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Energy and Lifetime-based Management of Directional Sensor Network Using Combined Meta-heuristic Optimization of Gray-Wolf and Tabu Search Approaches

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Abstract – Coverage and network lifetime are two important metrics within the directional sensor networks (DSN). One of the well-known methods to increase the network lifetime is to create a set of so-called cover-set (CS) sensors, one of which at any given time interval is responsible for covering all the defined objectives within the network. How to construct these CSs has been the problem investigated in many researches, in all of which, the main goal has been to create more CSs that are best in enhancement of network's lifespan. In this study, a combination of Gray-Wolf Algorithm (GWO) and Tabu Search (TS) has been used for creation and selection process of CS sensors. In order for performance validation of the proposed hybrid algorithm (HA) against other approaches, computer simulations were implemented. The simulation results illustrated that the proposed HA approach can provide the network with longer lifespan.

Keywords: Directional Sensor Network (DSN), Gray-Wolf-Algorithm, Tabu Search

1. Introduction

Recently, directional sensor networks (DSNs) have received attention among researchers due to their wide range of applications. These types of networks usually include a large number of directional sensor nodes enabled to set the sector with the limitations of the angle and covered radius. For example, DSNs include a number of sensors such as infrared, ultrasonic, and video used in various applications. These networks can be employed in such applications as agricultural, military, oil pipelines, etc. environments in which predetermined goals must be constantly monitored by the monitoring room [1-4]. Considering the limited capacity of the battery and the impossibility of recharging the sensors, the environment is one of the most important challenges of these networks. Solving this problem is computationally in the NP-hard category, and various methods, including accurate, innovative and meta-heuristic have been used to solve this problem. Although the solution to this problem has been presented in related studies, however, mostly they lead to sub-optimal solutions [5-7]. Sensor scheduling is one of the proposed techniques to manage energy consumption [1]. This technique divides the sensors into a number of cover-sets (CSs), each of which can meet the network coverage demands. When one CS is chosen and tuned for a certain time interval, the others are switched to inactive mode. Upon a CS is disabling, its associated sensors are also switched to disabled mode. The activity time of each sensor is determined in such a way so that to increase the lifetime of the network [8]. To provide a better understanding of the effectiveness of the sensor scheduling technique in increasing DSN lifetime, an example has been given in Fig. 1, in which a DSN with five sensors are supposed to monitor five predefined targets. Each sensor can be configured in one of three possible directions and one of two possible radii.

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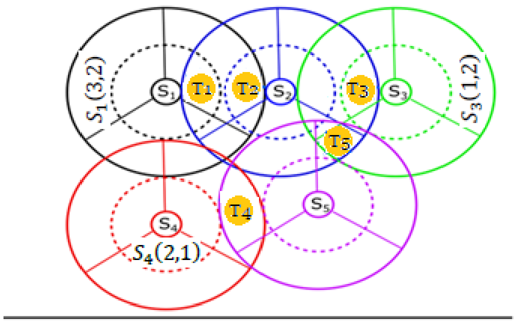

Fig. 1: A DSN with Multiple Sensors

According to fig.1, for this network, the four different coverages CS_1 ،CS_2 ، CS_3 and CS_4 construct a set of sensors that enable the monitoring capability of the complete environmental monitoring. The coverage areas can be calculated by (1) to (4), as follows, respectively.

