Expert Systems With Applications 92 (2018) 142–153

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Optimizing K-coverage of mobile WSNs

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ARTICLE INFO

Article history:
Received 16 April 2017
Revised 7 September 2017
Accepted 8 September 2017

Keywords:
Wireless Sensor Networks (WSN)
Genetic Algorithm (GA)
K-coverage problem
Mobility sensor networks

ABSTRACT

Recently, Wireless Sensor Networks (WSNs) are widely used for monitoring and tracking applications. Sensor mobility adds extra flexibility and greatly expands the application space. Due to the limited energy and battery lifetime for each sensor, it can remain active only for a limited amount of time. To avoid the drawbacks of the classical coverage model, especially if a sensor died, *K*-coverage model requires at least *k* sensor nodes monitor any target to consider it covered. This paper proposed a new model that uses the Genetic Algorithm (GA) to optimize the coverage requirements in WSNs to provide continuous monitoring of specified targets for longest possible time with limited energy resources. Moreover, we allow sensor nodes to move to appropriate positions to collect environmental information. Our model is based on the continuous and variable speed movement of mobile sensors to keep all targets under their cover all times. To further prove that our proposed model is better than other related work, a set of experiments in different working environments and a comparison with the most related work are conducted. The improvement that our proposed method achieved regarding the network lifetime was in a range of 26%–41.3% using stationary nodes while it was in a range of 29.3%–45.7% using mobile nodes. In addition, the network throughput is improved in a range of 13%–17.6%. Moreover, the running time to form the network structure and switch between nodes' modes is reduced by 12%.

1. Introduction

Wireless Sensor Networks (WSNs) are widely used in many applications such as industry (Elhoseny, Tharwat, Farouk, & Hassanien, 2017; Elsayed, Elhoseny, Riad, & Hassanien, 2017; Tuna, Gungor, Gulez, Hancke, & Gungor, 2013), environmental monitoring (Das & Bruhadeshwar, 2013; Elhoseny, Tharwat, & Hassanien, 2017; Ferentinos, Katsoulas, Tzounis, Bartzanas, & Kittas, 2017), health care (Hackmann et al., 2014; Hassanien, Tharwat, & Own, 2017; Shahin, Tharwat, Gaber, & Hassanien, 2017; Tharwat, Moemen, & Hassanien, 2016; 2017), and agriculture (Gaber, Tharwat, Hassanien, & Snasel, 2016; Srbinovska, Gavrovski, Dimcev, Krkoleva, & Borozan, 2015; Tharwat, Gaber, & Hassanien, 2016). Due to the limited energy, a sensor can remain active only for a finite amount of time. Thus, sensors are organized into different groups, namely sensor cover, in such a way that each cover monitors the targets for a certain duration, and the optimal use of the sensors increases the sensor network lifetime (Cerulli, Donato, & Raiconi, 2012). This motivates the deployment of redundant sensors to cover the area of interest and to organize the sensors to prolong the coverage time after a deployment. This problem is the *K*-coverage problem, which requires a minimum of *k* sensor nodes to monitor one target (Elhoseny, Elminir, Riad, & Yuan, 2016; Elhoseny, Yuan, El-Minir, & Riad, 2014; Elhoseny, Yuan, El-Minir, & Riad, 2016; Yang, He, Li, Chen, & Sun, 2015).

Many target coverage methods assume that the targets are known, and each target is covered by one sensor (Katsuma, Murata, Shibata, Yasumoto, & Ito, 2009; Liu, 2007; Lu, Li, & Pan, 2015). However, these algorithms have a serious drawback when a sensor runs out of energy. Hence, covering each target with more than one sensor at a time provides a more robust solution (Wan, Wu, & Shen, 2015). In Wan et al. (2015), the flow decomposition algorithm (FDA) was introduced and compared with Fixed Directional Sensor Scheduling Problem (FDSSP) that was proposed in Tang, Zhu, Zhang, and Hincapie (2011). The aim of FDA is to decompose the maximum flow into a set of single flows, and each

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[1] http://www.egyptscience.net.

http://dx.doi.org/10.1016/j.eswa.2017.09.008
0957-4174/

single flow represents a source to a sink path. The sensors of that path form a cover and the amount of flow passing through this path is equal to the lifetime of this cover. The FDSSP seeks a fixed directional sensor schedule which maximizes the lifetime. Factors such as sensor network topology, sensor activation mode, and sensor role must be taken into consideration for identifying an optimal network management solution (Liu, 2007; Lu et al., 2015; Mnasri, Thaljaoui, Nasri, & Val, 2015; Wan et al., 2015). In FDSSP, given a set of fixed directional sensors which have already been placed. In Tang et al. (2011), two versions of FDSSP were introduced. The first one was the Uniform initial Energy version (FDSSP-UE) in which all the sensor nodes are assumed to have the same initial energy. This version has many problems as reported in Tang et al. (2011). The second version was the Non-Uniform initial Energy version (FDSSP-NUE) in which different nodes may have different initial energy; and this version, i.e., FDSSP-NUE, was used for solving the problems of the FDSSP-UE. The Variable Power Network Lifetime (VP-NL) scheduling scenario was proposed in Yang and Gündüz (2015). In this scenario, it was assumed that each sensor can modulate its sensing range by dynamically varying its operating power, e.g., radar sensors. In VP-NL, A polynomial algorithm was proposed, and many experiments and numerical simulations were conducted to show its effectiveness. With the proliferation of sensors, a wireless sensor network is no longer stationary, which greatly expands the applications such as tracing animal movements applications (Gaber et al., 2016; Han et al., 2016; Wang, Xu, Wei, Gu, & Chen, 2010) and environmental monitoring (Hwang, Shin, & Yoe, 2010), in contrast to the stationary sensor networks. In many cases, monitoring the whole area might be unnecessary, especially if the dynamic nature of the observed processes is taken into account. When sensors are equipped with motion capabilities, monitoring a number of points of interest instead of the whole area increases the network performance and permits time-dependent coverage. In a mobile sensor network, combining target coverage with the connectivity of sensors to the data sink is still an open challenge (Fadel et al., 2015; Rawat, Singh, Chaouchi, & Bonnin, 2014).

Non-stationary K-coverage is often needed when a reliable monitoring capability is desired as in surveillance and military applications. Due to the energy constraint of wireless sensors and often infeasibility of replacement or recharging, it is necessary for the sensors to be densely deployed. Yet, keeping all sensors active will deplete their energy quickly. A typical scenario is multi-agent based corporative field monitoring. Mobile agents collect and transform data to ensure integrity and security in the parameter.

Different bio-inspired optimization algorithms have been employed in WSNs. For example, Particle Swarm Optimization (PSO) was used to optimize the fuzzy membership function to achieve the best results regarding the battery life of sensor nodes (Collotta, Pau, & Maniscalco, 2017). Due to the importance of clustering approach to achieve energy efficiency in wireless sensor networks, a hybrid swarm intelligence algorithm was utilized to optimize fuzzy rule table, and the proposed algorithm was utilized to cluster all sensor nodes into balanced clusters (Zahedi, Akbari, Shokouhifar, Safaei, & Jalali, 2016). In another research, Ant Colony Optimization (ACO) algorithm was used to achieve a complete coverage of the service region which maximizes the lifetime of the network (Liao, Kao, & Wu, 2011). Glowworm Swarm Optimization (GSO) was also employed to enhance the coverage as reported in Liao, Kao, and Li (2011). However, as reported in Yang (2014), some of the nature-inspired optimization algorithm have no explicit crossover such as in ACO (Liao, Kao, & Wu, 2011), and Ant Bee Colony (Karaboga, Okdem, & Ozturk, 2012), GSO (Liao, Kao, & Li, 2011), and PSO (Collotta et al., 2017). This may reduce the searching capabilities for these algorithms. On the other hand, Genetic Algorithm (GA) consists of three key genetic operations, namely, *crossover*, mutation, and selection, and both crossover and mutation operations provide the diversity for the new solutions, where the crossover provides limited diversity within the subspace, while the mutation operations can provide better diversity by exploring far-away subspaces (Metawa, Hassan, & Elhoseny, 2017; Tharwat, Gaber, Hassanien, & Elnaghi, 2017; Yamany et al., 2015).

