the cover set is not formed. HESL performs significantly better than the work addressed in [8].

Authors in [13] presented another heuristic for solving target coverage and aiming to prolong the achievable network lifetime. The addressed method is based on a genetic paradigm where the major intension is to provide partial coverage instead of full coverage to make the network functional for extended duration.

Chand et al. [14] addressed another heuristic for full target coverage where authors calculated a fitness function based on coverage and the remaining battery life of sensors. While constituting the cover set, sensors that maximize the fitness functions are chosen as part of the current cover set.

Gupta et al. [15] addressed one more heuristic where the objective function is threefold, which includes least required sensor selection; ensures K-Coverage over targets, and provides M-Connectivity. To make it work for full target coverage issue, if I set K = 1, M = 1, the methodology has a single criterion while prioritizing sensors for the cover set.

Raiconi et al. [17] also addressed another meta-heuristic based on a genetic algorithm where the prime objective is to maximize the network lifetime and ensure connectivity with the base station. To form a fitness function to decide the candidacy of participating sensors in the current cover set, the sensor with maximum coverage is chosen, which maintains connectivity with the base station directly or via relay nodes.

Further, work in [18] also discussed genetic algorithm based meta-heuristic for maximizing the total network lifetime. The addressed work designed a meta-heuristic where they customized the mutation operation of genetic paradigm by not activating those sensors in a chromosome which are neither part of coverage nor of connectivity.

In this paper, the author devised a modified mutation operation for genetic algorithm-based meta-heuristic for maximizing the total network lifetime while finding solution for target coverage problem. Generally, the genetic algorithm based heuristic goes through mutation operation after cross over where any random gene value flips from 0 to 1so that the newly produced child chromosome in crossover operation becomes a valid chromosome. Instead of flipping any random gene from 0 to 1, the proposed modified mutation operationflip only that gene value (sensor) which does not cover critical target. By doing so, one can keep alive those sensors, which cover the critical targets. As discussed in the

earlier section, the network is functional until the first target gets uncovered; thus, the proposed modified mutation operation tries to keep alive such sensors that provide coverage to the critical targets.

The proposed heuristic has the below advantages in contrast to the above-discussed algorithms [8, 9, 13–15, 17, 18].

a. The proposed meta-heuristic has considered residual energy while driving fitness function, which is proven to be useful for the long run of the network to be functional. There are works [13, 15, 16] in contrast that do not take residual energy into account.
b. The proposed algorithm is applicable to all kinds of networks, be a grid-based or regular network. Works in [23–26] only applicable to grid-based networks.
c. Though chromosomes are created randomly, the proposed meta-heuristic also ensures that the offspring are also valid.
d. The proposed meta-heuristic does not follow regular mutation; instead devised its own modified mutation operation, which ensures the prolonged coverage of critical targets.

3 Problem Statement

3.1 Network Assumptions and Problem Statement

I assume a deployed network WSN = {S, T}, where S = {s_1,…,s_p}, **p** number of sensors and T = {t_1,…,t_q}, be the set of **q** number of targets. Here, a homogenous network with respect to energy and sensing range is considered. In the given sensing proximity, sensors are assigned with energy (e_i) and sensing range r_i. A sensor $s_m (1 \leq \mathbf{m} \leq p)$ can monitor target $t_n (1 \leq \mathbf{n} \leq q)$ if t_n falling within the sensing range of s_m. Formally, S_C = {s_m|for each t_n there is a $s_m \in$ S_C such that s_m completely covers t_n}.The activation duration of a sensor cover S_C is defined as x(S_C). Further, the target is called covered if it is covered by at least one sensor in each cover set.