$$CS_1 = \{S_1(1,1), S_2(3,1), S_3(3,1), S_4(1,2), S_5(1,2) \quad (1)$$

$$CS_2 = \{S_1(1,2), S_3(3,1), S_4(1,2), S_5(1,2)\} \quad (2)$$

$$CS_3 = \{ S_1(1,2), S_2(1,2), S_4(1,2), S_3(2,2)\} \quad (3)$$

$$CS_4 = \{S_1(1,2), S_2(1,2), S_5(3,2), S_3(2,2)\} \quad (4)$$

In case a CS is set to be used continuously, the battery of the sensors will be drained very soon and the network will no longer be able to monitor all the targets. An efficient algorithm can schedule different CSs in different time intervals so that the battery of the sensors are not used uniformly and the battery of the sensors not scheduled in the current CS is preserved, thus leading to the power management of the sensors and as a result increasing lifetime of the network. Considering the importance of timing and finding the best CS, in this research, a combination of Gray-Wolf Optimization (GWO) and Tabu-Search (TS), called GWO-TS algorithm has been presented. The proposed combination Heuristic Algorithm (HA) take advantage of the global search ability of GWO as well as the local search ability of TS to achieve the optimal solution. It schedules the best CSs among the available CSs so that lifetime of the network increases.

2. Contributions and Paper Organization

In a DSN with a number of sensors, first, the best possible coverage sets are built up and then scheduled to increase the network's lifespan. The proposed GWO-TS, the Hybrid Algorithm (HA) utilizes the high global search capability of GWO and the local search capability of TS to provide the problem with high search capacity. Computer simulations have been performed for HA and the results are compared with those of several other algorithms. The rest of the paper is organized as follows. Section 2 briefly reviews studies and related works. Section 3 presents the definition of the problem. In section 4 and 5, respectively, the proposed algorithms and the corresponding results of the computer simulations are provided. Finally, in section 6, the research is concluded.

3. Literature Review

In recent years, DSNs have been used due to their applications and high capacity in collecting data from various environments, especially hard and inaccessible places with shortage of manpower or safety and/or hazardous for humans, has drawn a lot of attentions in the scientific community. Based upon the attractive properties of DSNs, the focus of this research is on monitoring the entire environment and construction of a CS in which the sensors encompass more than one radius and different energy levels such that to increase the monitoring time interval. In order to increase lifetimes in DSN networks, several challenges must be taken into account. First, due to restriction in the sensor's viewing angle, they cannot control all directions. This, in turn, will increase complexities compared to the traditional wireless sensor networks (WSN). Second, sensors include non-rechargeable nodes with limited battery level; therefore, it is necessary to provide efficient algorithms that use energy-saving techniques to resolve the target coverage's problem in DSN networks. In general, there are several techniques for timing. First, timely scheduling the sensor state from active to inactive and vice versa. Second, the correct setting of the sector number and third, the setting the radius of the sensor's covering range [9]. Therefore, through correctly setting the radius and angle of the directional sensor in each time interval and optimally using battery-limited sensors' energy, an effective step can be taken in increasing the lifespan of the network. In the following, the related studies in this field will be reviewed.

Authors in [10] were among the first to study DSNs and traditional methods of target coverage. The focus in their research was on increasing coverage by using the least number of active sensors to monitor targets' number. Besides, different algorithms were presented as solutions the problem. Furthermore, the multiple directional coverage set was introduced and it was proved that these types of problems are NP-hard. In another research, various innovative algorithms were proposed in order to create separate coverage sets, each of which with the ability to cover all the targets in the network [11]. Other researchers, also, presented the learning automata in other studies in order to cover multiple objectives. Their difference was in the coverage quality requirements, where the need to prioritize targets' coverage was brought up, e.g., in places where some targets must be monitored by more than one sensor [12-23]. In [24], combination of the two objectives, i.e., increasing the quality of the environmental coverage and lifespan of the network was discussed. This work is due to finding efficient algorithms in an environment wherein heterogeneous goals, such as smart-city related applications, are to be met. The authors showed that the greedy algorithms could achieve solutions close to optimal efficiency by measuring the quality of perception in a probabilistic manner.

In the context of network's lifetime maximization, in [6], an algorithm based on the column production plan was presented which creates a model with two different strategy levels, including genetic algorithm and linear programming, wherein the linear programming algorithm has two roles. First, it must avoid the local optima and second achieve optimality in the current solution [6]. In [25], a Gray Wolf Improved Algorithm (D-GWA) was proposed to schedule CSs; here, focus was on the k possible coverages in the adjustable sensor network, although it did not provide any solution to solve the full coverage problem [25]. In other researches related to finding the best CSs among adjustable sensors, the basic genetic algorithm (GA) was used in which the results were close to optimal [9, 14].