We propose a GA based method to optimize the coverage in WSNs to monitor specified targets for the longest possible time with limited energy. The sensor nodes are non-stationary and can move in the field to collect data. We make no assumption of the mobility speed of the sensors that can be at continuous or variable speed. GA has been applied to WSN (Ebrahimian, Sheramin, Navin, & Foruzandeh, 2010; Elhoseny et al., 2017; 2015; Shieh et al., 2016; Yuan, Elhoseny, El-Minir, & Riad, 2017). In our problem, the data transmission round is a time period that the data of targets are collected and transmitted to the base station. A GA-based method was proposed to optimize the sensor covers with a goal of maximizing the network lifetime by determining the mode of sensor covers. Based on a set of factors such as the coverage range of each sensor, expected consumed energy, the distance to the base station, and targets positions, the GA forms the covers after determining the optimum cover heads that are responsible for transferring the data to the base station. Thus, the proposed model ensures that the monitored area is fully covered by a minimum number of sensors.

This study has two main contributions. Firstly, GA-based cover forming method that creates all possible sensor covers. Secondly, a WSN covers management method that switches between different sensor covers to maximize the network lifetime. To form the sensor covers, the proposed model assumes that:

- The positions of the targets are known, which are stationary,
- All nodes are capable of transmitting data to the base station,
- All sensor nodes have the same amount of initial energy,
- Sensor network is adjusted after each data transmission round,
- The field has one base station, which, after each round, constructs the network for the next round, and
- The data transmission round starts when a sensor cover changes its mode (active/sleep).

The remainder of this paper is organized as follows: Section 2 summarizes the related work of the target covering problem. Section 3 explains the proposed model in details. It discusses the mathematical model, data representation, and the proposed GA algorithm for the target coverage problem. Section 4 summarizes the experimental results and discussions of our experiments. Finally, conclusions and future work are presented in Section 5.

2. Related work

Target covering problem has been attracting significant attention in WSNs (Berman, Calinescu, Shah, & Zelikovsky, 2004; Cardei & Du, 2005; Slijepcevic & Potkonjak, 2001). In Slijepcevic and Potkonjak (2001), a heuristic algorithm that selects mutually exclusive sets of sensor nodes was proposed. The members of a set cover the whole area completely, and only one of the sets is active at any time. This algorithm achieved a significant energy saving while fully preserving coverage. Cardi et al. proposed a method to extend the lifetime of the sensor network by reorganizing the sensors into a maximal number of disjoint set covers (Cardei & Du, 2005). Moreover, the sensors from the current active set are utilized for (1) monitoring all targets and (2) transmitting the collected information, while the nodes from all the other sets are in sleep mode. The method (Cardei & Du, 2005) achieved competitive results, and it outperformed the algorithm in Slijepcevic and Potkonjak (2001) in terms of the increased number of produced disjoint sensor covers. Berman et al. (2004) introduced a power efficient monitoring model which proposed: (1) an efficient data structure to efficiently represent the monitoring area; (2) an algorithm for sensor monitoring; and (3) distribution protocols to make a balance between the monitoring and communication power consumption. The results of their proposed model revealed a significant advantage in quality, flexibility, and scalability.

Cardei, Thai, Li, and Wu (2005a) improved the model that was introduced in Cardei and Du (2005) by increasing the lifetime of the network without the constraint that chosen set covers are disjoint; thus, a sensor may appear in different covers. The target covering was modeled as a Maximum Set Covers (MSC) problem, and two heuristic algorithms were employed to compute the sets based on linear programming and greedy approach.

Most studies in the field of wireless sensor network have assumed that the sensors have the same sensing range (Cardei & Du, 2005; Cardei, Thai, et al., 2005a; Slijepcevic & Potkonjak, 2001). On the other hand, in Cardei, Wu, Lu, and Pervaiz (2005), the sensors assumed to have adjustable sensing ranges; hence, the target covering problem was formulated as an Adjustable Range Set Covers (AR-SC) problem. Three heuristic algorithms were introduced to solve the AR-SC problem, and the goal was to maximize the numbers of set covers for the ranges associated with each sensor. One of the three algorithms was based on the Integer Programming (IP), and the other two algorithms were based on greedy approach. In different studies, each active sensor covered all targets in its sensing region (Cardei & Du, 2005; Cardei, Thai, et al., 2005a; Cardei, Wu, et al., 2005; Lu, Wu, Cardei, & Li, 2005; Slijepcevic & Potkonjak, 2001), whereas Liu et al. reported that each sensor covered only one target at a time, and the sensor can freely select its target to cover it. The optimal solution was finding the target observation schedule that maximizes the network lifetime (Liu et al., 2005). The findings of this work were enhanced in Liu, Wan, and Jia (2006), where each target was covered by at least K sensors, this is called K-coverage.

There are many studies that employ the bio-inspired algorithms to optimize the K-coverage problem. In Wang, Ma, Wang, and Bi (2007), the Particle Swarm Optimization (PSO) and Simulated Annealing (SA) algorithms were combined for energy-efficient coverage in WSNs. In another research, the Artificial Bee Colony (ABC) algorithm was used for finding the optimal deployment positions in a three-dimensional terrain (Mini, Udgata, & Sabat, 2011). Fish Swarm Algorithm (FSA) was utilized for coverage optimization of WSNs (Huang & Li, 2013). Wang, Guo, Duan, Liu, and Wang (2012), optimized the K-coverage problem using the Biogeography Based Optimization (BBO) algorithm, and they compared the performance of BBO with the ABC algorithm and Stud Genetic Algorithm (SGA). Their results demonstrated that the BBO algorithm yielded results better than both ABC and SGA algorithms. The PSO was combined with the Differential Evolution (DE) algorithm (PSO+DE) in Maleki, Khaze, Tabrizi, and Bagherinia (2013) to optimize the K-coverage problem, and the results proved that the PSO+DE algorithm increased the lifetime of the network by optimizing the coverage of the sensors in comparison with the standard PSO algorithm. GA has been used to extend the life of WSNs (Ebrahimian et al., 2010; Elhoseny et al., 2015). Ebrahimian et al. employed a GA-based model for K-coverage in WSN (Ebrahimian et al., 2010). The aim of the GA is to find K-coverage states that minimize the number of on-duty sensors. Mnasri et al. utilized the GA to search for sensor nodes in a WSN to (1) maximize the coverage area, and (2) optimize the audio localization in wireless sensor networks (Mnasri et al., 2015).

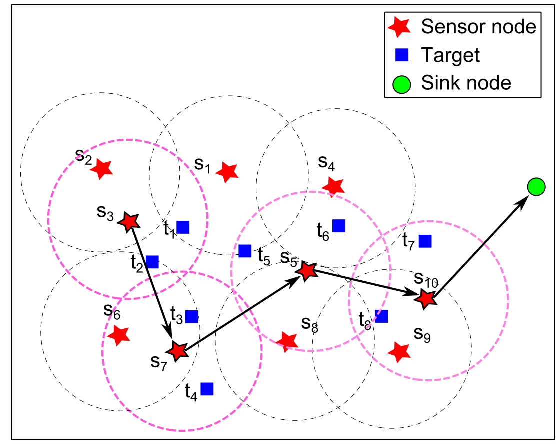


Fig. 1. An example of wireless sensor network with ten sensors and eight targets.

3. Methodology

3.1. Problem Statement

Let $N = (T, S)$ be a wireless sensor network, where $S = \{s_1, s_2, \ldots, s_m\}$ is a set of sensors with a sensing range R_s, $T = \{t_1, t_2, \ldots, t_n\}$ is a set of targets with known locations, m is the number of sensors, and n is the number of targets. Fig. 1 shows an example of the wireless sensor network with sensors and targets. Each target is sensed with one or more sensors, e.g. the target t_1 is covered with the sensors s_1 and s_3. The collected data are processed by a sink node. A sensor is in the *active* mode if it acquires or relays data, or both. A sensor in the *sleep* state when the sensor is not performing any tasks.

