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K-Coverage Model based on Genetic Algorithm to extend WSN lifetime

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***Abstract*—Currently, Wireless Sensor Networks (WSNs) are extensively used in target monitoring applications. Classical target coverage methods often assume that the environment is perfectly known, and each target is covered by only one sensor. Such algorithms, however, are inflexible especially if a sensor died, i.e. run out of energy; and hence, a target may need to be covered by more than one sensor which is known as K-coverage problem. K-coverage problem is time and energy consuming process, and the organization between sensors is required all the time. To address this problem, this paper proposes a K-coverage model based on Genetic Algorithm (GA) to extend a WSN lifetime. In the search for the optimum active cover, different factors such as targets' positions, the expected consumed energy, and coverage range of each sensor; are taken into account. A set of experiments were conducted using different K-coverage cases. Compared to some state-of-the-art methods, the proposed model improved the WSN's performance regarding to the amount of the consumed energy, the network lifetime, and the required time to switch between different covers.**

***Keywords*—** K-Coverage, WSN Lifetime, Target Monitoring, Genetic Algorithm

I. Introduction

Wireless Sensor Networks (WSNs) have been widely used for monitoring and tracking applications such as industry [1], [2], health care [3], and environmental monitoring [4]. Each sensor has a fixed range, and the sensors are organized into groups called sensor covers to monitor a set of targets distributed inside a specific area for a fixed duration. The classical target coverage algorithms assume that the environment is known, and these algorithms try to search for the optimal sensor covers that extend the network lifetime by covering each target by only one sensor [5], [6]. However, such algorithms are inflexible especially if a sensor died, i.e. run out of energy; thus, a target may need to be covered by more than one sensor. Covering a target by more than one sensor at the same time achieves continuous coverage. However, it is a time and energy consuming process, and the organization between sensors is a requirement all the time [7]. Hence, besides the energy, some optimization constraints such as time consumption, continuous coverage, covers structures, and sensor modes (ON/OFF) should be included [8]. This problem is known as the K-coverage problem which requires preserving at least K sensor nodes controlling any target to consider it covered [9]. Thus, the K-coverage is an NP-hard optimization problem that can be solved using metaheuristic optimization algorithms [10].

In [11], the flow decomposition algorithm (FDA) was introduced and compared with Fixed Directional Sensor Scheduling Problem (FDSSP) that was proposed in [12]. The aim of FDA is to decompose the maximum flow into a set of single flows, and each single flow represents a source to a sink path. The sensors of that path form a cover. The FDSSP seeks a fixed directional sensor schedule which maximizes the lifetime.

Genetic Algorithm (GA) is a widely used optimization algorithm [13], and it has been used frequently in different applications especially in WSN [14]. A GA-based method for K-coverage in WSN was proposed in [15], and the aim was to find K-coverage states using GA with a minimum number of on-duty sensors. In [16], a GA-based model was proposed to find the positions of sensor nodes in a WSN to maximize the coverage area in WSNs. The Particle Swarm Optimization (PSO) and Simulated Annealing (SA) algorithms were combined, and the novel algorithm (PSOSA) was used for energy-efficient coverage in WSNs [17].

However, all these algorithms assume that the sensor covers are static and cannot be changed during the network lifetime. We think that, preventing GA from restructuring the sensor covers after each round greatly affects the network lifetime. In our problem, the data transmission round can be considered as a time period that a cover needs to collect the data from all of its sensors and transmit it to the base station. It ends when WSN decides to switch between different covers.

In this paper, a GA-based model was used to get the optimum sensor covers that maximize the network lifetime, and then determine which sensor cover should be active for the current data transmission round. In other words, a GA was used to optimize the coverage requirement in WSNs to provide continuous monitoring specific area/targets for longest possible time with limited energy resources. Based on a set of factors such as the expected consumed energy, coverage range of each sensor, targets positions, and the distance to the base station, the GA forms these covers after determining the optimum cover heads that are responsible for transferring the

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data to the base station. The contributions of this work are:

- first, GA-based cover forming model that creates all possible sensor covers for K-coverage environments.
- second, a covers management method that switches between different covers to maximize the network lifetime.

The remainder of this paper is organized as follows: Section II explains the proposed model including the mathematical model, data representation, and the proposed GA algorithm for the target coverage problem. Section III summarizes our experimental results and discussions. Section IV presents the conclusions and future work.