In another network lifetime increasing research [26], an algorithm was suggested, specifically for camera-based sensor networks, for covering either the total targets or part/s of them; while in the first, the whole number of targets must be covered throughout the complete network's lifespan, within the partial coverage model, targets are weighted based on their position and importance. Based on this condition, only the targets whose sum weights was greater than a predetermined threshold should be covered during the network's lifetime. For this problem, authors proposed three different heuristic algorithms, all of which have been proven as being effective in increasing the network's lifetime.

The above-mentioned methods for covering targets by a sensor network are characterized by some shortcomings; they either had considered sensors with only one level of energy consumption, or in case of different levels with the ability to adjust the radius of the sensors, did not provide an optimal algorithm with respect to both energy saving and life-span increase. As a result, in order to have an optimal and efficient solution, there is a need to propose new hybrid algorithms. This is the main objective of the current study.

4. Problem definition

Usually, number of DSN nodes is several times the number of predetermined targets in the monitoring environment, so that they can monitor the desired targets in a long time and with more reliability [25-29]. Fig. 2 shows a typical directional sensor whose radius and angle can be adjusted for two and three different ranges and directions, respectively. Thus, such a simple sensor can be scheduled for 6 different modes.

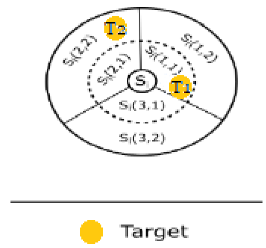

Fig. 2: A Typical Directional Sensor

In fig. 2, if the sensor S1 is set toward the second direction and smallest radius, it cannot cover any target. It cannot track a target even if it is set to the highest radius in the third direction. According to Fig. 1, it can cover the targets of the environment and transmit their information to the well node only in two different directions and with two different radii. The symbol $S_k(i,j)$ shows that the sensor S_k is active, in turn, in the i-th and j-th direction and radius. The symbol $\Delta^{i,a}$ is the energy consumption of the sensor S_i whose radius is set to a. Assuming the homogeneity of all sensors, the symbol Δ^1 is considered equal to one for normalization. In other words, if the sensor is set at the smallest radius, it consumes one unit of power and in this setting, it has a lifetime of $L_1 = 1$. The value of $\Delta^{i,a} = b$ means that if the sensor S_i is continuously set at the radius a, its power consumption b is equal to the state it has in the base radius (the smallest possible radius, i.e., one). That is, if the desired sensor is set to the shortest adjustable radius, its lifetime would be one. The variable $\Delta_a = y$ refers to the fact that if the consumption radius is a, its energy consumption will be y. For example, the variable $\Delta_2 = 3$ means that if the radius of the sensor becomes double, the energy consumption will be tripled; therefore, L_2 would be equal to $L_1/3$. In these networks, sensors can be scheduled for only one direction and a given radius. The important point is that each sensor can be active for only one radius and direction, respectively. The objective of the problem is to maximize the network lifetime using the existing sensors and continuously monitoring all the predetermined targets in the monitoring environment. Suppose a set of *n* existing sensors, each of the maximum range and the maximum number of angular sectors in different directions. Furthermore, assume that adjustment can be made in M different rounds such that a variety of different CSs can be constructed, in which each CS_j can be scheduled for the time interval T_j. Therefore, the objective function would become as in (1), which should be maximized subject to the constraints , as in the following.