The network lifetime is defined as the period from the network being set up till (1) one or more targets cannot be covered by at least one sensor, or (2) a route between each sensor to the sink cannot be found. The network lifetime is maximized in the Connected Target Coverage (CTC) problem, which can be modeled as a Maximum Cover Tree (MCT).

Our model identifies the maximum number of non-disjoint sets of the sensors, namely sensor cover, which is bounded by $C_{\max}$ such that at a given point of time all targets are monitored and only one sensor in a cover is active. Let C be the set of sensor covers, i.e., $C = \{C_1, \ldots, C_{\max}\}$. Each sensor cover, C_k, $C_k \in C$, is enough to cover all the targets in the network. The lifetime of a sensor cover C_k is denoted by $X(C_k)$, and it cannot exceed the remaining energy of a sensor in C_k, which has the minimum lifetime, i.e., $X(C_k) = \min\,[C_k(b_i)]$. The objective of the target coverage problem is to generate a maximum number of sensor covers to prolong the network lifetime.

The energy-efficient target coverage problem is formulated as a maximization problem that aims to maximize the total lifetime of all sensor covers, i.e., $\Sigma_k X(C_k)$), (we shall refer to x_k) as indicated in Eq. (1). Hence, the goal of target coverage problem is to find the complete family of sensor covers which has the maximum aggregated network lifetime among all the families of sensor covers.

$$
\begin{aligned}
&\text{Maximize} \quad \sum p x_p \\
&\text{subject to} \\
&\qquad \sum_p B_{ip} x_p \le b_i (\forall s_i) \\
&\qquad x_p \ge 0 (\forall C_p)
\end{aligned}
\tag{1}
$$

where p represents the index of sensor covers, x_p is the sensor cover, s_i is the sensor node with index i, b_i indicates the lifetime

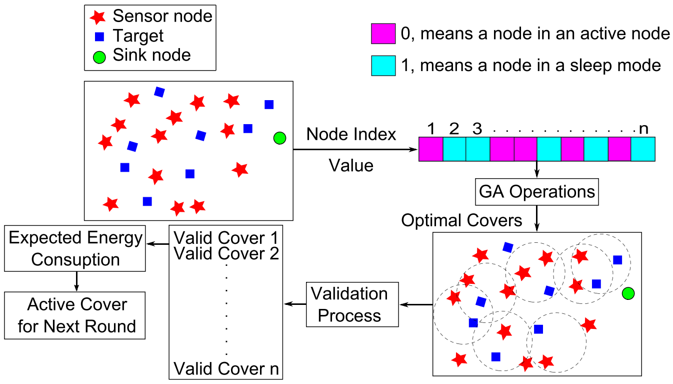


Fig. 2. The framework of our proposed model.

for the sensor s_i, C_p is the sensor cover with index p, and B is constant for the constraint matrix and it is defined as:

$$B_{ij} = \begin{cases} 1 & \text{if } s_i \in C_p \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

An example of the working field with eight targets and ten sensor covers is shown in Fig. 1.

3.2. A Genetic Algorithm-based Method

The GA goal of our model is to maximize the network lifetime. The framework of our proposed model is shown in Fig. 2. As shown, our model consists of three main phases. In the first phase, is called *encoding* phase, the system is initialized, i.e., the sensor nodes are distributed in a working field, and then a binary chromosome is used to encode the sensor nodes within the field. In the second phase, is called *optimization* phase, the GA randomly generates a set of chromosomes that forms its initial population. Dependently, GA algorithm runs after each round 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, is called *validation* phase, each chromosome is evaluated to make sure that all targets are covered. By getting all possible covers, the expected consumed energy of each proposed cover is calculated to determine which one will be active for the coming round.

3.2.1. Cover Head Selection Factors

In the search for the suitable cover heads, the following network properties are considered:

- The distance between a cover head and the base station,
- Remaining battery power, and
- Expected consumed energy.

Simultaneously, 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 total consumed energy for all of its sensors. The consumed energy E_s of a normal sensor node s is the summation of energy used to:

1. acquire l bits of data ($E_s^A(l)$),
2. receive l' bits of data ($E_s^R(l')$),
3. process l'' bits of data ($E_s^P(l'')$),
4. transmit l'' bits of data over a distance d ($E_s^T(l'', d)$), and
5. move from location x to location y.

$$E_s = E_s^A(l) + E_s^R(l') + E_s^P(l'') + E_s^T(l'', d) + E_s^M(x, y), \tag{3}$$

where $E_s^R = E_i + l'E^*$, E_i is the idle energy expenditure, $E_s^T = E_i + l''d^n$, $n = 4$ for long distance transmission, $n = 2$ for short distance

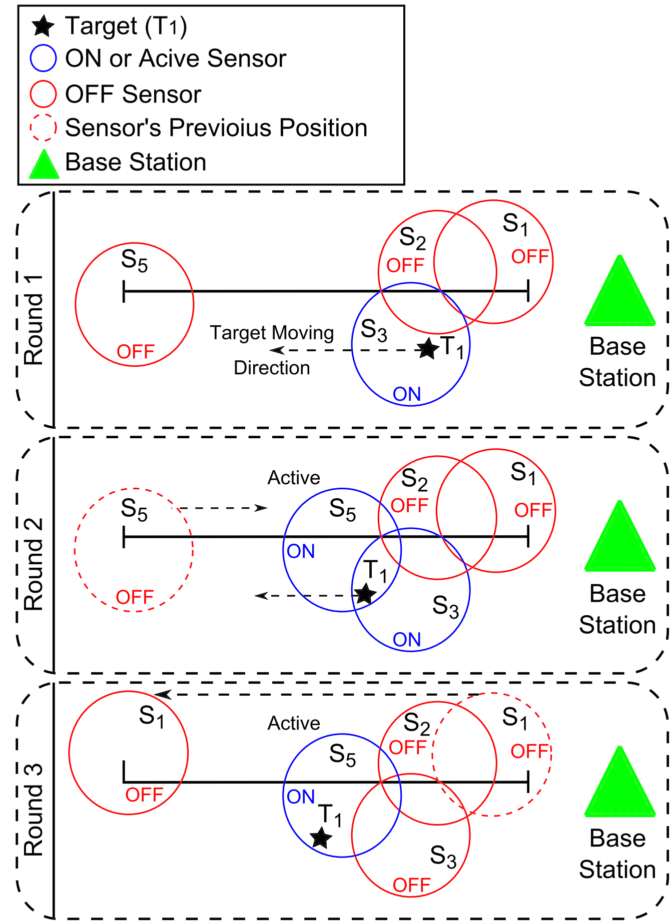


Fig. 3. Sensor mobility after each round to keep covering all targets during their movement.

transmission, and E^* represents the cost of beam forming approach for energy reduction.

Assuming a first order radio model (Yuan et al., 2017), for a cover with N_s members, the energy expenditure of a cover is the summation of transmission, receiving, and mobility energy cost of all member nodes as follows:

$$E = \sum_{i=1}^{N_s - 1} E_{i,s}^T + (kE_s^R + E_{s,B}^T) + E_s^M, \tag{4}$$

where the first term is the total energy used to transmit messages from cover members to the head, E_s^R is the energy used by the head node s to receive messages from the member nodes, $E_{s,B}^T$ gives the energy used by the head node s to transmit aggregated messages to the base station, and E_s^M is the moving energy cost used for sensor mobility. In our model, we assume that the working field is fully controlled by the base station. Depending on the transmitted data from sensor nodes after each round, the base station estimates the target speed and its moving direction.

When computing the energy consumption of a sensor node to transmit or receive a message of l bits, we adopt the following formulas for the transmitter energy consumption E^T and receiver energy consumption E^R:

$$E^T = E_e + ld^n \tag{5}$$

$$E^R = E_e + lE^* \tag{6}$$

where E_e is the idle energy expenditure and d is the distance between the transmitter and receiver. Depending on the distance be-

Table 1
Network properties.

