A new hybrid genetic algorithm with tabu search for solving the temporal coverage problem using rotating directional sensors.

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A new hybrid genetic algorithm with tabu search for solving the temporal coverage problem using rotating directional sensors

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Abstract In recent years, technological developments of directional sensors and wireless sensor networks have resulted in the emergence of an innovative class of wireless sensor networks termed "directional sensor networks". The nature of this type of sensors has led to substantial problems associated with these networks. One of the most important problems in this context is coverage problem that arises due to the nature of the directional sensor nodes. The coverage can be measured in two ways: positional or temporal. In temporal coverage, the directional sensors rotate periodically round themselves in a repetitive process. Thus, in each time slot, those targets that are positioned within the sensor nodes radius receive their desired coverage. In this model, if a target is left uncovered, it is said that the target has remained in darkness. The main task defined for the temporal coverage model is the minimization of the total dark time for all the targets in the network.

To solve the temporal coverage problem, this paper presents a hybridized model comprising Genetic Algorithms (GAs) and Tabu Search (TS). Such hybridization was performed to get benefits of solution space explorations done by GA together with the solution exploitation that is realized by TS. In the proposed model, GA acts as the main algorithm and TS is added to enhance the individuals of the population. The proposed hybrid model is mainly aimed to identify the best initial directions of the existing sensors in such a way that the total dark time could be minimized. The results obtained from the experiments conducted for evaluation of the algorithm performance confirmed the superiority of the proposed hybrid algorithm over the other algorithms (whose results were compared to those of the proposed one) in terms of minimizing the total dark time of the targets.
Keywords Directional sensor networks, Temporal coverage, Genetic algorithm, Tabu Search

1 Introduction

In recent years, sensor networks have been implemented for a variety of applications such as environment monitoring, battlefield surveillance, and health care. Each sensor network is consisted of several tiny sensor nodes each of which is equipped with some components in order to sense, process, and communicate the data gathered from the area of interest. A general assumption is that sensors are totally omnidirectional and have an omni-angle of sensing range. Directional sensors however may have only a limited angle of sensing range, which is due to some cost considerations and technical limitations. Visual, infrared, and ultrasonic are three example of extensively-used directional sensors [1]. Adopting a number of techniques, we can improve the sensing competency of directional sensors. One of these techniques is placing several directional sensors of the same type on each single node; each directional sensor in this condition monitors a certain area. The second technique is to provide a mobile component for each sensor node so that it can rotate round itself. Another technique is to provide the sensor nodes with a certain device that makes them capable of switching to different directions [3].

In the present paper, the last technique was adopted to help the sensors switch to different directions when needed. It is worth mentioning that each sensor node in this study holds only a single sensor.

One of the most critical problems in DSNs is coverage that is generally defined as collecting data from a given area. In DSNs, the coverage problem requires some particular solutions and techniques to enhance the coverage level. This is because of exceptional features of directional sensors, i.e., line of view and angle of view. Considering the above-mentioned specifications, the selection of direction for sensor nodes directly affects the coverage. Literature confirms that a method for enhancing coverage in DSNs is adjusting the sensor nodes' direction (i.e., motility) [1, 4, 5]. The motility aims at selection of the most appropriate direction in a way to minimize occlusions and overlaps. Most of the studies conducted on coverage problem select an appropriate direction for sensor nodes, then the sensors start to rotate toward the selected direction and remain stable. This model may face a condition in which some targets might remain uncovered for a long period of time. This problem can be solved through the deployment of extra sensors despite the fact that this task cannot simply done. The reason is that in some applications, the monitoring site is not accessible. As a result, this coverage type cannot be used in to some applications. In some applications of a higher level of sensitivity thus all targets must be under a full coverage, which results in more effectively use of motility. For this purpose, the temporal coverage model that utilizes the rotating directional sensors is introduced [6].

A temporal coverage model can be formed through the use of the directional sensors' motility and considering the coverage time of a target. Sensors in a temporal coverage model periodically iterate the coverage operations (orientation) successively. In other words, each sensor rotates around itself during a defined period of time. These types of sensor nodes are termed rotating directional sensors [8–10]. Similar to [6], the present study assumes that the time is divided into
some equal slots. If a target is not monitored by any sensor in any time interval, we say it has remained in darkness. In this regard, the temporal coverage is mainly aimed to minimize the total dark time of the targets. The sensors in the temporal coverage model need to select an appropriate initial orientation, which can diminish the dark time of the targets in the network. The NP-hardness of the problem has been already proved in [7]. As a result, to find an efficient solution to this problem, we need to apply the approximate algorithms with polynomial performance.