3.2 Linear Programming Formulation (LP)

The above-defined system model completely represents the target coverage problem. Now the same can be formulated in the form of linear programming. To depict this, the constraint matrix, C_M can be written as below.

$$C\_M_{ij} = \begin{cases} 1, & \text{if sensor } s_i \text{ is in sensor cover } S_j \\ 0, & \text{otherwise} \end{cases}$$

Now, the target coverage problem in the form of a linear program formulation can be represented as follows.

$$\text{Maximize} \quad \sum_r x_r$$
$$\text{subject to} \quad \sum_r C\_M_{ir} x_r \leq e_i \quad \text{for all sensors} \quad s_i$$

$$x_r \geq 0, \quad \text{for all sensor covers } S\_C_r$$

The constraint matrix is explicitly beforehand if the number of cover sets is known in advance. Since the deployed network is dense, the total number of the generated cover set is prohibitively large. Therefore, conventional approaches available for solving LP cannot be applied here to solve the above stated LP. In order to solve it, various column generation heuristics are addressed by researchers [7–15]. All the addressed heuristics so far [7–15] in the literature tries to reach the achievable upper bound calculated for the network lifetime.

3.3 Optimal Upper Bound

The upper bound of a deployed network is dependent on the target which is covered by the least number of sensors in a homogenous network where each sensor is assigned with the same battery life. Such poorly covered targets are called critical targets. In the case of a heterogeneous network, a critical target is the one whose summation of batteries of covering sensors is least among the rest of the network targets.

3.3.1 Illustration 1

Let us consider 4 sensors, namely s_1, s_2, s_3, and s_4, and 3 targets, t_1, t_2, and t_3. The sensors' coverage relationship with targets is depicted in the following matrix, where entry 0 shows that a sensor does not cover the respective target, whereas entry 1 represents that the corresponding sensor covers the particular target. Further, it is assume that each sensor is assigned a unit battery.

	t1	t2	t3
s1	1	0	1
s2	1	1	0
s3	1	0	1
s4	1	1	1

As depicted in the above coverage relationship matrix, target t_2 is covered by only two sensors (s_2 and s_4) with a unit battery each. Therefore, the upper bound on this network is 2 units. None of the heuristics can achieve a total network lifetime of more than 2 units for this particular network scenario.

The upper bound calculation discussed in Illustration 1 is completely effected by how these critical targets are covered. Therefore, the network lifetime is prolonged if one can ensure prolonged coverage of these identified special targets (critical targets). None of the above-discussed methodologies [13–18] concern about the critical target's coverage.The next section discusses the proposed heuristic, which is GA inspired where cover set generation operationis performed with extra caution by keeping the critical target alive for maximum possible duration.A modified mutation operation for the proposed genetic algorithm is introducedto perform this strategy where the critical target's longevity is on the highest priority while mutation operation takes place.

4 Proposed Meta-Heuristic

The three major steps, namely selection, crossover, and mutation, will be discussed in genetically inspired meta-heuristic. The following flowchart depicts all the steps involved in the proposed meta-heuristic.

4.1 Evolutionary Technique: Genetic Algorithm (GA)

Forthe last decade, Genetic Algorithm (GA) based meta-heuristics are proven to be an appropriate methodology for the optimization problems. The genetic algorithm starts with the initial population, which consists of random solutions called chromosomes. The chromosome is a binary string where elements are called genes. The size of the chromosome (i.e., number of elements/genes) is decided by the number of sensors deployed in the network. The absolute quality of the chromosome is dependent on the fitness function. In the case of target coverage, a cover set is represented by a chromosome. So, one can say that the gene value i, $1 \leq i \leq p$, equal to 1 only when sensor s_i participates in the corresponding cover set, and 0 otherwise.

In general, a genetic algorithm comprises of three vital phases; first selection, second crossover, and finally, mutation. Before performing any of the phases, GA initiates the initial population (pool), which is consists of randomly generated chromosomes. While performing selection, two-parent chromosomes are randomly selected from the pool and are further responsible for producing child chromosomes. Once the selection of parent chromosomes is made, the crossover operation happens where two-parent chromosomes produce child chromosomes after exchanging their genetic information with each other. Finally, mutation operation undergoes to which helps in generating a better solution when compared withthe parent. After performing these major steps, the child chromosome's quality is further examined by recalculating the fitness function's value. To provide the efficient methodology for the target coverage issue with the help of genetic algorithm based methodologies, all the GA based heuristics differs in the way how they calculate the value of the fitness function so that the network lifetime can be prolonged. Several GA-based heuristics [13–18] in Sect. 2 are focused on the number of sensors in a cover set to evaluate fitness function (Fig. 1).