Properties		Values
Number of nodes		100
Initial node energy		0.5 J
Idle state energy		50 nJ/bit
Data aggregation energy		5 nJ/bit
Amplification energy	$d \geq d_0$	10 pJ/bit/m^2
(cluster head to base-station)	$d < d_0$	0.0013 pJ/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

Table 2
Network lifetime for $K = 1$, $K = 2$, and $K = 3$.

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

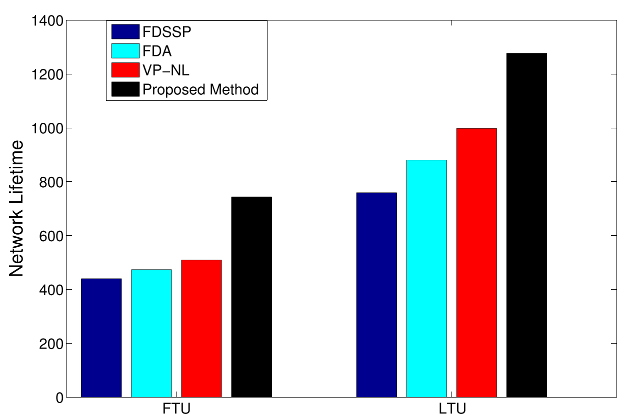


Fig. 4. Comparison between the proposed model and FDSSP, FDA, and VP-NL methods in terms of network lifetime.

tween the transmitter and receiver, the transmission energy consumption E^T is proportional with different orders of the distance and it can be modeled with a proper power term n. In our model, we use $n = 4$ for long distance transmission, i.e., transmitting messages from cover head to base station, and $n = 2$ for short distance transmission, i.e., sending messages from a sensor node to its cover head. E^* in Eq. (6) represents the cost of beam forming approach to reducing the energy consumption.

The mobility energy cost E_s^M for a sensor s depends on a proposed energy-aware distance $\varepsilon\vec{D}$, and $\varepsilon\vec{D}$ is computed depending on the Euclidean distance ϱ_d between the starting point x to the end point y, and take into account the environmental hindrances such as trees or buildings. Each hindrance h has a weight w which represents its ability to consume the node energy. Let $W = \{w_1, w_2, w_3, \ldots, w_n\}$, so, the $\varepsilon\vec{D}$ for a sensor s with sensing field f that contains a set of n hindrances h can be represented by Eq. (7). Fig. 3 depicts sensors mobility in three consecutive rounds to keep covering all target during their movement. Based on targets movement speed and direction, the base station updates sen-

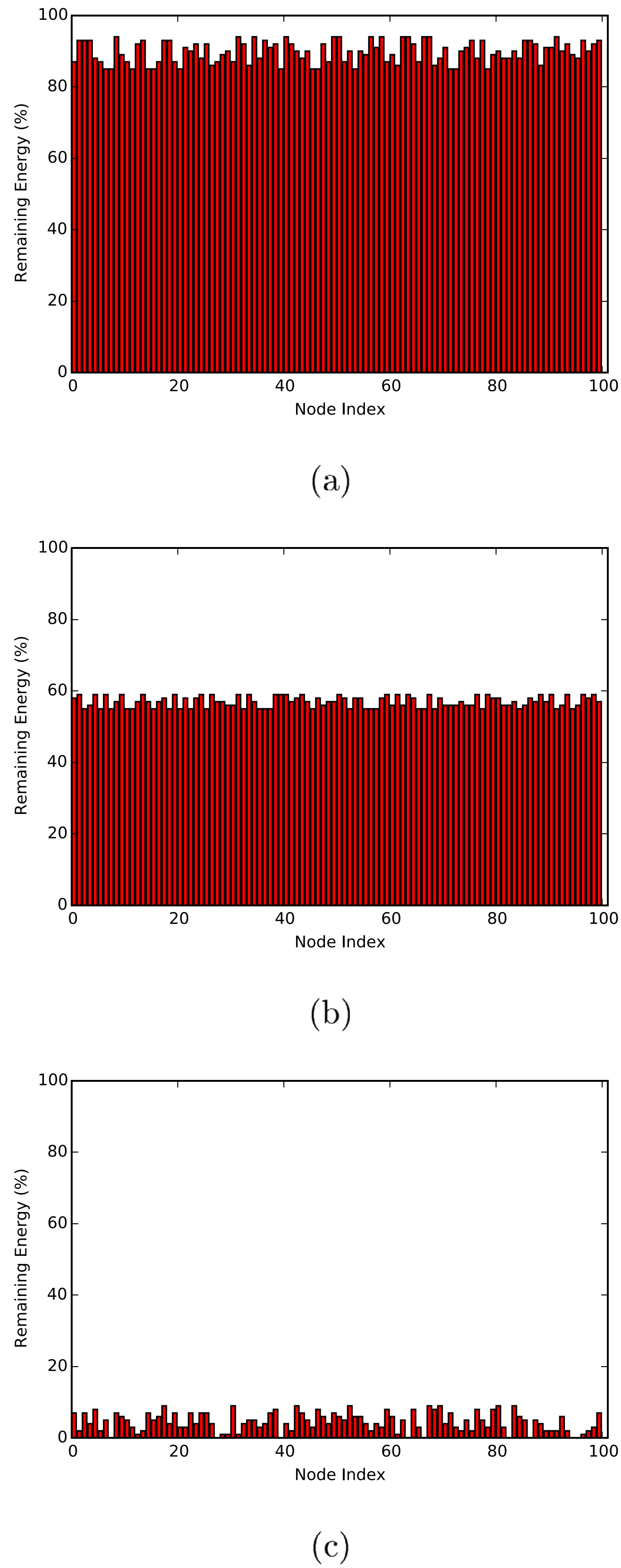


Fig. 5. The percentage of the remaining energy of the all network sensor nodes distributed in 100 m × 100 m field. (a) round 200, (b) round 500, and (c) round 1000.

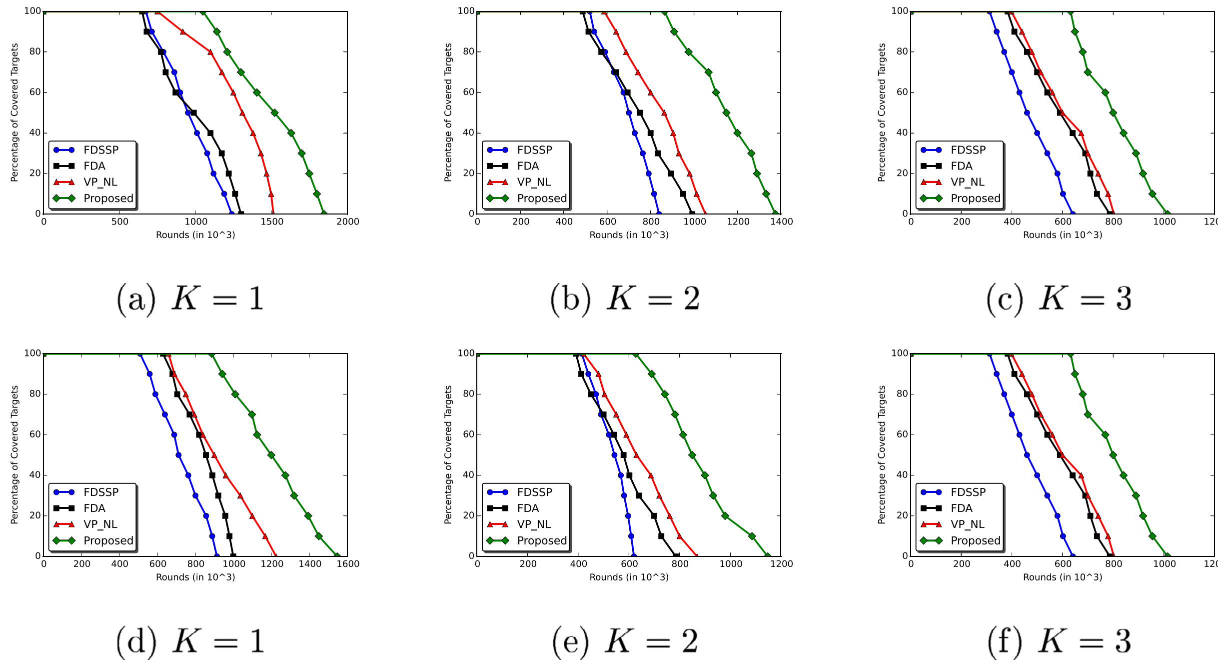


Fig. 6. Covered targets in terms of network transmission rounds K. (a), (b), and (c) are results of the field size of 100 m × 100 m with 10 targets (d), (e), and (f) are results of the field size of 200 m × 200 m with 20 targets.