Literature consists of some studies aiming at solving the temporal coverage problem in DSNs; although, it seems that new metahuristic approaches have not received adequate attention specifically with regard to their high competency in solving the complicated problems. In addition, more recent research has been conducted on the use of hybridized methods in order to make use of all strengths of two or more methods, especially the meta-heuristics, in a single model for solving hard combinatorial optimization problems. Therefore, this paper proposes a new hybrid algorithm combining GA-based algorithm and a Tabu search (TS) as a solution to the temporal coverage problem. The genetic algorithm was employed to select appropriate initial orientations for the available sensors in a way to minimize the total dark time and TS was used to improve individuals of the population. A number of experiments were conducted to investigate the impacts of different parameters on the final performance of the proposed algorithm. A comparative study was also carried out comparing the results obtained from the proposed algorithm and those of several algorithms recently introduced to literature. Based on the final results, the algorithm proposed in this paper was found superior to the others regarding the solution of the temporal coverage problem.

The rest of the paper is presented as follows: Section 2 discusses the studies conducted formerly in this field of study. Section 3 presents an introduction to temporal coverage problem. Section 4 describes the hybridization of meta-heuristics. Section 5 describes the proposed hybrid algorithm to solve the problem in hand. Section 6 reports the experiments carried out for evaluation of the proposed algorithm performance. Finally, section 7 concludes the paper.

2 Related work

One of the key problems in directional sensor networks (DSNs) is coverage. The coverage measurement in DSNs is classified into two categories: positional and temporal. In the positional type, more area is expected to be covered. Positional criteria is used in both area coverage and target coverage. If time is a criteria, then the challenge is how to increase the coverage time for targets or area. The research conducted by Ai and Abouzeid [2] was one of the first studies conducted on target coverage problem in DSNs. They modeled the problem of maximum coverage with the minimum sensors in order to obtain maximum number of targets covered by minimum number of active sensors. Reviewing the literature, we can find several studies that attempt to solve the target coverage problem in DSNs [12, 13]. In the rest of this section, we present a review of the studies conducted on temporal coverage problem in networks with rotating directional sensors (RDS).

The authors in [7] were the pioneer in investigating the rotating directional sensors. This type of sensors are capable of changing their orientation and turning
around themselves. As argued by the authors, if the rotation speed of the sensors is a constant value, when a rotation cycle is completed, we will have a constant and specific cycle called "period". The duration of a period can be divided into equal time slots; thus, when an RDS starts from a certain initial direction in the first time slot, it follows a regular sequence of orientations in the next time slots one after another. Authors in [7] took into consideration a scenario comprising a set of objects and a set of constant rotating directional sensors while proposing a concept titled "dark time". A target is assumed in darkness if it is not monitored by any active sector of an RDS during a time slot. At first, the authors discussed the initial orientation problem in case of an RDS already placed in the area. In addition, they confirmed the NP-hardness of the problem and proposed a greedy algorithm to solve it. Their algorithm is composed of multiple iterations; in each orientation, the algorithm takes care of those sensors that have not been oriented yet. For each sensor in the network, the algorithm takes into account all of the initial orientations and finally selects a pair (RDS, initial orientation) in a way to minimize the total dark time for all of the points. The algorithm operation is terminated in two conditions: either the orientation of all RDSs has been completed or the total dark time of all the points is equal to zero. Another problem is how to place and make oriented minimum number of RDSs, which is also an NP-hard problem. To solve this problem, two algorithms were proposed. In case of the third problem, RDSs are used in order to make sure the detection of a maximum number of intruders that attempt to cross the covered area.

The authors in [10] formed a motility for the sensors through combining the directional sensors with robotic devices like step motors. These sensors were termed rotatable and directional sensors (R&D). Using these R&D sensors, they also proposed a prototype of an event driven surveillance system. Each sensor node in this system periodically rotates and during each rotation, it stops and monitors the targets in the network. This type of surveillance was termed temporal coverage. An R&D sensor deployment problem was formulated, which attempted to deploy a minimum number of R&D sensors for coverage of a certain set of targets so that each target can be monitored by a ratio of time in each frame. The problem was proved as an NP-hard one and two heuristics were introduced as a solution to the problem. The main idea was computing the disks covering all targets at first, then selecting a subset of these disks for performing the coverage task by the R&D sensors so that all targets are covered d-time.