4.2 Chromosome Generation

Chromosomes are strings of 0 s and 1 s and can be defined as $\{cg_i | cg_i \in (0,1), \forall i, 1 \leq i \leq p\}$. Here, the chromosome's length is equivalent to the size of the sensor network (i.e., |S|) in the network. Fortarget coverage, the chromosome represents a cover set. Thus, the gene value 1 and 0 represents the *active* and *sleep* status of sensor nodes in that particular cover set.

$$cg_i = \begin{cases} 1, & \textit{if } \text{sensor } s_i \text{ is active} \\ 0 & \textit{otherwise} \end{cases}$$

4.2.1 Illustration 2

To explain the chromosome representation, consider a network of 7 sensors and 4 targets whose coverage relationship is depicted in the following table (Fig. 2).

By following simple greedy rule, consider S_1, S_3, and S_7 as part of a cover set as collectively; these three sensors are covering all the targets. Thus, to depict this cover set in the form of a chromosome, it can be shown as below in Fig. 3.
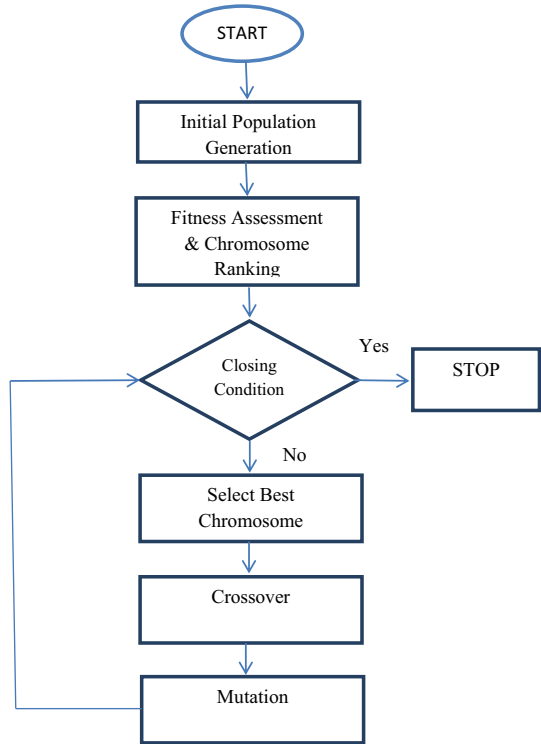
Fig. 1 Flow of the proposed heuristic

Fig. 2 Sensor-target coverage

	T1	T2	T3	T4
S1	1	0	1	0
S2	0	0	1	0
S3	1	0	0	1
S4	1	1	0	1
S5	1	1	0	0
S6	0	0	1	1
S7	0	1	1	0

Fig. 3 Chromosome representation

Sensor →	S1	S2	S3	S4	S5	S6	S7
Gene value →	1	0	1	0	0	0	1

Here, one can see that the gene value corresponding to S_1, S_3, and S_7 are 1 showing these three sensors are active in the given cover set, and the rest of the genes are 0 depicting that they are inactive in the same cover set.

4.3 Early Population Generation

The initial pool of chromosomes is formed by randomly generating these strings of 0 s and 1 s. As discussed in the previous section, the size of chromosomes depends on the number of sensors in the network. The following algorithm is used to generate the initial population to start with GA based solution for the target coverage.

```
Input: S (#sensors), K (size of population)
Output: K (number of chromosomes)
    1. bool String [K]
    2. init P ={}
    3. for i =1 to K
    4.     for j=1 to S
    5.         String [j] = random()%2
    6.     end for
    7. P= P∪String
    8. end for
```

Algorithm to generate the initial population (K)

4.3.1 Proposed Fitness Function

The quality of some newly generated chromosome is primarily dependents on the fitness function which has been used. The fitness function comprises of certain objectives which are collectively met while performing a certain operation of the selected procedure. In the proposed meta-heuristic, the following objectives are aimed to meet in order to prolong the network lifetime.