II. The Proposed Model

The working steps of our proposed model are shown in Fig 1. This model consists of three main phases. In the first phase, a binary chromosome is used to encode the sensor nodes within the entire field. In the second phase, after each round, GA run at the base station to choose the optimum number of cover heads (represented by 1). Depending on the sensing range of each sensor and the targets positions, covers will be formed. In the third phase, each chromosome is evaluated to make sure that all targets are covered. By getting all possible covers, the expected consumed energy of each one is calculated to determine which one will be active for the coming round. The optimization goal of our model is to maximize the network lifetime.

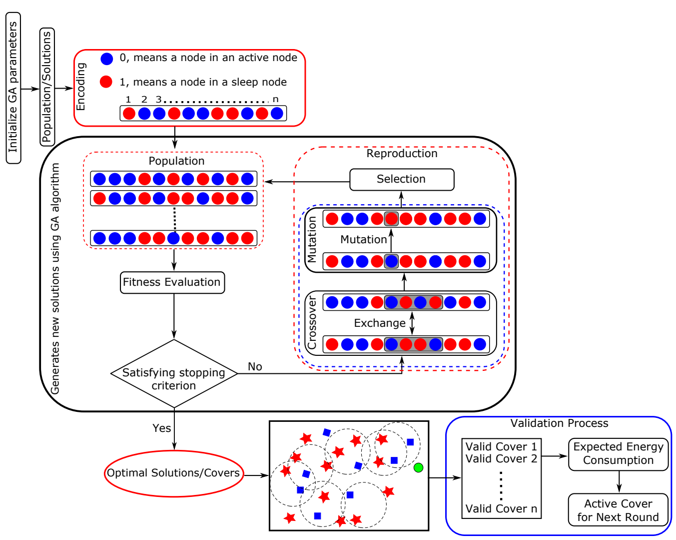

Fig. 1: The working steps of the proposed method.

In search for the suitable cover, a set of nodes should be active. To choose these nodes, three factors, namely, the distance between the cover head and the base station, the expected consumed energy, and the amount of the remaining battery power, are taken into account. The expected consumed energy is considered to choose the active cover for the next round. The consumed energy E in a cover consists of the energy that is used to transmit messages to the sink point, i.e. base station. Assuming the first order radio model [14], for a cover with N_s members, the energy expenditure of a cover is the summation of transmission and receiving energy cost of all member nodes, with assumption that, the data transmission is applied in one direction, i.e. from sensor nodes to the base station, the total energy expenditure of a cover is given by, $E = \sum_{i=1}^{N_s-1} E^T_{i,B}$, where $E^T_{i,B}$ is the amount of consumed energy during the data transmission process from a sensor i to the base station B. The energy consumption E^T of a sensor node to transmit a message of l bits is calculated as follows:

$$E^T = E_e + ld^n \tag{1}$$

where E_e represents the idle energy expenditure and d is the distance between the transmitter and receiver and it can be modeled with proper power term n. In our model, $n = 2$ for a short distance (d_0), i.e., the distance between two different nodes, where $n = 4$ for long distances (d_1), i.e., the distance between a node and the base station. As indicated in Equation (1), the transmission energy consumption E^T is proportional with different orders of the distance d, and can be modeled with proper power term n. Using the consumed energy, the energy of a node s can be calculated as follows, $\tilde{E}_s = E(0) - \sum_{t=1}^{T} E^T_s(t)$, where $E(0)$ is the initial energy of the node and t denotes the network lifetime in terms of transmission rounds. In practice, the remaining energy of every node is updated in each round. Also, in our model, we assumed that each active node sends only one message per round; in other words, we can say the count of transferred message at each round is equal to the count of the active cover members.

A. *GA Fitness Function*

In our proposed model, each gene in the chromosome indicates a sensor node in the field, and the value of a gene can be either one, i.e. active node, or zero, i.e. sleep node.

GA generates new chromosomes through crossover and mutation operations and evaluates their fitness. In the proposed model, the fitness function of GA consists of the remaining energy $\tilde{E}$, the total expected energy expenditure ΔE, and the distance between the sensor node and the sink point $d(s, B)$. Hence, using Equation (1) we can compute the energy cost for each node and by aggregating the energy costs of all nodes, the expected energy expenditure ΔE is estimated. The fitness function is hence defined as follows:

$$f = \frac{\tilde{E}}{NE(0)} + \frac{E'}{\Delta E} + \frac{1}{\sum_i d(s_i, B)} \tag{2}$$

where E' denotes the total energy cost if the messages are transmitted directly from the sensor nodes to the base station, N is the total count of sensors, and it is used to get the total amount of the remaining energy for the network. In this fitness function, the remaining energy and the expected energy expenditure are normalized so that they are in the same order.