In [8], the deployment problem of R&D sensors was defined for heterogeneous targets. They considered an equal d-time for all targets since the targets are assumed homogeneous. In case some of the targets have different d's-time, those targets are assumed heterogeneous, and a different d is allocated to each target. Considering the heterogeneous targets, the authors also introduced a generalized R&D sensor deployment and proved its NP-hardness. The aim of this problem, as the author maintained, is minimizing the R&Ds deployment in a way to satisfy the requirements of the temporal coverage. As a solution to this problem, the authors proposed also a heuristic method.

In [6], two solutions were proposed to the temporal coverage problem. In the first one, the problem is formulated as a problem of integer linear programming (ILP) optimization. The use of this method has potential to reach the optimal solution to the temporal coverage problem. Because the problem is NP-hard and ILP is a centralized method, the authors developed a heuristic solution termed...
distributed initial orientation algorithm (DIOA). Using local information, DIOA
selects a direction for the RDS nodes, and avoiding the possible overlaps, it at-
ttempts to get closer to an optimal solution. Though literature contains several
studies conducted on temporal coverage problem, GA-based algorithms have been
overlooked in the solution of the problem. Accordingly, the present paper attempts
to take the advantage of GA in offering a solution to the temporal coverage prob-
lem.

3 Problem Definition

The present paper takes into account the following scenario. A set of targets are
placed in specified locations within a 2-D Euclidean field. The field is assumed
with no barrier. A set of rotating directional sensors were also distributed in the
field randomly to monitor the targets. Each sensor in the network is aware of not
only its own position (that is informed to the sensor through global positioning
systems), but also the position of the targets within the monitoring area [6]. Each
sensor in this network has several non-overlapping directions. In each unit of time,
only one direction of a single sensor is active (i.e., working direction). In addition,
each sensor is equipped with an extra component whose responsibility is switching
the working direction of a sensor considering the condition. A target positioned in
both the sensing range of a sensor and the field of view of that sensor is assumed
under coverage. In the temporal coverage model, each time period is divided into
some time slots; each target receives at least one time slot of coverage in a period.
Remember that the sensors in our designed network are homogeneous in the fol-
lowing features: the type of the sensors, the number of sectors, and the shape of
the sensing sector (angle of view and radius coverage (Rs)). To further clarify the
problem, we provide Fig. 1 showing a snapshot of a network that contains eight
targets and three directional sensors. In this example network, each directional
sensor consists of three directions. The notations used in this study are listed in
Table 1.

Table 1 Notations

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Number of sensors</td>
</tr>
<tr>
<td>m</td>
<td>Number of targets</td>
</tr>
<tr>
<td>w</td>
<td>Number of directions per sensor, w≥1</td>
</tr>
<tr>
<td>d_{i,j}</td>
<td>j-th direction of i-th sensor</td>
</tr>
<tr>
<td>s</td>
<td>A sensor, for all i = 1, 2,...,N</td>
</tr>
<tr>
<td>t_{m}</td>
<td>A target, for all m = 1, 2,...,M</td>
</tr>
<tr>
<td>l_{i}</td>
<td>Lifetime of sensor s_{i}</td>
</tr>
<tr>
<td>S</td>
<td>Set of sensors, S = s_{1}, s_{2},...,s_{N}</td>
</tr>
<tr>
<td>T</td>
<td>Set of targets, T = t_{1}, t_{2},...,t_{M}</td>
</tr>
</tbody>
</table>
**Problem:** How to select a set of directional sensors with appropriate initial orientation in a way to minimize the total dark time?