4.4 Objective 1: (Selection of minimal critical sensors in a cover set)

A critical sensor is a sensor that covers poorly covered (*critical*) target(s) in the designated network of sensors. Sincethe networks' achievable lifetime proportionally depends on the coverage of critical targets, intense care for coverage of such targets is a must. Therefore, in this work, the prime concern is to minimize the usages of critical sensors. Consider **S,** number of total sensors in the network, and **S_r,** number of critical sensors out of these **S** sensors. Hence the foremost objective is defined as below.

$$\text{Minimize } F_1 = S_r/S \quad (1)$$

4.5 Objective 2: (Selection of minimum sensors in total within a cover set)

After covering critical targets, this objective encourages us to minimize the usages of sensors for the rest of the target's coverage. Consider, K sensors are minimally required to cover remaining targets, and then another objective function is defined as

$$\text{Minimize } F_2 = K/S - S_r \quad (2)$$

Thus, this work has two objectives to be fulfilled at once in every iteration of the cover set. In order to construct the fitness function, which comprises of multiple objectives, the weight sum approach (WSA) [22] is addressed. While following WSA methodology, every objective is first multiplied by a weighted value, say W_i. Finally, the fitness function is calculated by adding these individual values to get a single scalar objective function. This

objective function is known as the fitness function. Here, in this work, the fitness value of these two objective functions F_1, F_2, respectively is represented as follows:

$$\textbf{Fitness} = W_1 \times (1 - F_1) + W_2 \times (1 - F_2) \tag{1}$$

$$\textbf{Fitness} = W_1 \times (1 - S_r/S) + W_2 \times (1 - K/S - S_r) \tag{2}$$

$$\textit{Objective} : \textit{Maximize}\ \textbf{Fitness} \tag{3}$$

The proposed meta-heuristic consider $W_1 + W_2 = 1$, where $0 \le W_i \le 1$, $\forall i$, $1 \le i \le 2$ with the prime concern of maximizing the fitness function defined in (3).Here the quality of the chromosome is measured by the fitness function results. One can try various combinations of W_1 and W_2 values and check the fitness value.

4.6 Selection

After generating the initial population pool, there are various methods; rank selection, Roulette-wheel selection, and tournament selectionto choose valid chromosome. A valid chromosome is the one that represents a complete cover set. Further, the fitness function is applied to choose chromosomes that is valid and has a better fitness value. Once this selection procedure is over, new chromosomes are generated with the help of crossover operation and call themchild chromosomes. Next, this work discusses the crossover operation in detail.

4.7 Crossover

To generate new chromosomes, two of them are selected randomly, and then crossover operation is performed. So far, in the literature, many crossover operations are addressed where few of them are listed as two-point crossover, one-point crossover, and uniform crossover [22]. Here, the proposed meta-heuristic in this work applies one-point crossover where a single crossover point is applied. After choosing the cross over point, two-parent chromosomes are selected to interchange their gene values after cross point onwards, as depicted in Fig. 4.

4.8 Modified Mutation

The crossover operation produces new chromosomes and calls them child chromosomes. Further, one has to test the fitness function value of these new chromosomes to check their
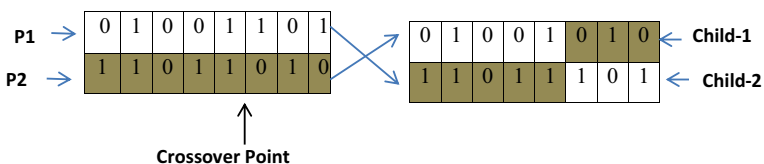