III. Experimental Results and Discussion

In this section, a set of experiments were conducted to evaluate the performance of the proposed model using three different K-coverage cases. In addition, the amount of the consumed energy at each sensor node at a specific transmission round was evaluated. Table I lists the network parameters that

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were used in these experiments, where E_{fs} is the energy of free space and E_{mp1} is the energy for mobile sensing. In running GA, we used the population size of 30 for 30 generations. The crossover probability and mutation probability were 0.8 and 0.006, respectively.

TABLE I: Network properties.

Properties		Values
Number of nodes		100
Initial node energy		$0.5J$
Idle state energy		$50nJ/round$
Data aggregation energy		$5nJ/bit$
Amplification energy	$d \geq d_0$	$10pJ/bit/m^2$
(cluster head to base-station)	$d < d_0$	$0.0013pJ/bit/m^2$
Amplification energy	$d \geq d_1$	$E_{fs}/10 = E_{fs1}$
(node to cluster head)	$d < d_1$	$E_{mp}/10 = E_{mp1}$
Packet size		400 bits

In all experiments, the period between the start of the network until the first target becomes uncovered was used as the network lifetime. Each experiment was run ten times, and the average performance of the ten runs was calculated. In each experiment, the nodes of the targets were randomly placed in the field with the condition that all targets are completely covered by the network. Moreover, in our experiments, the dimensions of the first and second environments were $100m \times 100m$ and $200m \times 200m$, respectively.

In the first experiment, three sub-experiments were conducted to evaluate the proposed model using three different K-coverage cases (the value of K was one, two, and three). In this experiment, the round time at which the first target becomes uncovered (FTU) and the round time at which the last target become uncovered (LTU) are reported in each experiment. The results of this experiment are summarized in Table II.

TABLE II: Network lifetime (secs) for $K = 1, 2,$ and 3.

Coverage	Method	$100m \times 100m$		$200m \times 200m$	
		FTU	LTU	FTU	LTU
$K = 1$	FDSSP	675	1240	509	914
	FDA	650	1301	630	1000
	VP-NL	751	1514	689	1225
	Proposed	1050	1847	886	1547
$K = 2$	FDSSP	520	839	414	620
	FDA	487	992	391	785
	VP-NL	586	1053	421	869
	Proposed	864	1375	627	1148
$K = 3$	FDSSP	312	641	209	300
	FDA	383	787	301	417
	VP-NL	398	803	210	524
	Proposed	632	1015	402	728

As reported in Table II, it can be concluded that increasing the coverage level, i.e. the value of K, the sensing field increases in the way that makes the sensors consume more energy to transfer the collected data; and hence, the network lifetime decreases as illustrated in Table II. In other words, the network lifetime is inversely proportional with the value of K. Moreover, to further prove that our proposed model is better than other related work, as illustrated in Table II, a comparison with the most related work, i.e., FDSSP [12], FDA [11], and VP-NL [5]; was conducted as shown at Fig. 2. From this table, it can be remarked that our proposed model improved the performance of the network regarding to the network lifetime using different values of K. Further, the improvement that our proposed model achieved was in the ranges of 26% to 41.3%. The key achievement of our proposed method is the balancing between all sensors in terms of the remaining amount of energy by keeping all sensors mostly at the same energy level.

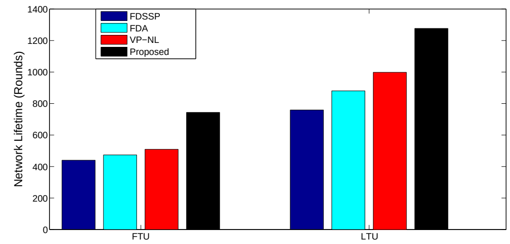
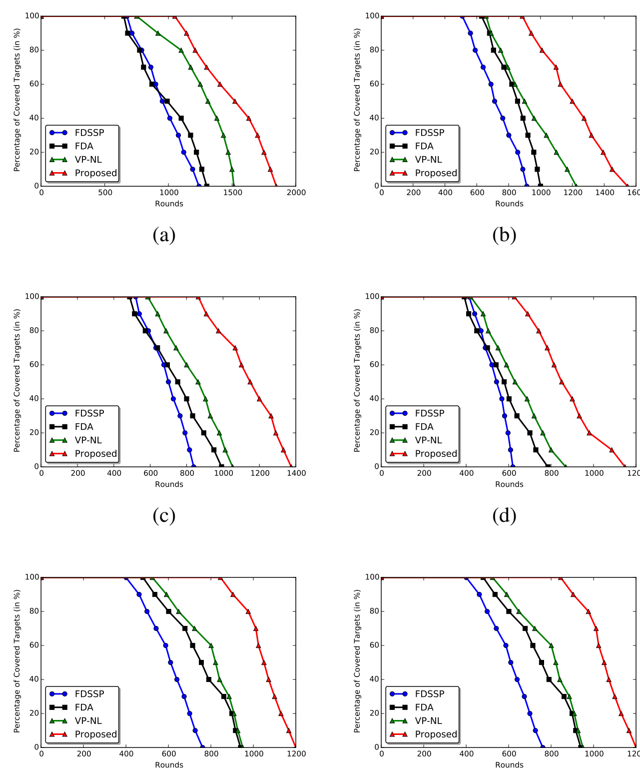