$$\text{Max } f(t) = \sum_{j=1}^{M} T_j$$

Subject to,

$$\sum_{i=1}^{n}\sum_{j=1}^{M}\sum_{r=1}^{Ranges} X_{ij}^{d,r} \times \Delta^r \times T_j \leq \beta \quad \text{where } d \in \{1,2,\ldots,Sectors\},\ X_{ij}^{d,r} \in \{0,1\}$$

$$\sum_{k=1}^{p} y_{kj} = |p| \quad \text{, where } y_{kj} \in \{0,1\}$$

$$T_j > 0,\ \forall\ i=1,2,\ldots,M$$

where, the binary decision variables $\mathbf{X}_{ij}^{d,r}$ stands for the activation of the *i*-th sensor in the *d*-th direction, *r*-th radius and *j*-th circle, and y_j , shows whether the desired sensor is active in the current round r not. The condition, shows that the scheduling can be continuously done for all the sensors whose power are not consumed entirely. In other words, when one sensor is active for a specific time interval in a round, its power will be reduced to a certain extent, which implies the maximum utilization of sensors. The binary decision variable, y_{kj}, shows the k-th target in the j-th round is monitored by at least one sensor, while parameter p indicates that the total number of targets must be monitored in the *j*-th round. In mathematical form, the binary variables should be summed up to p. Relationship, shows the activation times are positive. An efficient algorithm should provide the proposed problem formulation of DSN with lifespan as long as possible subject to the power consumption of sensors.

5. The Proposed Algorithm

This section begins with an overview of GWO and TS algorithms. Then, a hybrid algorithm to solve the coverage-scheduling problem in DSN networks will be introduced.

5.1Overview of Gray Wolf Algorithm (GWO)

The Gray Wolf Algorithm (GWO) is one of the algorithms inspired by nature. More specifically, it is inspired by the social and hunting behaviors of gray wolves. Gray wolves, as top predators in nature, have complex behavioral pattern in group coordination and leadership, which can be used as a model to search the optimization space. The Gray Wolf algorithm, with its simple structure and random search mechanism, has a high ability to achieve global optimum and escape local optimum. With proper adjustment and customization of its operators, it has high flexibility in various application areas of optimization and solving multi-objective problems. It is also very suitable for solving discrete and nonlinear problems because it does not require gradient information. In nature, gray wolves live in groups wherein each group has a certain hierarchy. Group members can be divided into four categories:

1. Alpha: The leader of the group which determines the main decisions such as when to hunt, where to rest, and other behaviors of the group. The other wolves must follow these orders.

2. Beta: The second position in the group, which helps Alpha in carrying out the orders and assumes the leadership role whenever Alpha is absent.

3. Gamma: This category includes wolves lower in the hierarchy, whose duties include guarding and searching for prey.

4. Omega: The lowest rank in the group, which acts as the most submissive member and follows orders submitted from all other wolves.

This behavioral hierarchy is used in the GWO algorithm to find the optimal solution. Alpha is selected as the current/first best solution while beta and gamma are selected as the second and third best solutions. Omega acts as the remaining population and follows the other top three groups.

The steps of the GWO algorithm can be summarized as follows:

1. The population of wolves is randomly initialized in the search space.

2. The wolves are divided into three groups, alpha, beta, and gamma, which represent the best, second, and third solutions, respectively.

3. Each wolf is updated to go closer to the prey.

4. The algorithm continues until a stop criterion is reached.

GWO Pseudocode

Step 1: randomly initialize the population of gray wolves X_i (i = 1, 2, …, n)
Step 2: Initialize the value of a = 2, A and C (using (3))
Step 3: Calculate the fitness of each member in the population

$$X\alpha = Member\ with\ best\ fitness\ value$$
$$X\beta = Second\ best\ member$$
$$X\delta = Third\ best\ member$$

Step 4: for I = 1 to N (maximum number of iterations)
Update the position of all the omega wolves using (4)-(6)
Update a, A and C (using (3))
a = 2(1 – t / T)
Calculate finesses of all search agents
Update $X\alpha, X\beta$ and $X\delta$
End for
Return $X\alpha$

5.2 Overview of Tabu Search Algorithm

The Tabu search (TS) algorithm is a memory search strategy. It is a neighborhood-based local meta-heuristic method. This algorithm explores the solution space by constantly replacing the most recent solution with the best-unvisited neighbor solution, while the new solution may be even less efficient. Of course, the new less effective solution is chosen as it might lead to finding better solutions in the future. In general, the objective is to find the global optimum in the shortest possible time interval. Technically, the algorithm tries to surpass local optima and find the global optimum or an approximate solution close to it. The algorithm starts a new search while it temporarily stops evaluation of the previous solutions; finally, it would find the global optimum or the best local solution. Using this method, it uses a list called the tabu, in which every solution chosen up until now will be included.