Fig. 4 Crossover representation

Table 1 Sensor–target matrix

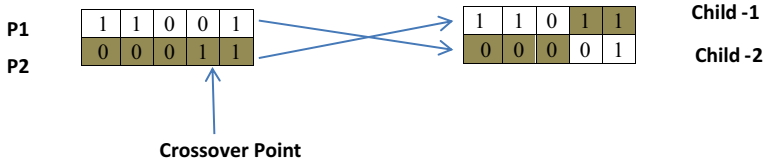| Sensor/Target	T1	T2	T3	T4
S1	0	1	1	1
S2	1	0	1	0
S3	1	0	1	1
S4	0	0	1	0
S5	1	1	0	1

Fig. 5 Mutation

candidacy for the chromosome population pool. In this process, those child chromosomes with higher fitness value than the parent chromosome then applied a genetic paradigm to replace the parent chromosome and consider this newly produced child chromosome as part of the population. However, there are chances that the child chromosome is invalid. A chromosome is called invalid when it is not representing a cover set. In order to make it a valid chromosome, there is another operation (called a mutation) that has to be performed. In general, while performing the mutation operation, there is a flip of a gene value from 0 to 1 to make it a valid chromosome. To do so, the gene values which are going to be flipped are selected randomly.

4.8.1 Illustration 3

The following example depicts the functionality ofthe mutation operation. For this scenario, I consider 5 sensors and 4 targets, and each sensor has 1 unit battery.The Table 1 entries would be 1 if a sensor that covers the corresponding target, otherwise 0.

Suppose during crossover operation; there are two parent chromosomes (cover sets) chosen as given below:

As one can observe in Fig. 5, there are two child chromosomes (cover sets) that are produced after crossover operation. As it is known that the chromosome represents a sensor cover, but as shown in the above Fig. 5, the Child-2 is somehow not representing a cover set because all the targets are not covered by the selected sensor (S_5). Since Child-2 is not a valid sensor cover, mutation operation is used to make it valid cover set by turning on one of the sensors (s_1 or s_2 or s_3 or s_4) by flipping one bit from 0 to 1. Thus, the mutation operation is needed in such situations while generating valid chromosomes.

The proposed heuristic do not turn on random sensors; instead, activate that sensor that does not cover the critical target. As shown in Table 1, target T_2 is critical because it is covered by only two sensors (s_1 and s_5). Thus in order to make Child-2 valid chromosome (i. e. cover set), and avoid activating s_1 (by flipping gene value from 0 to 1). By doing so, the proposed modified mutation strategy can extend the coverage of critical targets by keeping

alive critical sensors for a longer period, which further prolongs the total achievable network lifetime.

5 Simulation Result

5.1 Simulation Setup

This section discusses the network scenario and various parameters considered in order to evaluate the performance of the proposed heuristic. Here, two square sensing areas, each of size 300×300 M^2 and 200×200 M^2 are taken into consideration for simulation. In both the networks, a heterogeneous sensor network is considered in which sensors may have different initial energy level. In this experimentation, sensors are carrying the same sensing range (100 M). This work considered random deployment of sensors as well as targets. Every simulation value is an average of 50 problem instances. The complete simulation is performed on MATLAB (R2016). In Table 2, all the simulation parameters are mentioned. For the proposed meta-heuristic, the initial population of 60 chromosomes are considered, and the mutation rate as 3%.The termination criteria for the proposed meta-heuristic are fixed to 150 iterations.

5.2 Selected Energy Model

Energy optimization is the prime considerations while designing and deploying sensor nodes in the WSNs. As discussed earlier, the energy in the network is limited and non-rechargeable also. Therefore, it becomes a vital need to design a sensor node such that its battery life can be maximized [27]. Most of the node's energy is consumed through data sensing, information processing, and power units [28]. It has been discussed in many works that the power unit has three different modes, namely sleep, active, and idle. The consumption of power is primarily depends on the state [29]. For the last few decades, many energy conservation models have been designed and addressed for WSNs. Few of them include the probabilistic model [30], a hybrid model [31], and an energy conservation model based on a simulator [32] in WSNs.