To further explain the temporal coverage and the effects of selecting appropriate initial directions, an example can be given as follows. Fig. 2 depicts a scenario of the temporal coverage model where each RDS node possesses three sectors. In this example, the number of time slots is equal to the number of sectors of the directional sensors. In the first time slot, each sensor starts its move from a definite sector, i.e., it begins its monitoring operation. In Fig. 2.a, for sensors $s_1$, $s_2$, and $s_3$, the initial directions are $d_{1,1}$, $d_{2,2}$, $d_{3,3}$, respectively. Considering these initial directions, the total dark time for all targets is 4-time units, whereas the total dark time for initial directions depicted in Fig. 2.b is 5-time units. The simple instance given above confirms the effect of initial direction on total dark time. Therefore, if initial directions for RDSs are selected properly, the total dark time can be minimized.

![Fig. 1 An example network with three directional sensors and eight targets](image)

![Fig. 2 An example of the effect of choosing the initial direction in temporal coverage model](image)

### 4 Hybridization of meta-heuristics

According to the authors in [16], in hybridization, two or more algorithms are combined fully or partially, aiming at improving the performance of stand-alone
search methods applied to optimization problems. To this end, new hybridized model need to encompass the best characteristics of all members in order to perform at a higher level. Two main aspects in every hybridization process are: the type of hybridized methods and the hybridization level. Regarding the first aspect, two general cases can be considered: A) meta-heuristics + meta-heuristics, and B) meta-heuristics + specific search method. In case B, a meta-heuristic method is combined with another type of search method, including an exact algorithm, constraint programming, dynamic programming, or other artificial intelligence techniques. The present study adopts the case A; it combines two meta-heuristics, namely GA and TS. On the other hand, the hybridization level refers to the extent of coupling between the meta-heuristics, the execution sequence, and the control strategy.

Hybridization Level: The hybridization level falls into two levels: loosely coupled and strongly coupled. In the former, the hybridized meta-heuristics keep their own identity, i.e., their flow is completely utilized in the hybridization process. This state is recognized as the high-level hybridization. On the other hand, in the strongly coupled hybridization, the hybridized meta-heuristics interchange their inner processes, which results in a low-level hybridization [16].

Execution sequence: The hybridized methods operate in two modes: sequential (through which the meta-heuristics flows are run sequentially), or parallel (through which the meta-heuristics flows are run in parallel) [16].

Control strategy: In every hybridized model, two types of strategies are taken into action: Coercive strategy in which the main flow is that of one of the meta-heuristics and the flow of the other meta-heuristics is subordinated to the main one; and Cooperative strategy in which the meta-heuristics explore the solution space in a cooperative way (finally, they can explore different parts of the solution space) [16].

5 The proposed GA(TS) hybrid algorithm

This section proposes a hybrid model for solving the temporal coverage problem. In designing hybrid meta-heuristics, at least two major issues are needed to be taken into consideration: 1) how to select the methods (from among exact methods, simple heuristic methods, or meta-heuristic methods), and 2) how to combine the selected methods to form one hybrid method. To construct this model for the purpose of this paper, two popular meta-heuristics, i.e., GA and TS were taken into account. The two algorithms were selected for this study due to the following reasons. First, exploration of appropriate initial directions needs to be done very fast in order to be well adapted to dynamic nature of sensor networks. As a result, a fast convergence of the main algorithm (GA) is required. This can be obtained by providing a proper tradeoff between exploration and exploitation of the search space. Second, for the purpose of achieving a proper initial directions very quickly, there is a need to combine the exploration of the solution space through the use of a population of individuals with the exploitation of neighborhoods of solutions through local search. In this regard, GA and TS best represent the population-based and local search methods, respectively [16]. Therefore, the hybridization of two meta-heuristics running within a sequential environment was taken into consideration. Thus, a low-level hybridization and the coercive control strategy were
considered. In the hybrid model proposed here, GA acts as the main algorithm, while TS is responsible for enhancing the population. It should be noted that the TS procedure is applicable to all individuals of the current population; but the problem is that it is computationally costly. In our case, where the objective is to quickly find appropriate initial directions for the sensor in network, the TS is implemented with a small probability. This parameter is able to effectively tune the convergence of GA since TS typically well improves the individuals. The generic pseudo-code of proposed algorithm is presented in Algorithm 1. In the following, the two GA and TS algorithms are explained in detail regarding their role in the solution of the problem in hand.