sors locations as shown at Fig. 3.

$$\varepsilon\vec{D}_s = \rho_d\{x, y\} + \sum_{i=0}^{n} h_i w_i \tag{7}$$

Using the consumed energy, we can compute the remaining energy of a node s as follows:

$$\tilde{E}_s = E(0) - \sum_{t=1}^{T}(E_s^T(t) + E_s^R(t) + E_s^M(t)) \tag{8}$$

where $E(0)$ is the initial energy of the node and t denotes the network lifetime in term of transmission rounds. Note that unless a node serves as the cover head in a round its receiving energy expenditure E^R is zero. In practice, the remaining energy of every node is updated in each round.

3.2.2. Chromosome Encoding and Fitness Function

Each gene in the chromosome represents a sensor node in the field. The value of a gene can be either 1 or 0, where 1 indicates that the corresponding node serves as cover head and 0 indicates a non-head node.

GA generates new chromosomes through crossover and mutation operations and evaluates their fitness. The crossover operation is performed with two randomly selected chromosomes determined by a crossover probability to regulate the operation. When the crossover is excluded, the parent chromosomes are duplicated to the offspring without change. Varying the crossover probability alters the evolution speed of the search process. In practice, the value of crossover is close to 1.

The mutation operation involves altering the value at a randomly selected gene within the chromosome. Similarly, a mutation probability is used to regulate the performance of mutation. Different from the crossover probability, the mutation probability is usually fairly small. Essentially mutation operation could create completely new species, i.e., an arbitrary locus in the fitness landscape. Hence, it is a means to get out of a local optimum.

The fitness function aims to reduce the energy consumption as possible. For that, it evaluates the consumed energy and the expected amount of consumed energy for the proposed sensor cover after each round. Dependently, GA chooses the sensor cover that minimizes the energy exhaustion at a specific data transmission round. Hence, in our model, the GA is not only used to get all possible covers, but also, it selects the lowest energy consumption cover at a specific data transmission round. Mathematically, the fitness function of GA consists of the remaining energy $\tilde{E}$, the total expected energy expenditure ΔE, and the distance between the cover head and the base station. Assume that in each round a sensor node transmits a fixed number of bits to the head node, which is then aggregated and relayed to the base station $d(s, B)$. Hence, using Eqs. (5) and (6) we can compute the energy cost for each node and by aggregating the energy costs of all clusters following Eq. (4) the expected energy expenditure ΔE is estimated. The fitness function is hence defined as follows:

$$f = \frac{\tilde{E}}{NE(0)} + \frac{E'}{\Delta E} + \frac{1}{\sum_i d(s_i, B)} \tag{9}$$

where E' denote the total energy cost if the messages are transmitted directly from the sensor nodes to the base station. In this fitness function, we normalize the remaining energy and the expected energy expenditure so that they are in the same order.

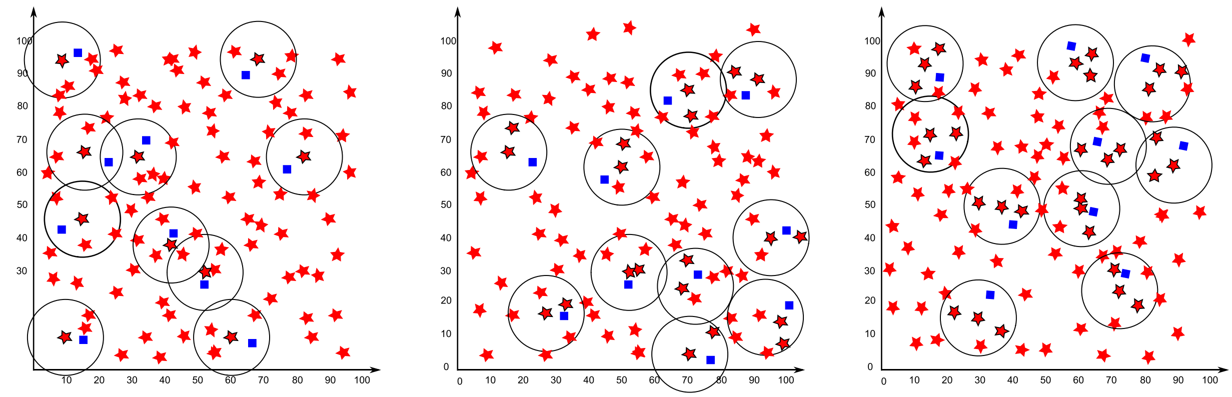
4. Experimental Results and Discussion

In this section, different experiments were conducted to evaluate the performance of the proposed model.

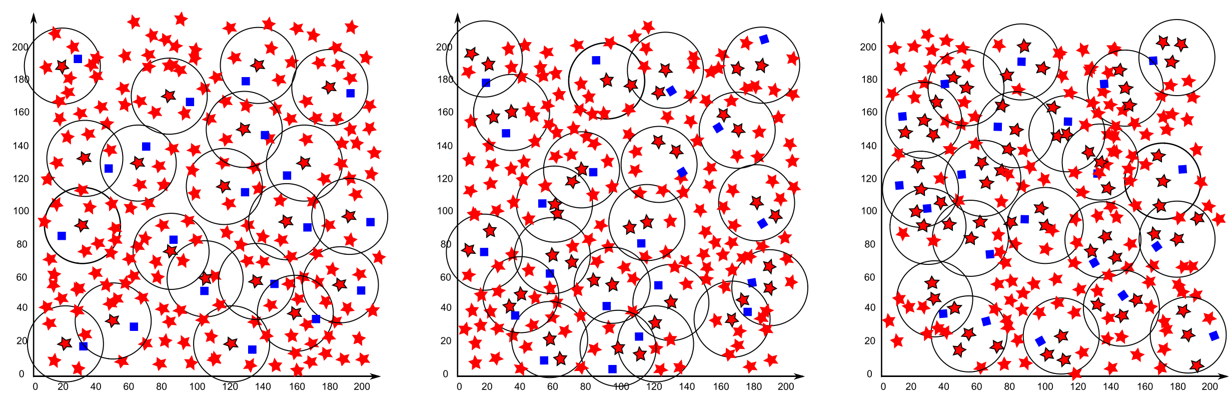
The first experiment was carried out to evaluate the proposed model using three different K-coverage cases. The second experiment was to test the performance regarding the amount of the consumed energy at each sensor node at a specific transmission round. In the third experiment, the aim was to measure the performance of the proposed model compared to the state-of-the-art methods.