All the aforesaid methods are based on the communication protocol model that consists of the application layer, transport layer, network layer, data link layer, and physical layer. The detailed energy consumption models which are being used by the physical layer are

Table 2 Simulation parameters

Parameter	Value
Sensing Area	$200 \times 200M^2$, $300 \times 300M^2$
# Sensors	50–250
# Targets	20–100
Sensing Range	100 M
Mutation Rate	3%
Cover-set Working Time	0.50 units

mainly discussed in [33–35]. The energy model in [36] gives details of the physical layer energy usages per bit data processing are as follows:

The energy required to receive (E_{rx}) and transmit (E_{tx}) a packet of size P-bit is given below.

$$E_{rx} = P \times E_{amp} \tag{4}$$

$$Etx = P \times \left(E_{amp} + \varepsilon_{fs} \times d^n\right) \tag{5}$$

Here, ε_{fs} and E_{amp} are the transmission/reception circuitry parameters, and **n** is the path-loss exponent.

The LEACH protocol clearly observed that energy consumption increases while increasing the distances between nodes [37]. The energy required in transmitting and receiving **k-**bit of data is defined in Eq. 6 as below.

$$E_{rx}(k, d) = k.E_{elec} + k.\varepsilon_{fx}d^2 \text{if } d < d_0 \tag{6}$$

$$E_{rx}(k, d) = k.E_{elec} + k.\varepsilon_{fx}d^4 \text{if } d \geq d_0 \tag{7}$$

$$E_{RX}(k) = k.E_{elec} \tag{8}$$

$$E_{DA}(k) = k.E_{da} \tag{9}$$

Here, E_{elec} denotes the circuitry depletion of the sender/receiver, ε_{fs} is amplifier coefficients of free-space, and E_{da} is the amount of energy consumption while compressing unit data [37]. The proposed meta-heuristic in this work is also based on the above-stated energy model in Eq. (8–11) to obtain the optimal conditions to minimize the consumption of energy.

5.3 Performance Analysis

Here, an extensive simulation is discussed, which further claims the superiority of the proposed meta-heuristic with modified mutation operation. In order to calculate the fitness function value, one has to decide on the values of weights W_1 and W_2 so that both the objective functions can be evaluated.

5.4 Experiment-1

In this experiment, random values of W_1 and W_2 (between 0 and 1) are taken.Then, based on these values, the network lifetime is calculated with the help of the proposed fitness function. Here, there are fixed 50 targets with varying sensors between 50 and 250. The network is considered to be heterogeneous, and their batteries are varying between 1 and 2 units. This experiment is carried out on two different network scenarios which include 200*200M^2, and 300*300M^2 as shown in Tables 3 and 4, respectively. The researchers [22] clearly mentioned that accurately finding these weightswith precise values, even one is quite familiar with the problem domain and its necessity.Thus, the proposed meta-heuristic experiments with almost 30 combinations of both the weights (i.e.W_1 and W_2).Out of these

Table 3 Network lifetime achieved in sensing area $200 \times 200 M^2$ with various weight values of W_1 and W_2

Sensors	W1=0.6,W2=0.4	W1=0.5,W2=0.5	W1=0.4,W2=0.6	W1=0.45,W2=0.55	W1=0.35,W2=0.65
50	8	8	7	7	6
100	15	13	14	12	10
150	31	28	28	25	23
200	36	33	31	29	27
250	45	42	41	40	36

Table 4 Network lifetime achieved in sensing area $300 \times 300 M^2$ with various weight values of W_1 and W_2

Sensors	W1=0.6,W2=0.4	W1=0.5,W2=0.5	W1=0.4,W2=0.6	W1=0.45,W2=0.55	W1=0.35,W2=0.65
50	8	7	6	5	5
100	12	11	11	10	8
150	28	26	25	22	21
200	33	30	28	24	25
250	42	40	38	35	33

combinations, only promising five weights values combinations have been selected after complete exercise.