Algorithm 1 : Proposed Algorithm
Step 1: Setting the parameters of the proposed hybrid algorithm
Step 2: Initializing the population and setting Gen to 1, where Gen is the current generation
Step 3: Evaluating each chromosome in the population based on the defined objective
Step 4: Checking whether the termination criteria is met?
   If yes, going to Step 7
   If no, going to Step 5
Step 5: Generating the new population
   Step 5.1: Using the genetic operators to generate the new population
   Step 5.2: Applying TS algorithm to improving the quality of each chromosome
Step 6: Setting Gen to Gen +1 and going to Step 3
Step 7: Obtaining the best solution as the output

The aim of the proposed GA-based algorithm is to select initial sensor directions properly in a way to minimize the total dark time. In GA, as a population-based algorithm, each individual denotes a possible solution. The individuals are successively subjected to a number of processes: evaluation, selection, crossover, mutation, and replacement. All these processes are done based on the natural evolution principle suggested by Charles Darwin. This paper makes use of the Steady State version of GA in which a few appropriate individuals of the population are chosen and crossed. Next, the worst individuals are removed and their place is occupied by the newly-produced descendants. The remaining of the individuals survive and pass to the next generation. In the following, the proposed algorithm is presented in detail.

Representation: To solve a problem using GA, one of the key steps is translating the available solutions in the search space of the problem into chromosomes. To this end, the present paper makes use of an integer-based representation to model a chromosome. In this model, each chromosome is encoded using an integer vector of length $N$; here $N$ denotes the total number of sensors in the network. In other words, each chromosome contains genes as many as the sensors existing in the network. Each gene of the chromosome represents the state of a sensor. That is, each gene shows the initial direction selected by the sensor corresponding to that gene. Here is an example further clarifying the proposed model. Let us assume that a network comprises 5 sensors; thus, the length of the chromosomes is set to 5. Let each sensor have three sectors; thus, the value of the gene corresponding to each sensor is set to a value in the range of 1-3.
<table>
<thead>
<tr>
<th>Sensor Number</th>
<th>$s_1$</th>
<th>$s_2$</th>
<th>$s_3$</th>
<th>$s_4$</th>
<th>$s_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gene Value</strong></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

**Fig. 3** An example chromosome for the network.

**Initial population:** As GA is a population-based algorithm, to initiate the algorithm, there is a need for an initial population. In this paper, an initial population of chromosomes is created randomly.

**Fitness:** An important step to solving the problem using GA is to design an appropriate fitness function. The responsibility of fitness function is calculating the level of a chromosome quality based on the predefined objectives. In this paper, the proposed algorithm’s objective is the selection of sensors with appropriate initial direction so that the total dark time can be reduced as much as possible. It worth mentioning that the chromosomes with less total dark time are more desirable for the purpose of this paper.

**Selection, crossover and mutation:** Generally, the reproduction operation of GA is composed of three main stages: selection, crossover, and mutation. In the selection stage, chromosomes are selected using methods like tournament selection, roulette-wheel selection, rank selection, and so on. Those chromosomes that have a better fitness value (it depends on the problem whether it is maximization or minimization) are more likely to be selected. In this study, we used the roulette-wheel selection method. Through the crossover operation, the selected chromosomes start the production of new child chromosomes. To this end, the operation is performed specifically on the two chromosomes selected from the existing population in the previous stage. Literature offers a variety of crossover types such as uniform crossover, single-point crossover, and double-point crossover. Among all, the single-point crossover is used for the purpose of this paper where a crossover point is randomly selected; next, the two parent chromosomes begin the exchange of their information (see Fig. 4). The crossover operation normally results in new offspring. Following this stage, the mutation operation is started through which a gene of the new offspring is selected and its value is changed in order to produce better offspring that represents a better solution (see Fig. 5). In other words, through the mutation operation, the value of the gene of a given sensor is changed by selecting a new initial orientation for the corresponding sensor of that gene.
Stopping criterion: The proposed algorithm terminates once the number of consecutive iterations reaches its maximum level.

Local search by Tabu Search: Tabu search (TS), which was originally proposed by Glover et al. (1997), refers to a meta-heuristic method that is applicable to different combinatorial optimization problems. With the use of TS, searching process can find such solutions that do not reduce the objective function value in case the solutions are allowed. Typically, it can be achieved through keeping track of the final solution considering the action utilized for the transformation of one solution to the next. This is consisted of a number of elements, including the move attributes, neighborhood structure, aspiration criteria, tabu list, and termination criteria. TS is widely recognized as one of the most effective local search strategies applicable to different problems [17]. In the present paper, TS is used as the local search strategy in the proposed HA for solving temporal coverage problem. Various neighborhood generation structures such as swap, reversion and insertion are applied in this study. In the following, the general process of TS is described.

