Energy Efficient Backbone Formation Using Particle Swarm Optimization Algorithm in Wireless Sensor Networks

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Abstract

Connected dominating set (CDS) problem is a promising approach for backbone formation in wireless sensor networks. Selecting proper nodes to construct the CDS in order to prolong the network lifetime is an important issue when designing connected dominating set algorithms in wireless sensor networks. In this paper, we propose an energy efficient connected dominating set (CDS) scheme in wireless sensor networks which prolongs the network lifetime. In proposed algorithm, we use an optimal weight based on the minimum residual energy and maximum effective degree of nodes for backbone formation to prolong the network lifetime. The optimal weight coefficients are determined using particle swarm optimization (PSO) algorithm. Then, when selecting nodes for dominating set (DS) formation, these coefficients will be used. If the degree of a node is more than coefficient of degree constraint and energy of a node is less than coefficient of energy constraint, the node won't be selected for DS formation. The message and time complexity of the proposed algorithm is O(n). Simulation results show that proposed algorithm outperforms the other methods in terms of network lifetime.

Keywords: Wireless sensor network, Network backbone, UDG model, PSO Algorithm

1. Introduction

Wireless sensor networks (WSN) are composed of hundreds or thousands of sensor nodes which are deployed in an unprotected environment to collect the surrounding information and then transmit report messages to a sink node. The potential applications of sensor networks are highly varied, such as battlefield surveillance, target tracking and environmental monitoring [1, 2]. As sensor networks have limited and non-rechargeable energy resources, energy conservation and maximization of network lifetime are commonly recognized as a key challenge in the design and implementation of wireless sensor networks [2, 3].

In order to effectively extend the lifetime of a WSN, many algorithms construct a virtual backbone of the network and only use the nodes in the virtual backbone to receive and transmit data for data collection [3]. Connected dominating set (CDS) plays an important role in the construction of virtual backbone in wireless sensor networks [3, 4].

It is assumed that we use a graph G = (V, E) to represent a WSN. In this graph, V is the set of nodes in network and E is the set of edges that shows all links in the network [5, 6]. If two nodes are located together in one transmission range, there is an edge between them. It means they could be related to each other, if all the nodes have the same transmission ranges, graph G will be known as a Unit Disk Graph (UDG), otherwise G is a general graph. [5] Unit Disk Graph (UDG) is shown in Figure 1.
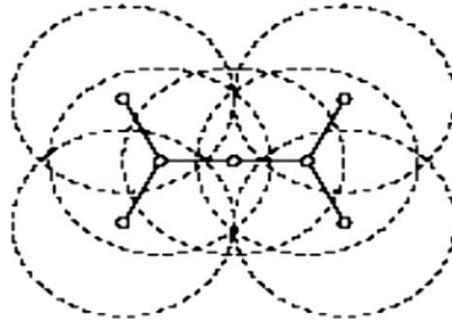
Figure 1. Unit Disk Graphs (UDG) [5]

Independent set (IS) is a subset of network nodes with no two neighboring members. Maximal Independent Set (MIS) is an independent set with maximum of possible members in a graph [5]. Dominating set (DS) S of graph G is a subset of vertex set V such that every vertex v ∈ V is either in S or adjacent to a vertex of S [6]. If the sub-graph induced by <S> is connected, dominating set S is called a connected dominating set (CDS) [8]. The connected dominating set having the minimum cardinality is called the minimum connected dominating set (MCDS). MCDS problem has shown to be NP-Hard [7, 8].

A CDS can be used as a virtual backbone to help each node transfer its data to the sink [3]. The non-CDS nodes can turn off their communication module to save energy when they have no data to be transmitted out [4]. Many researches focus on finding the minimum connected dominating set (MCDS) to construct the network virtual backbone.

In this paper, we propose a backbone formation algorithm for prolonging network lifetime in wireless sensor networks. In proposed algorithm, optimal coefficients of maximum effective degree and minimum residual energy of nodes are determined using PSO algorithm. Then, when selecting nodes for DS formation, these coefficients will be used. If the degree of a node is more than coefficient of degree constraint and energy of a node is less than coefficient of energy constraint, the node won't be selected for DS formation. The message complexity and time complexity of the proposed algorithm is O(n). Through simulation contrasted with previous work, we show that our proposed algorithm can outperform in terms of network lifetime.