5.2.1 Performance of the TS forbidden algorithm

In an optimization problem, in order to reach the optimal solution, the TS search algorithm starts with an initial solution. In the next step, the algorithm selects a solution close to the current one from the neighboring solutions, and if it is not already in the tabu list, it moves towards it. The compatibility function will be used for this selection. At this moment, if the processing time is to be considered, the neighbor that improves the processing time will be selected. In a similar way, if distance is of significance, a neighbor will be selected so that it affects positively the path, i.e., shortening the distance. Here, if the chosen neighbor/solution is already in the tabu list, the breathing list will be checked. Based on this check-up, if the neighbor's solution is better than the one found so far, that neighbor would be selected even if it were already included in the tabu list. The tabu list avoids being stuck in the local optimum. After a number of movements are entered the tabu list, some other members of the list will be discarded. The number of times the solutions or movements are placed in the tabu list is determined based upon a parameter called tabu tenure. Moving from the current solution to those of the neighbors continues until a termination condition of the algorithm is met. The termination condition, for example, can be considered a certain or pre-given number of moves to the neighbors' solutions, that is, when this number of movements are reached, the algorithm will no longer migrate to the neighbors and/or end.

The Tabu Search Pseudocode

```
Set x=x0;
Set length (L) =z;
Set L={};
Repeat
    Generate a random neighbor x';
     If x' ∉   L then
        If length (L) > z then
            Remove oldest solution from L;
            Set x'∈L;
        End if
    End if
    If x'< x then
        x=x';
    end if
Stop if stopping criteria satisfy
```

5.3 Proposed GWO-TS Hybrid Algorithm (HA)

5.3.1 Creating the objective function

Since the objective of the problem, here, is to increase the lifetime of the network, the fitness function is defined according to the network's lifespan. From this perspective, among the different CSs, the one which has the lowest total battery consumption of the configured sensors the most desirable. Therefore, the fitness function calculates the level of total battery's energy consumption of the sensors configured in a CS. The amount of the batteries' consumed energy by a CS, $\boldsymbol{Cover_a}$, is calculated as,

$$\boldsymbol{F_1(Cover_a)} = \sum_{\forall\, S_i(j,l)\,\epsilon\, Cover_a}^{|Cover_a|} \Delta^l \qquad (5)$$

The (5) shows that the CS with the lowest level of battery consumption is more desirable. In the GWO algorithm, if two CSs in the same population, each representing a candidate solution, have the same fitness values, another distribution factor called F2 will be called for. This new factor indicates how the batteries consumptions are distributed throughout the network according to the configured radius. This factor indirectly enforces the uniform usage of all the available batteries, which will potentially increase the network's lifespan. The distribution factor for $\boldsymbol{Cover_a}$ can be calculated using,

$$\boldsymbol{F_2(Cover_a)} = \frac{\sum_{d=1}^{m} \sum_{\forall\, S_i(j,l)\epsilon F_3(t_d)}^{|F_3(t_d)|} \Delta^l}{\boldsymbol{m}} \qquad (6)$$

which is supposed to become minimized; that is, overlaps in the coverage ranges of sensors for target monitoring would be minimized. This minimization of overlapping sensors' ranges would lead, in turn, to minimizing the total energy consumption, since in this way less energy would be wasted for covering the overlapped areas of the network. In (7), $\boldsymbol{F_3(t_d)}$ denotes the list of sensors in $\boldsymbol{Cover_a}$ with the ability to monitor targets $\boldsymbol{t_d}$, which is defined as follows,

$$\boldsymbol{F_3(t_d)} = \{S_i(j,l)\epsilon Cover_a \mid t_d\ \epsilon\ \boldsymbol{ToT}[S_i(j,l)]\} \qquad (7)$$