As depicted in Tables 3 and 4, with the weight $W_1 = 0.6$ and $W_2 = 0.4$, the proposed algorithm achieves a reasonable better network lifetime when it is further compared with other weights combinations. Therefore, the rest of the experiments in this work will be carried out with weight values $W_1 = 0.6$ and $W_2 = 0.4$.

5.5 Experiment-2

Here, this section examines the performance of the proposed meta-heuristic in terms of achieved network lifetime. Further, the outcome of the proposed heuristic is compared with few existing works [15, 18, 27] which have addressed the same target coverage problem in the heterogeneous sensor network for maximizing network lifetime. In order to do that, a simulation was done on two scenarios. In the first one, sensors were varying between 50 and 250 and fixed 50 targets in the sensing area of $200 \times 200 M^2$ (Fig. 6a) and $300 \times 300 M^2$ (Fig. 6b), respectively whereas in the second case, sensors were fixed (250) and varying targets between 50 and 200 in the sensing area of $200 \times 200 M^2$ (Fig. 7a) and $300 \times 300 M^2$ (Fig. 7b) respectively. All the experiments were performed with the same sensing range (100 m), and different battery levels are chosen randomly within the range between 1 and 2 units. As demonstrated in Tables 3 and 4, the values of weights $W_1 = 0.6$ and $W_2 = 0.4$ are chosen for the best results for both the scenarios. The rest of the simulation parameters are as shown in Table 2.

As depicted in Fig. 6a and b, it can be easily observed that the performance of the proposed heuristic is comparatively better when compared to the other works [15, 18, 27]. The primary reason behind this improvement is due to the proposed modified mutation operation while validating the newly created chromosomes. The proposed mutation operation ensures not to activate that sensor set, which is covering critical targets. This way of restricting the participation of these specific sensors will help in extending the coverage duration of such poorly covered targets. It has been discussed earlier that network is called operational until the first target
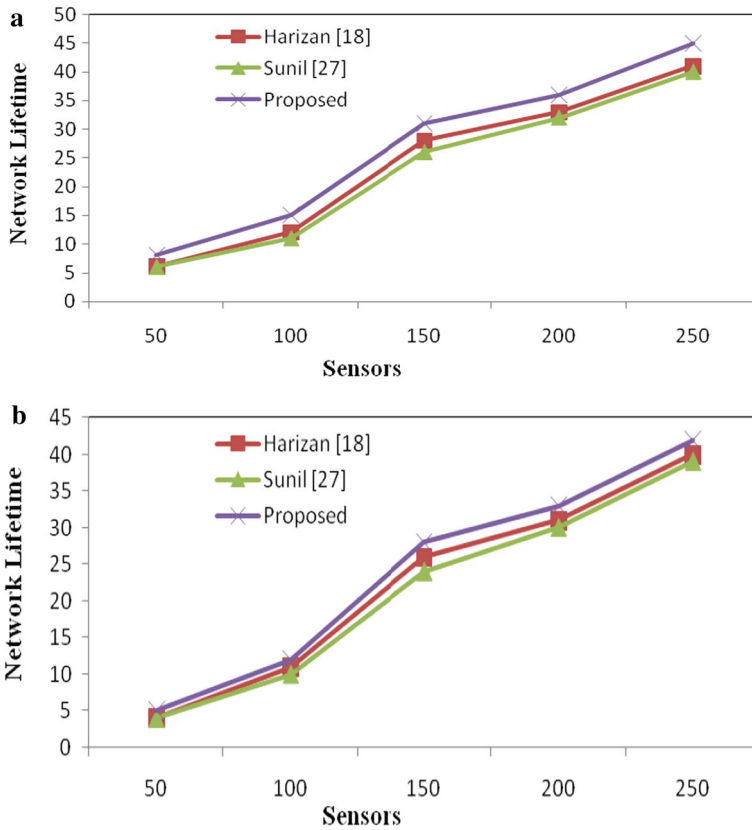
Fig. 6 **a** Network lifetime achieved in sensing area 200×200 M^2 with various algorithms. **b** Network lifetime achieved in sensing area 300×300 M^2 with various algorithms

becomes uncovered. As the critical target set will be uncovered first in the deployed sensor network. This extended coverage of such critical targets results in increased network lifetime. None of these existing works [15, 18, 27] takes this fact of extending critical target coverage into consideration.