4.1. Experimental Settings

Table 1 lists the network parameters that were used in all experiments. In running GA, we used the population size of 30 for

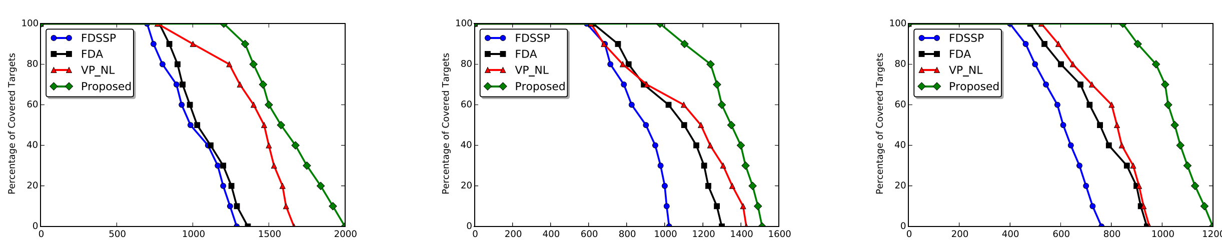


(a) $K = 1$ (b) $K = 2$ (c) $K = 3$

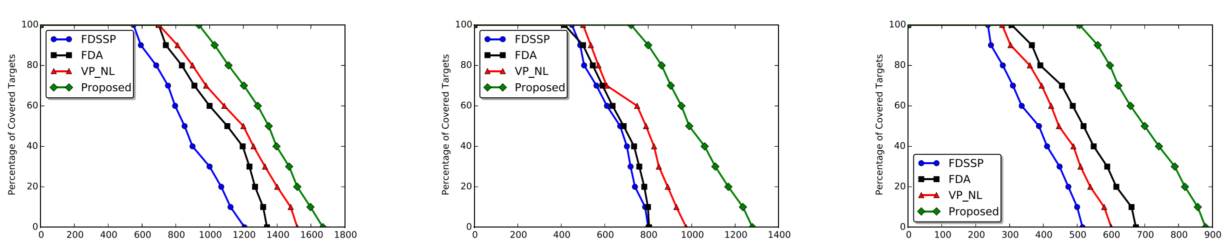


(d) $K = 1$ (e) $K = 2$ (f) $K = 3$

Fig. 7. Sensor placements and covers (depicted in different colors). (a), (b), and (c) are results of the field size of 100 m × 100 m with 10 targets (d), (e), and (f) are results of the field size of 200 m × 200 m with 20 targets.



(a) $K = 1$ (b) $K = 2$ (c) $K = 3$



(d) $K = 1$ (e) $K = 2$ (f) $K = 3$

Fig. 8. Covered targets in terms of network transmission rounds K with sensors mobility. (a), (b), and (c) are results of the field size of 100 m × 100 m with 10 targets (d), (e), and (f) are results of the field size of 200 m × 200 m with 20 targets.

30 generations. The crossover probability and mutation probability are 0.8 and 0.006, respectively.

In the evaluation of computational time, the experiments were conducted in a PC with Core i5-2400 CPU at 3.1 GHz, 4GB memory and the system was running Windows 7 and the programs were implemented with MATLAB R2012a.

In our experiments, the period between the start of the network until covering the first target 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. In all experiments, there were two different working environments, the dimensions of the first and second environments were 100 m × 100 m and 200 m × 200 m, respectively.

4.2. Proposed Model in a Static Field

In this section, all the experiments were conducted in a static field, i.e., the sensors were fixed.

- In the first experiment, three sub-experiments were carried out to evaluate the proposed model using three different K-coverage cases, where the value of K was 1, 2, and 3. 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 2.
  As shown in Table 2, as we increased the coverage level, i.e., the value of K, the sensing field increased in the way that makes the sensors consume more energy to transfer the collected data; and hence, the network lifetime decreased. In other words, the network lifetime is inversely proportional with the value of K. The table presents a comparison with three related methods, i.e., FDSSP, FDA, and VP-NL. It is clear that our proposed model improved the performance of the network in terms of the network lifetime using different values of K. The improvement that our proposed model achieved was in the range of 26%–41.3%. Fig. 4 illustrates a comparison between the proposed model and FDSSP, FDA, and VP-NL methods. The key achievement of our proposed model is the balancing between all sensors in terms of the remaining energy by keeping all sensors mostly at the same energy level.
- Our second experiment evaluates the performance regarding the amount of the consumed energy at each sensor node at a specific transmission round. The balanced energy exhaustion between all sensors implies the better performance. In this experiment, 100 nodes were randomly placed in a field of 100 × 100 m with $K = 1$. Ten experiments were performed with randomly placed nodes and targets, and the average energy levels of all nodes at the transmission rounds of 200, 500, and 1000 were visualized. Fig. 5 illustrates the average remaining energy in terms of percentage with respect to the initial energy of nodes in the field using the proposed model.
  As shown in Fig. 5, the remaining energy is inversely proportional with the number of rounds. Moreover, the network lifetime is extended by avoiding high energy consumption at one node while other nodes keep saving their energy.
- In our third experiment, a comparison was performed regarding the targets covering time. The network lifetime in this experiment is determined by the first target that becomes uncovered. In this experiment, 100 nodes were randomly placed in a 100 m × 100 m and 200 m × 200 m environments to cover different numbers of targets. Fig. 6 depicts the average number of covered targets throughout the entire network lifespan in case of $K = 1, 2,$ and 3. In this figure, the nodes were randomly placed in: (a) a 100 m × 100 m environment to cover 10 targets and (b) a 200 m × 200 m environment to cover 20 targets. The x-axis is the number of network transmission rounds (in thousands); whereas the y-axis represents the percentage of active nodes. The numbers of nodes deployed in the field in both cases are shown in Table 1.
  As shown in Fig. 6, the network transmission continues, the number of active nodes decreases because more nodes deplete their energy. Fig. 7 shows an example of sensor placements and covers distributed at the working field using the different cases. It is clear that our proposed model extends the network lifespan by increasing the targets coverage time in all cases.

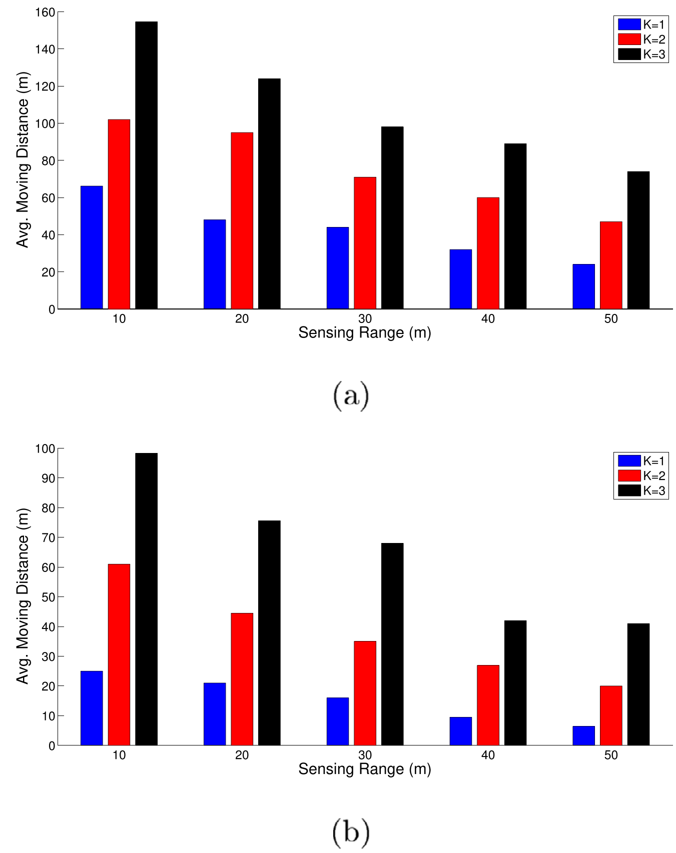


Fig. 9. The sensing range vs. the average moving distance using 50 sensor nodes distributed at (a) 100 m × 100 m working field (b) 200 m × 200 m working field.

Table 3
Average and standard deviation (STD) of the experimental run time to get the remaining energy of each node.

Rounds		200	500	800	1100	1300
100 m ×	Mean	0.401	0.332	0.279	0.147	0.332
100 m	STD	0.014	0.037	0.098	0.032	0.074
100 m ×	Mean	0.215	0.321	0.197	0.246	0.207
100 m	STD	0.086	0.049	0.052	0.035	0.044

For further analysis of these experiments, Table 3 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., 100 m × 100 m and 200 m × 200 m, that we discussed above, and when the value of K was one.