The rest of this paper is organized as follows: Section 2 presents an overview of related work. Section 3 briefly reviews particle swarm optimization (PSO) algorithm. Section 4 describes the system model. The proposed algorithm is presented in Section 5. The simulation results are presented in Section 6. Finally, the main conclusions are presented in Section 7.

2. Related Work

The construction of connected dominating set in wireless networks has been extensively studied for many years [9-12].

Kui *et al.*, [3] proposed an energy-balanced connected dominating set scheme (DGA-EBCDS) for data collection in wireless sensor networks. This method makes the energy consumption among nodes more balanced. Furthermore, the routing decision in DGA-EBCDS considers both the path length and the remaining energy of nodes in the path; it further prolongs the lifetime of nodes in the backbone.

Raei *et al.*, [4] proposed an energy-aware distributed algorithm for MCDS problem in UDG with constant approximation ratio and time complexity of O(n) and message complexity of O(n). This algorithm consists of two phases; in the first phase, a maximal

independent set (MIS) of the network graph is computed. The second phase is to choose the minimal number of the nodes to make the DS connected, i.e., CDS.

Akbari Torkestani [6] proposed an approach to the connected dominating set based backbone formation in wireless sensor network. In this approach, the delay-constrained energy-efficient backbone formation problem is modeled by the equivalent degree-constrained minimum weight connected dominating set problem first. Then, a learning automata-based heuristic is proposed to find a near optimal solution to the proxy equivalent connected dominating set problem.

A degree-constrained extension of the CDS problem called OMCDS (Optimal degree-constrained Minimum-weight CDS) [7] was proposed for modeling the delay bounded energy-efficient backbone formation in wireless sensor networks. The purpose of OMCDS is minimizing the total weight of the CDS and finding the optimal degree constraint simultaneously. OMCDS constructs the network backbone by finding a near optimal solution to the proxy equivalent OMCDS problem, where the residual energy of the sensor is defined as the node weight.

Dai and Wu [13] proposed a heuristic method for backbone formation in wireless and ad hoc networks. They proposed a CDS-based backbone formation algorithm in which the backbone initially is set to network hosts having two unconnected neighbors. Then, the backbone is pruned by removing the hosts whose neighbors are the neighbors of the other hosts of the initial backbone too.

A MIS-based greedy algorithm was proposed [14] for finding the connected dominating set (CDS) in wireless networks. This algorithm is consisted of two stages. In first stage, MIS of the network is constructed and in second stage, MIS nodes are constructed by using a Steiner tree.

A CDS-based intelligent backbone formation algorithm [15] was proposed for wireless ad hoc networks. At each iteration of this algorithm, a CDS of the network is constructed and the size of the CDS is compared with a dynamic threshold.

3. Particle Swarm Optimization (PSO) Algorithm

Particle swarm optimization (PSO) algorithm is a heuristic global optimization method developed by Kennedy and Eberhart in the mid 1990s. PSO is a population-based random search algorithm inspired by the social behavior of bird flocks and has been applied to solve many combinatorial optimization problems [16, 17]. PSO is initialized with a population of random solutions and the potential solutions, called "particles", in PSO search through the solution space [17].

Suppose that particle *"j"* has g-dimension as Eq. (1):

$$X_j = [X_{j,1} X_{j,2} \ldots \ldots \ldots X_{j,g}] \tag{1}$$

Each particle can be shown by its current speed and position. In PSO, the speed and position of each particle change according to the following equation [16].

$$v_{j,g}^{(t+1)} = w v_{j,g}^{(t)} + c_1 r_1 \left(Pbest_{j,g} - x_{j,g}^{(t)} \right) + c_2 r_2 \left(gbest_{j,g} - x_{j,g}^{(t)} \right) \tag{2}$$

$$v_{min} \leq v_{j,g}^{(t)} \leq v_{max} \tag{3}$$

$$x_{j,g}^{(t+1)} = x_{j,g}^{(t)} + v_{j,g}^{(t+1)} j = 1,2, \ldots \ldots, n \quad , \quad g = 1,2, \ldots \ldots, m \tag{4}$$

In these equations, $v_{j,gt}$ and $x_{j,gt}$ stand for separately the speed of the particle *"j"* at its *"t"* times and the g-dimension quantity of its position; $P_{bestj,g}$ represents the g-dimension quantity of the individual *"j"* at its most optimist position at its *"t"* times. $G_{bestj,g}$ is the g-dimension quantity of the swarm at its most optimist position. In order to avoid particle being far away from the searching space, the speed of the particle created at its each direction is confined between v_{min}, and v_{max}. If the number of v_{max} is too big, the solution is far from the best, if the number of v_{max} is too small, the solution will be the local optimism.