In order to steer the energy consumption of batteries towards more uniform pattern, and at the same time choose the CS with the lowest energy consumption, the final fitness function can be obtained as

$$\boldsymbol{Fitness}(Cover_a) = \boldsymbol{\beta_1}.\boldsymbol{F_1(Cover_a)} + \boldsymbol{\beta_2}.\boldsymbol{F_2}(Cover_a) \quad (8)$$

The coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are non-negative values smaller than one, which imply importance of the energy and the overlapping level of the sensors' coverage in a CS of the model, respectively. For the purpose of simplicity and characterizing each effect with the same importance, their values are taken to be equal to 0.5. These parameters' values are determined by the system administrators depending on their corresponding priorities.

Since meta-heuristic algorithms run forever, conditions must be applied to terminate them. Decision on what condition to adopt is determined by the designers, which can include a pre-given number of iterations, achievement of a threshold fitness or observing no tangible improvement in the obtained solutions, etc. In this study, the condition to terminate the algorithm's execution is maximum number of iterations, MaxGen, whose value is determined experimentally based on trial and error.

5.3.2 Operational Steps of the Proposed Algorithm

In the proposed algorithm, the process of construction of CSs is such that in each step of the algorithm, a sensor that can cover the most targets is selected. Then, the list of out-of-range targets is updated. In addition, the set of minimal tunable sensors would be updated. This is done by discarding sensors, which currently are participating in the process of forming the CS. This process continues until formation of a CS, which provides the whole targets with coverage. These steps are implemented using GWO algorithm, which aims to achieve the optimal global solution in each iteration until finding the top three coverages. Then, these top three coverages will be examined by TS algorithm towards finding locally optimal solution in the neighborhood of each solution. Here, TS algorithm tries to find better solutions around each top three solutions in the case of possibility of any improvement. At the end, it would find the best possible solution for CS.

5.3.3 Test and Evaluation of the Proposed Algorithm

In order to evaluate the proposed method properly, its efficiency for different scenarios will be compared against the existing methods. Then, using the statistical description and performance of different settings, the superiority of the proposed combined method will be verified. The considered settings for evaluation are listed in Table 2. In addition, due to the lack of a standard baseline dataset, the data are generated by the Merkle distribution under the following conditions. The monitoring environment includes an area of the area 500 by 500 meters; number of sensors' directions assumed three with a viewing angle of 120 degrees; the radii of sensors can be adjusted for 50 and 100 meters; the monitoring environment adopts a random deployment model.

Scenario 1:

According to table I, eight different scenarios have been considered for this scenario. The number of targets and sensors are variable and increased by a random factor. In the first setting, there are 10 predetermined targets in the monitoring environment, in which a network comprised of 30 sensors attempt to provide full coverage while increase the monitoring period of these targets. In this scenario, the proposed HA algorithm as well as the D-GWA and GA-based methods provide the best possible CS with full coverage of the targets. When the second setting with 15 targets and 40 sensors is in place, the same outcome with the best CS is expected to be found as well. This process continues for all the eight settings of the scenario, so that the best CSs of each setting are found by the algorithms. The corresponding results of algorithms are compared in Fig. 3.