First, the TS parameters are set and the tabu list is set to empty mode; then, the initial solution is generated and set as the current solution. Remember that this initial solution is generated in the same way a chromosome is produced in GA. After that, the stopping criteria are checked whether they are satisfied; if satisfied, the optimal solution is obtained as the output; if not satisfied, novel neighborhood solutions are generated using the neighborhood function. Then, the generated solutions are evaluated in the same way a chromosome is evaluated in GA. Next, the aspiration criteria are checked whether they are met or not. If
yes, the solution that satisfies the criteria is set as the current solution; but if it is not met, the optimal solution is selected, which is not tabu solution in the neighborhood solutions, and it is set as the current solution. Afterwards, the tabu list is updated and then the stopping criteria are again checked whether they are satisfied or not.

6 Simulation Results

In this section, the algorithm proposed for solving the temporal coverage problem is examined conducting a number of experiments. To this end, a simulator was designed using the MATLAB programming language. To do the evaluation more efficiently, the performance of the proposed algorithm was compared with that of several algorithms of other types such as greedy algorithm [7] and randomized. To compare the algorithms, two metrics were applied to all [6]: first, the dark time percentage of all targets in the network. Second, $\delta t$ that signified the target coverage quality that here refers to the number of time slots covering a target; it shows the number of time slots during which each target was monitored by the sensors. To model a DSN, a number of targets were scattered randomly in the field of study (of the size of $100(m) \times 100(m)$), and some sensors with the sensing range $r$ and sensing angle $\frac{2\pi}{4}$ were also distributed in the field to monitor the targets. In this paper, the sensing range, the number of sensors, and the number of targets were set by default to 15$m$, 20, and 100, respectively. The sector angle of each sensor was fixed at $\frac{2\pi}{4}$, thus, the number of both sectors and time slots were set to 4, too. Each test was iterated for ten times and the average results were presented in diagrams. Remember that the simulator’s validity was confirmed through performing a variety of scenarios. In the proposed algorithm, the probabilities of crossover and mutation were set to 0.2 and 0.05, respectively.

Experiment 1. This experiment was conducted to examine the effect of the number of sensors on the total dark time of the targets in temporal coverage problem. To do this, the number of sensors was ranged between 20 and 100, with incremental step 20, and the other parameters were remained at their default state. Each run of the algorithm resulted in an initial direction for RDS nodes that perform monitoring task. Next, for each algorithm, the total dark time of the targets was calculated. The obtained results shown in Fig. 6 confirmed the superiority of the proposed algorithm over the greedy and random algorithms in terms of minimizing the total dark time. As can be seen in Fig. 6, in case only a few sensors were used, the total dark time for all algorithms was roughly equal. However, with increasing the number of sensors, the proposed algorithm kept distance from the others. This was because of selecting appropriate initial direction for each sensor in the network. In general, selection of appropriate directions in NP-hard problems is a difficult task. The nature of the greedy-based algorithms may result in limitation in the selection of appropriate directions for other sensors. Consequently, these sensors may miss their chance of having an appropriate direction. The greedy-based algorithm thus has a high percentage of dark time in comparison with the proposed algorithm; however, its performance is better than that of the random algorithm. In the proposed algorithm, since different solutions in the search space are examined and the crossover and mutation operations nor-
mally result in new solutions in this space, we are able to make a better decision for the selection of the initial directions.