An Inertia weight *W* is a proportional agent that is related with the speed of last time. The bigger *W* is, the bigger the PSO's searching ability for the whole is, and the smaller *W* is, the bigger the PSO's searching ability for the partial. Experimental results show that PSO has the biggest speed of convergence when *W* is between 0.8 and 1.2. While experimenting, *W* is confined from 0.9 to 0.4 according to the linear decrease as Eq. (5), which makes PSO search for the bigger space at the beginning and locate the position quickly where there is the most optimist solution.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \qquad (5)$$

c_1 and c_2 represent the speeding figure, regulating the length when flying to the most particle of the whole swarm and to the most optimist individual particle. If the figure is too small, the particle is probably far away from the target field, if the figure is too big, the particle will maybe fly to the target field suddenly or fly beyond the target field. The proper figures for c_1 and c_2 can control the speed of the particle's flying and the solution will not be the partial optimism. In many algorithms, these values are selected so that $c_1 + c_2 \leq 4$. r_1 and r_2 represent random fiction, and 0-1 is a random number.

4. System Model

Network and energy model are described in this section.

4.1. Network Model

A sensor network consisting of *N* sensor nodes uniformly deployed over a vast field is considered for continuously monitoring the environment. The network has the following characteristics:

- Nodes are dispersed randomly following a uniform distribution in a 2-dimensional space.
- Sensor nodes and the sink are all stationary after deployment.
- The sink is considered a powerful node with enhanced communication and computation capabilities with no energy constraints.
- All sensors have the same transmission range. (Network is considered as a Unit Disk Graph (UDG)).

In this paper, we consider a wireless sensor network where data is periodically reported from the sensor nodes to the sink. Data collection and transmission proceeds in rounds. The backbone nodes are on when they are sending and receiving data. Nodes that are not in the backbone will go to the sleep mode.

4.2. Energy Model

The energy model presented in [18] is adopted for the communication energy dissipation. Eq. (6) is used to calculate the transmission energy, denoted as $E_{Tx}(k, d)$ required for a "k" bits message over a distance of "d".

$$E_{Tx}(k, d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\varepsilon_{amp}d^4, & d \geq d_0 \end{cases} \quad (6)$$

To receive an k-bit message, the energy required is calculated by Eq. (7).

$$E_{Rx}(k) = kE_{elec} \quad (7)$$

The electronics energy, E_{elec}, is the energy dissipated per bit to run the transmitter or the receiver circuit, and depends on factors such as the digital coding and modulation, whereas the amplifier energy, $\varepsilon_{fs}d^2$ or $\varepsilon_{amp}d^4$, depends on the acceptable bit-error rate.

In this model, both the free space (d^2 power loss) and the multipath fading (d^4 power loss) channel models were used, depending on the distance between the transmitter and receiver. If the distance is less than a threshold, the free space (fs) model is used; otherwise, the multi path (mp) model is used.

5. Proposed Algorithm

In this paper, we use an optimal weight based on the minimum residual energy and maximum effective degree of nodes for backbone formation. The optimal weight coefficients are determined using particle swarm optimization (PSO) algorithm. The parameters of optimal weight are defined as follows:

- Coefficient of minimum residual energy of nodes: This parameter is coefficient of average energy of live nodes. This means that if the energy of a node is less than this coefficient, the node won't be selected as the backbone node.

- Coefficient of maximum effective degree of nodes: This parameter is coefficient of maximum degree of live nodes. If the degree of a node is more than this coefficient, the node won't be selected as the backbone node.