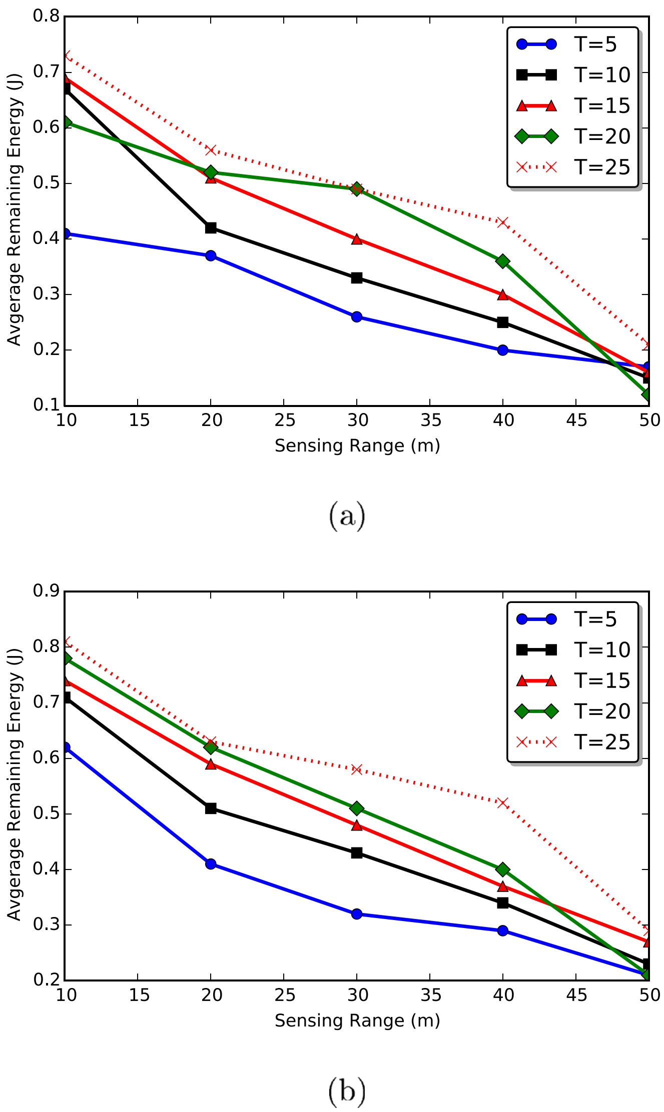


Fig. 10. The sensing range vs. the remaining energy using a 100 m × 100 m working field with 50 (a) mobile sensor node (b) static sensor node.

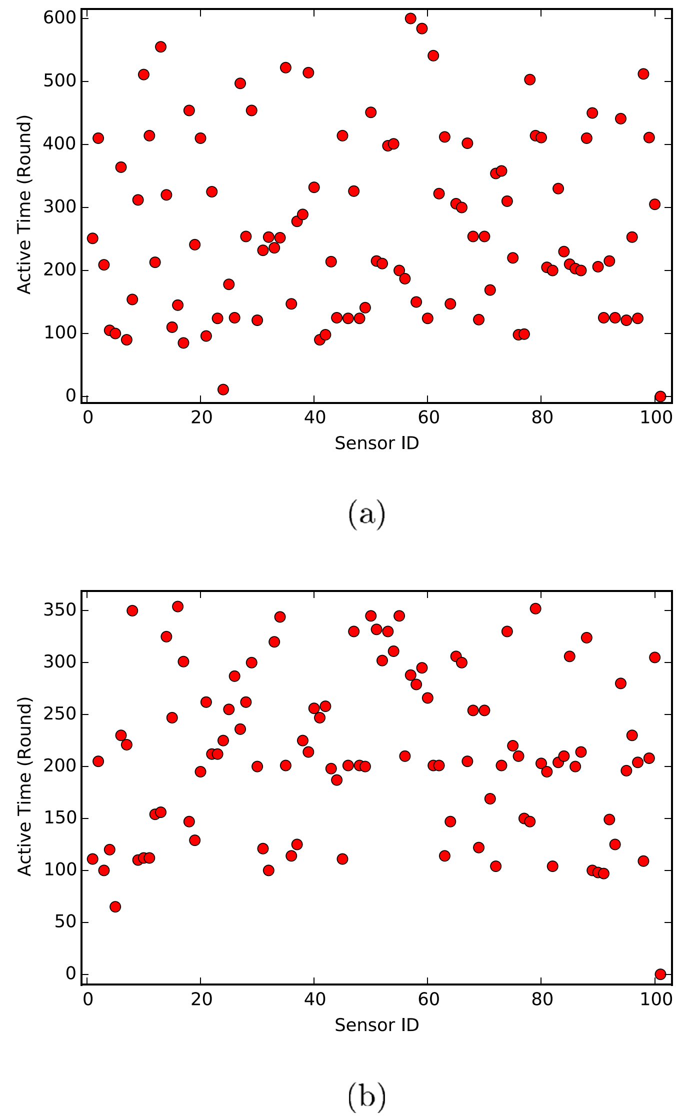


Fig. 11. The active time for each sensor node using 100 sensors distributed in (a) 100 m × 100 m working field (b) 200 m × 200 m working field.

4.3. Proposed Model in a Dynamic Field

In this section, all the experiments were carried out in a dynamic field to measure the effect of sensors mobility on the covering time.

- In the first experiment, the performance of the proposed model was evaluated using three different *K*-coverage cases, where the value of *K* was 1, 2, and 3. The results of this experiment are summarized in Fig. 8.
  Fig. 8 depicts the average number of covered targets throughout the entire network lifespan in case of $K = 1, 2,$ and 3. In this figure, the nodes were randomly placed in: (a) a 100 m × 100 m environment to cover 10 targets and (b) a 200 m × 200 m environment to cover 20 targets. As shown in this figure, as the network transmission continues, the number of active nodes decreases as more nodes deplete their energy. Compared to the previous experiments at which all sensors locations are static (see Section 4.2), Fig. 8 illustrates that the network lifetime was extended by allowing sensors to be mobile. As a result, sensors mobility leads to longer targets covering. Hence, our proposed model extends the network lifespan by increasing targets coverage time in all sensors mobility cases.
- This experiment was run to test the influence of the sensing range of the sensors on the average moving distance. In this experiment, 50 sensors were used and the value of *K* was 1, 2, and 3. At the first experiment (see Fig. 9 **(a)**), the sensors were distributed at 100 m × 100 m sensing field while we used 200 m × 200 m for the second experiment (see Fig. 9 **(b)**).
  As shown in Fig. 9, the sensing range greatly affects the average moving distance. The reason why is because the same space can be covered by more sensors at the same time. This means that the bigger sensing range, the larger amount of targets that are covered by the same sensor node. So, there is no need to move additional sensors from their locations to cover a target.
  In the same context, a sensor with a bigger sensing range consumes more energy than others. Accordingly, the average remaining energy of a sensor node increases with less sensing range. Fig. 10 proves this fact using two different cases. At Fig. 10 (**a**), 50 mobile sensor node are distributed in a field size 100 m × 100 m. Applying the same experiment by distributing 50 stationary sensors in a field size 100 m × 100 m leads to the same result as shown in Fig. 10 (**b**).