Fig. 2: Comparison between the proposed method and FDSSP, FDA, and VP-NL methods in terms of network lifetime.

Further, another experiment was conducted to measure the performance regarding the targets covering time. For that, the network lifetime in this experiment was determined by the first target that becomes uncovered. In this experiment, 100 nodes were randomly placed in a (1) $100m \times 100m$ to cover 10 targets, and (2) $200m \times 200m$ environments to cover 20 targets. Figure 3 shows the results of this experiment.



(a) (b) (c) (d) (e) (f)

Fig. 3: Covered targets in terms of network transmission rounds (a and b) $K = 1$, (c and d) $K = 2$, (e and f) $K = 3$. The field size is (a, c, and e) $100m \times 100m$ (10 targets) (b, d, and f) $200m \times 200m$ (20 targets).

Figure 3 depicts the average number of covered targets

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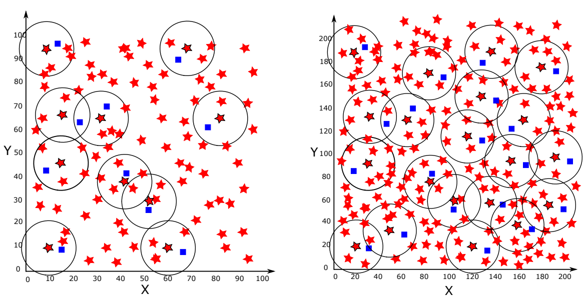
throughout the entire network lifespan in case of $K = 1$, $K = 2$, and $K = 3$, respectively. In both figures, the x-axis shows the number of network transmission rounds (in thousands); whereas the y-axis displays the percentage of live nodes. The numbers of nodes deployed in the field in both cases are summarized in Table I. As displayed in the figures, as the network transmission continues, the number of active nodes decreases as more nodes deplete their energy. Figure 4 presents an example of sensor placements and covers distributed at the working field using different cases. Moreover, Figs. 3 illustrates that our proposed model extends the network lifespan by increasing targets coverage time in all cases.



(a) (b)

Fig. 4: Sensor placements and covers when $K = 1$.

For further analysis of these experiments, Table III lists the average and standard deviation of the experimental run time to get the remaining energy of each sensor nodes using the two different cases, i.e. $100m \times 100m$ and $200m \times 200m$, that we discussed above, and when the value of K was one.

TABLE III: Average and standard deviation (STD) of the experimental run time to get the remaining energy of each node.

	$100m \times 100m$				$200m \times 200m$			
Round	200	500	800	1100	200	500	800	1000
Average (secs)	0.401	0.332	0.279	0.147	0.215	0.321	0.197	0.246
STD (secs)	0.014	0.037	0.098	0.032	0.086	0.049	0.052	0.035

IV. Conclusions

Wireless Sensor Networks (WSNs) have been used for different monitoring and tracking applications. In such applications, covering the target by more than one sensor at the same time achieves continuous coverage. This paper proposed a new K-coverage model based on Genetic Algorithm (GA) to extend a WSN lifetime. The expected consumed energy is considered to choose the active cover for the next round. Compared to some state-of-the-art methods, the proposed method improved the WSN's performance regarding to the amount of the consumed energy, the network lifetime, and the required time to switch between different covers. Moreover, our proposed method provides a framework that can be used in both a static and mobile environments which can be used to extend the network lifetime in a K-coverage model. Besides, the performance of our model needs to be tested in reality as a future work direction.

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