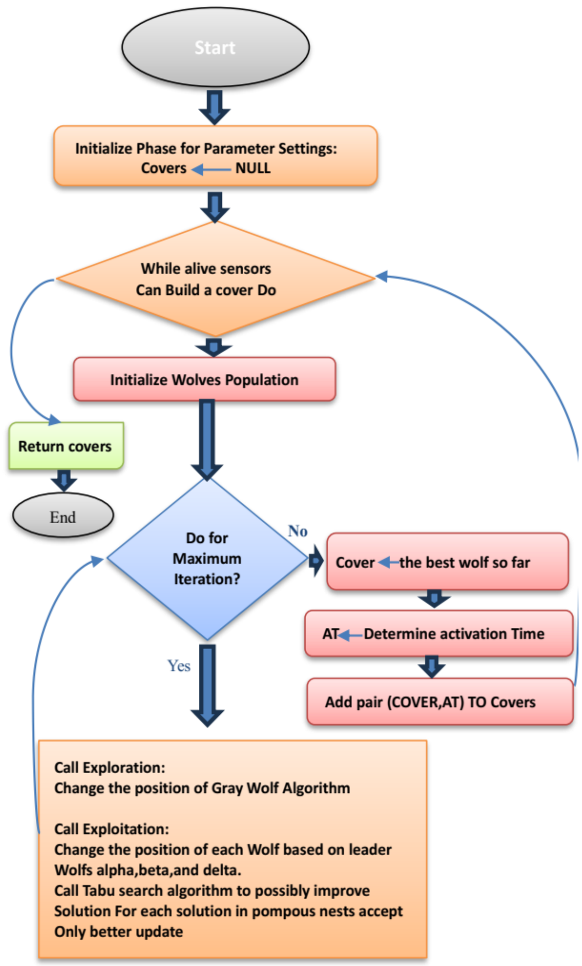

Fig.3: The Block Diagram of the Hybrid Algorithm.

Table I: characterization of Scenario 1.

Setting's No.	No. of Targets	No. of Sensors
1	10	30
2	15	40
3	20	50
4	30	70
5	40	90
6	50	100
7	100	200
8	200	500

In Fig. 4, the results of all the algorithms have been shown for each setting of the scenario1. As it is clear from the figure, except for the fifth setting, , the proposed HA algorithm is superior to D-GWA and GA-based algorithms with respect to both construction of the optimal CSs and providing longer monitoring period of the targets.

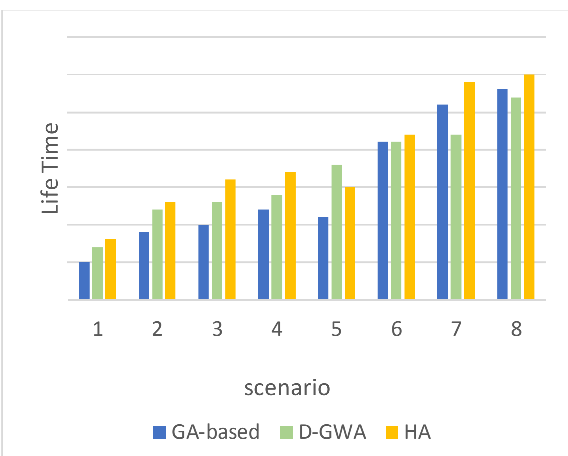

Fig. 4: Performance Results of Different Algorithms for Scenario 1.

Scenario 2:

According to table II, in the second scenario, eight different number of sensors have been considered versus a fixed number of targets. The scenarios are fixed. The first setting of this scenario is characterized by 50 predetermined targets in the monitoring environment and 60 sensors in the network. The objective of all the algorithms is to provide full coverage with best CS and increase the network's lifespan as much as possible. The number of sensors increases up to 400 for the 8th setting. Fig. 5 compares results of the proposed HA algorithm with those of D-GWA and GA-based ones.

Table II: characterization of Scenario 2.