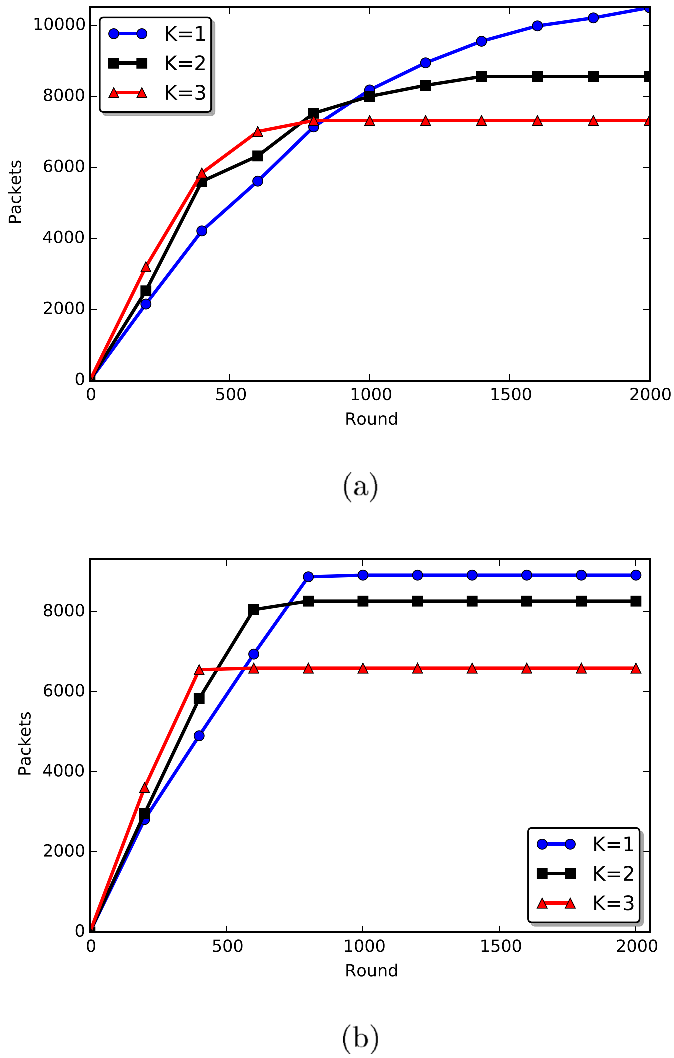


Fig. 12. The network throughput using 100 mobile sensor node distributed in (a) 100 m × 100 m working field (b) 200 m × 200 m working field.

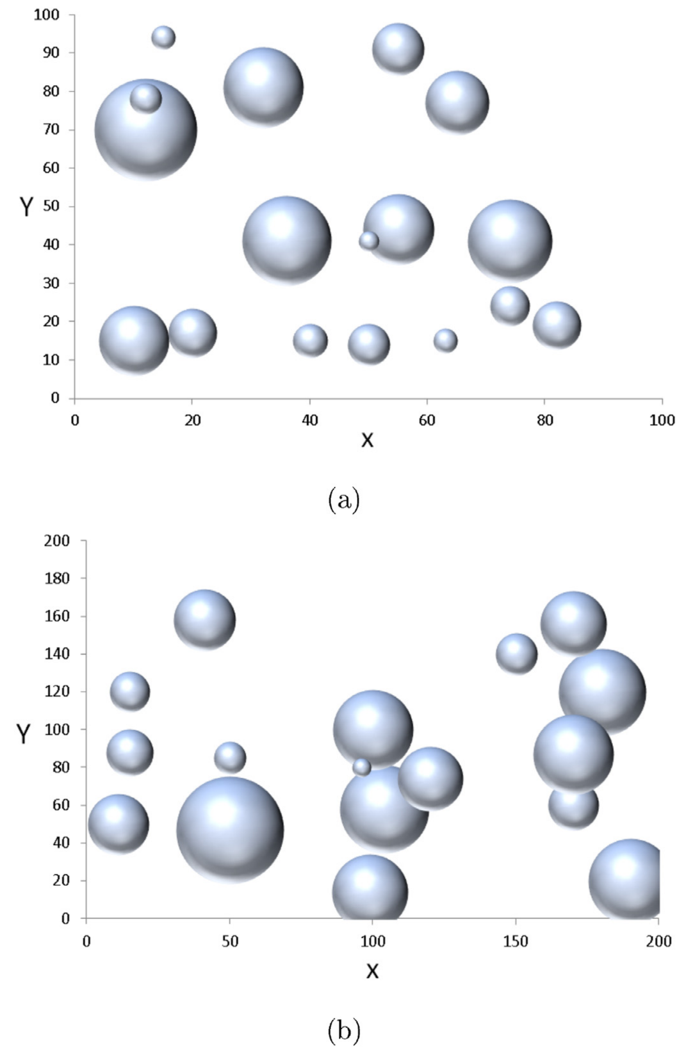


Fig. 13. Spatial and frequency view of energy-aware distances for each mobile sensor node using 100 sensor node distributed in 100 m × 100 m working field (b) 200 m × 200 m working field, with $K = 2$.

- In the most of the conducted experiments, it was remarked that the proposed model avoids the high energy consumption at one node by switching its active status (ON/OFF) according to the current status of its neighbors at each round. This experiment was conducted to test the ability of our model to make a balance between all sensors. The results of this experiment are summarized in Fig. 11 (**a** and **b**), where 100 stationary sensor were distributed in a 100 m × 100 m and 200 m × 200 m working fields, respectively.
As shown in Fig. 11, the active time is distributed between all nodes in the way that guarantees the energy consumption balancing. However, in few cases, the active time of one or more sensors is higher than the corresponding active time of the rest sensors that can be occurred when a target or more is covered by a few numbers of sensors. Hence, it is noticed that the active time for the neighbors' sensors is closer.
- The network throughput is completely depending on the amount of transferred data from sensor nodes to the base station. Hence, the longer network lifetime, the higher network throughput. As discussed above, our proposed model extends the network lifetime in terms of the first and the last node become unavailable. This experiment was carried out to examine the network throughput of our model. In this experiment, 100 mobile sensor node was distributed in a 100 m × 100 m and 200 m × 200 m working field. The results of this experiment are displayed in Fig. 12.
As shown in Fig. 12 (**a** and **b**) it can be remarked that the network throughput inversely proportional with the value of K. In other words, as we increased the coverage level, the network throughput decreased. This is because increasing the coverage level consumes more sensor's energy to transfer the collected data; and hence, reduces the network lifetime and consequently network throughput.
- The energy-aware distance is different from node to another. This experiment was carried out in a 100 m × 100 m and 200 m × 200 m working fields, where the number of sensors was 100 in a dynamic environment and $K = 2$. The goal of this experiment is to show how the energy-aware distances are changed across the nodes. The results of this experiment are illustrated in Fig. 13.
As shown in Fig. 13 (**a** and **b**), this distance is extremely related to the node location. These two figures show the spatial and frequency view of sensor nodes moving to/from different locations throughout the network lifetime. The size of the sphere is proportional with the energy-aware distance a sensor moved to cover a target.

5. Conclusions

Wireless Sensor Networks (WSNs) are widely used for monitoring and tracking applications such as industry, environmental monitoring, health-care, and agriculture. Depending on the application, covering a specific area might cover the whole area, this is so-called area coverage problem or target coverage problem. The goal of the target coverage algorithms is searching for the optimal sensor covers which extend the network lifetime. In classical algorithms, it is assumed that the environment is perfectly known, and this can be achieved by covering each target by only one sensor. However, these algorithms have a number of serious drawbacks especially if a sensor died, i.e., run out of energy; hence, each target needs to be covered by more than one sensor at the same time to achieve continuous coverage.

This study has two main contributions. Firstly, GA-based cover forming method that creates all possible sensor covers. Secondly, a WSN covers management method that switches between different sensor covers to maximize the network lifetime. In this paper, the proposed model used the GA to optimize the coverage requirements in WSNs to provide continuous monitoring of specified targets for longest possible time with limited energy resources. Moreover, we allow sensor nodes to move to appropriate positions to collect environmental information. Our model is based on the continuous and variable speed movement of mobile sensors to keep all targets under their cover all times. There are three main processes of our GA-based method. First, a binary chromosome is used to encode the sensor nodes within the entire field. Then, GA starts working 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. Finally, each chromosome is evaluated to make sure that all targets are covered.

A set of experiments in different working environments and a comparison with the most related work are performed. In terms of the network lifetime, the improvement that our proposed method revealed was in a range of 26%–41.3% using stationary nodes, and it was in a range of 29.3%–45.7% using mobile nodes. Further, the network throughput is improved in a range of 13%–17.6%. Moreover, the running time to form the network structure and switch between nodes' modes is reduced by 12%. However, the proposed method is tested against the homogeneous model of WSN in which all sensors have the same capabilities. Additional experiments are required in future to measure its performance in additional environments such as the environment with sensors heterogeneity.

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