Once again it is clearly depicted in the Fig. 7a and b that the proposed meta-heuristic performs exceptionally well as compared to the other research contributions in terms of network lifetime. Besides, it is evident from Fig. 7a and b that the lifetime of the network sharply decreases while increasing targets in the fixed sensing area. Since an increasing number of targets with the same set of fixed sensors, more sensors are needed in the cover set, which in turn decreases the achieved network lifetime.

Thus, Figs. 6a–b and 7a–b, shows that the proposed meta-heuristic performance is exceptionally better than existing research contributions [15, 18, 27].
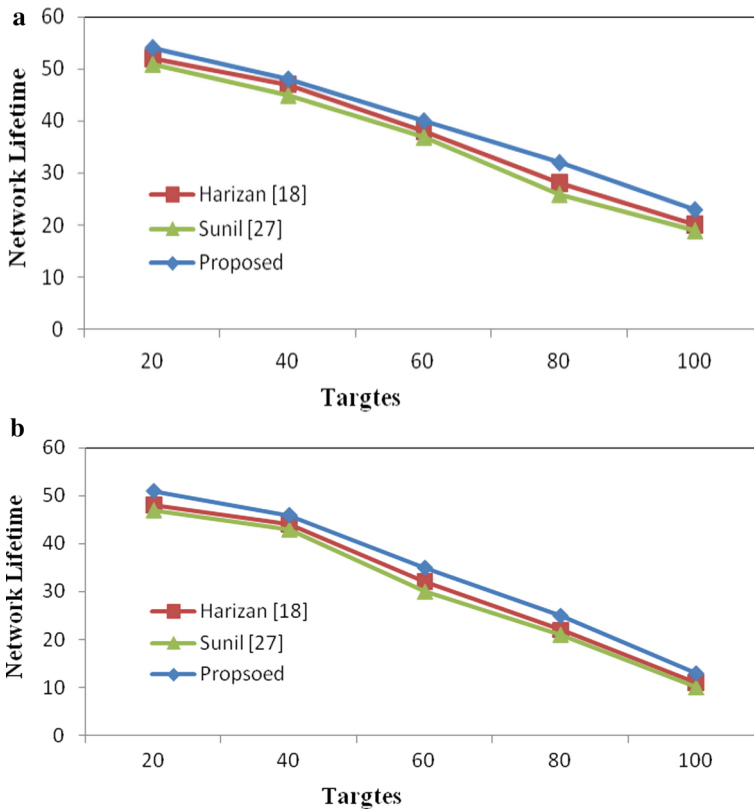
Fig. 7 **a** Network lifetime achieved in sensing area 200×200 M^2 with various algorithms. **b** Network life-time achieved in sensing area 300×300 M^2 with various algorithms

6 Conclusion

In this research work, the author has proposeda novel genetic algorithm inspired heuristic for prolonging the lifetime of the network for target coverage problems inWSNs. The research works [15, 18, 27] done so far on the addressed issue to extend the achievable network lifetime is also based on the genetic algorithm paradigm. The proposed meta-heuristic is based on a ***modified mutation*** operation instead of a conventional mutation. In conventional mutation, any random gene value is flipping from 0 to 1 in order to make the newly created chromosome valid. The modified operation does not flip the random gene value from 0 to 1; instead it first checks the critical target coverage and then decides which gene value should be flipped. To do so, the modified mutation operation flips only that gene's value for which the corresponding sensor does not cover critical targets. By applying a mutation operation this way (***modified mutation***), one can extend the coverage of critical targets, which in turn extend the achievable network lifetime.

In the future, the author wants to extend this work for various other variants of target coverage which includes, target Q-Coverage, Target Connected Coverage, Partial Coverage, Connected K-Coverage, and many more.

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