Experiment 2. This experiment was aimed to examine the influence of sector angle on the total dark time of the targets in the network. To this end, the sector angle was varied among 45°, 90°, 120°, and 180°, and the rest of parameters were set to the default values. Remember that in this experiment, the number of sectors and the number of time slots were the same. For instance, with sector angle 45°, both the number of sectors and the number of time slots was 8. The obtained results presented in Fig. 7 show that when the sector angle increased, the total dark time of all algorithms decreased. The reason was that with increasing the sector angle, each sector was able to cover more targets in each time slot, hence decreasing the total dark time of all the targets.
Experiment 3. This experiment was carried out to test the impact of sensing radius on the total dark time. For this purpose, the sensing radius was set to 10(m) to 30(m), with incremental step 5(m), and the rest of parameters remained in their default values. The results are presented in Fig. 8, showing that increasing the sensing radius caused the total dark time to reduce. This was because with higher sensing radius, each sensor direction was capable of monitoring more targets, which reduced the total dark time. The results obtained from the experiments totally confirmed the superiority of the proposed algorithm over the other algorithms in terms of minimizing the total dark time.
**Experiment 4.** This experiment was conducted to test the effect of the number of sensor nodes on the time slot number of the coverage in temporal coverage model. To do this, the number of sensor nodes was increased from 20 to 100, with incremental step 20. The remaining parameters were fixed at their default values. Here, each sensing period was divided into four slots; therefore, a four-slot coverage (4-δt) is equivalent to the perfect temporal coverage, i.e., dark time = 0. In this experiment, the results of only the proposed algorithm are presented (see Fig. 9). In Fig. 9, the parameter depicted as the output shows the number of targets that have different coverage in the temporal coverage model. The results indicate that with a few number of sensors, the number of targets covered in a period with only one time slot is more than those covered with two, three, or four time slots. Such pattern goes on until the number of sensors is 40. This is because with 40 or more sensors, there will be adequate sensors for a better temporal coverage.

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**Fig. 8** Effect of sensing radius on the total dark time

![Graph showing the effect of sensing radius on the total dark time.](image-url)
Experiment 5. This experiment compared the coverage quality of the proposed algorithm with that of the other algorithms. To this end, the number of sensors was set to a value between 20 and 100, with incremental step 20, and the default values of the other parameters were remained fixed. In this experiment, each sensor node had four sectors to each of which a time slot was allocated. Thus, when a target was monitored in one of these slots, it was supposed to receive a full coverage. In other words, in this state, the target came out of darkness and the highest coverage quality was achieved. Fig. 10, 11, 12, and 13 demonstrate the coverage of the algorithms with 1 slot, 2 slots, 3 slots, and 4 slots, respectively. As can be seen in the figures, the proposed algorithm had the least use of 1-slot and 2-slot coverage, while the Random algorithm used the maximum number of these coverage states. It should be noted that the fewer 1-slot or 2-slot coverage used by an algorithm, the more efficient coverage will be provided. When the number of sensors ranged from 20 to 40, the proposed algorithm covered the highest number of targets with 3-slot coverage. An increase in the number of sensors led to a decrease in the number of 3-slot coverage in case of the proposed algorithm. Fig. 13, which presents the results of 4-slot coverage of the algorithms, confirms that the proposed GA-based algorithm had the highest rate of this coverage state. It can be seen that greedy algorithm had the least number of 4-slot coverage. The results confirmed the superiority of the proposed algorithm in terms of solving the temporal coverage problem.
Fig. 10 Comparison of 1-δt coverage for GA, Greedy, and Random

Fig. 11 Comparison of 2-δt coverage for GA, Greedy, and Random
Fig. 12 Comparison of 3-δt coverage for GA, Greedy, and Random

Fig. 13 Comparison of 4-δt coverage for GA, Greedy, and Random
7 Conclusion

The present study proposed a hybrid algorithm comprising GA (the main algorithm) and TS (the subordinate member) to find an effective solution to the temporal coverage problem. The objective of this hybridization was solving the problem through selecting the most proper initial directions of the sensors present in the network in a way to minimize the total dark time. To evaluate the proposed algorithm performance, a number of experiments were conducted and the obtained results were compared to those of some other algorithms recently introduced in literature. Aiming at comparing most reliably, we applied two criteria, i.e., total dark time and coverage quality, to all the algorithms. The results obtained from the experiments showed that the proposed algorithm outperformed the others (i.e., greedy based and randomized algorithms) regarding the criteria mentioned earlier. In other words, the proposed algorithm showed its high capability to identify the appropriate initial directions for the sensors working in the network and to provide a higher quality coverage on the targets.

8 Declarations

8.1 Ethical Approval

Not applicable.

8.2 Competing interests

Not applicable.

8.3 Authors’ contributions

All authors declare that they have no conflict of interest that are relevant to the content of this article. (applicable for submissions with multiple authors)

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8.5 Availability of data and materials

The following information was supplied regarding data availability: Data will be made available on reasonable request.
References