Setting's No.	No. of Targets	No. of Sensors
1	50	60
2	50	80
3	50	100
4	50	120
5	50	150
6	50	200
7	50	300
8	50	400

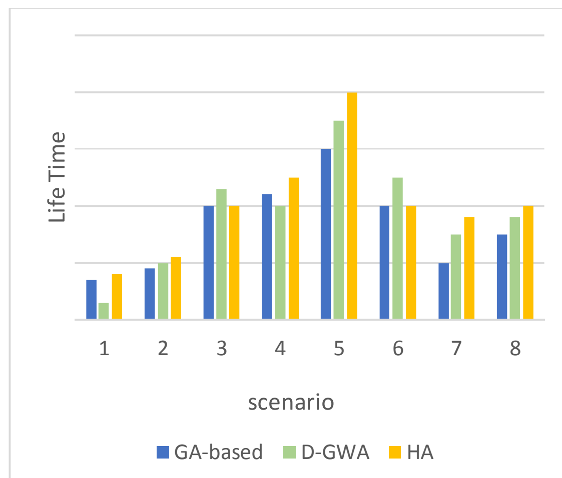

Fig. 5: Performance Results of Different Algorithms for Scenario 2.

Scenario 3:

According to table III, in the third scenario, eight different settings based upon the different number of targets while the same number of sensors, contrary to the scenario 2, have been considered. However, similar to the previous scenarios, here again, the objective of all optimization algorithm is to find CSs in the sense they provide full coverage of all predetermined targets and longest period of target monitoring by sensors. The number of targets starts from 50 and rises up to 350. Fig. 6 compares outcomes of the proposed HA versus those of D-GWA and GA-based algorithms. From this figure, it can be seen that the proposed HA algorithm is superior to other algorithms regarding the network's lifespan.

Table III: characterization of Scenario 3.

Setting's No.	No. of Targets	No. of Sensors
1	50	500
2	70	500
3	80	500
4	100	500
5	120	500
6	150	500
7	250	500
8	350	500

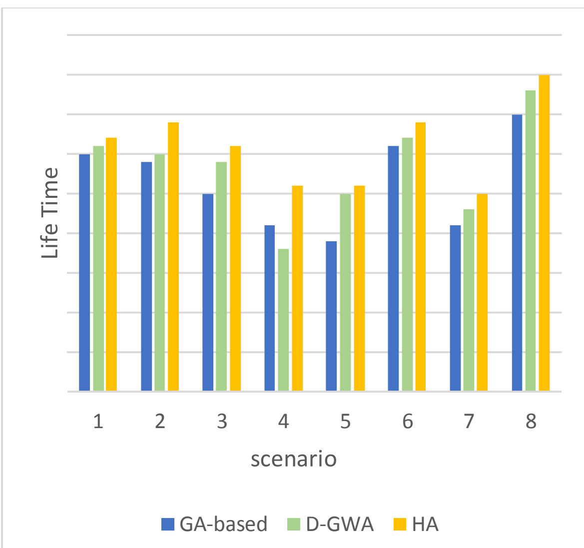

Fig. 6: Performance Results of Different Algorithms for Scenario 2.

6. Conclusion

In this research, the problem of increasing network's lifetime in directional sensor networks (DSN) was addressed. Since formulation of problem give rises to an NP-hard structure, which is hard to solve, a Hybrid algorithm (HA) using the Gray-Wolf-Optimization (GWO) method has been developed to tackle the problem. The HA provides several advantages as follows. It uses a global search operator to explore the overall search space efficiently. It takes advantage of Tabu Search (TS) algorithm to, locally, search areas around each globally found solution. Finally a new fitness function, which aims at providing an optimal cover-set (CS), i.e., a set of configured sensors whose energy consumptions as well as overlaps between coverage areas of individual sensors are minimum. The efficiency of the proposed HA algorithm was compared against existing advanced Algorithms D-GWA and GA-based under different scenarios. Furthermore, in order to consider fairness in comparison, all algorithms were tested/simulated under the same settings for each scenario. Moreover, computer simulations were performed using random datasets for different scenarios in order to avoid potential biases towards candidate algorithms. The simulation results verified superiority of the proposed HA algorithm, except for two cases in the second and third scenarios, to D-GWA and GA-based meta-heuristic algorithms regarding lifetime of the network. To sum up, the proposed HA algorithm is promisingly capable of finding the optimal solution with respect to increasing the network's lifespan in practical circumstances.

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