In our proposed algorithm, selection of backbone nodes is done based on the proposed algorithm in [4]. In this algorithm [4], all nodes in WSN are distributed in a two dimensional plane. The network topology is modeled in UDG. This algorithm consists of two phases. In the first phase, a maximal independent set (MIS) of the network graph is computed. The second phase is to choose the minimal number of the nodes to make the DS connected, *i.e.*, CDS.

In our propose algorithm, at the beginning of the network setup, particle swarm optimization (PSO) algorithm is run only once, and the optimal coefficients of minimum residual energy and maximum effective degree of nodes are determined with the aim of maximizing the network lifetime. Then, in each round, sensor nodes send their average residual energy and maximum degree to the sink node. The sink node multiplies the specified optimal coefficients in these two values and sends the result that is degree and energy constraint to the sensor nodes in the network. Then, in the first phase of the EA-MCDS-UDG algorithm for MIS formation, if the degree of a node is more than coefficient of degree constraint and energy of a node is less than coefficient of energy constraint, the node won't be selected for MIS formation.

The proposed method is a dynamic algorithm and in each round, sensor nodes send their average residual energy and maximum degree to the sink node. Sensor nodes for sending their average residual energy and degree to the sink node don't send additional messages in the network. This work is done through marking certain bits in data packets by the nodes in the sending path. Thus, similar to EA-MCDS-UDG algorithm, the message and time complexity of the proposed algorithm is O(n).

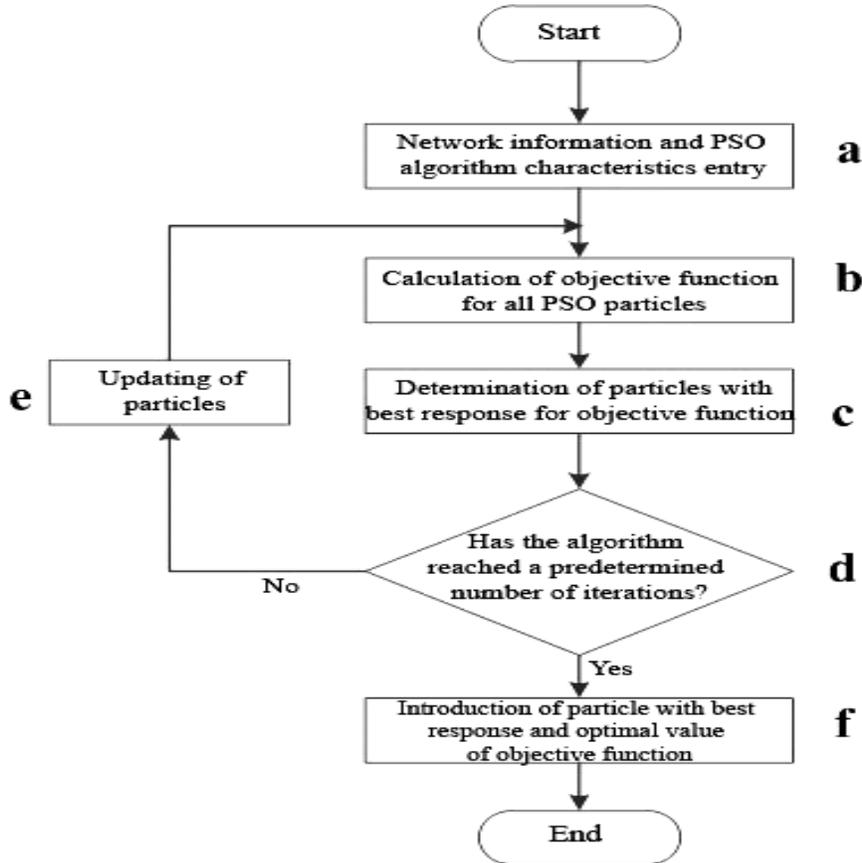Figure 2 shows the flowchart of optimal coefficients determination algorithm.

Figure 2. Flowchart of Optimal Coefficients Determination Algorithm

a) In this stage, the network information is given as input data to the program. The information includes the area size, the number of nodes, transmission rang of each node, location of each node, initial energy of each node, number of data packets transmitted and their information, T_{max} and PSO algorithm information such as number of particles, number of desired iterations and coefficients of c_1 and c_2.

b) In this stage, objective function is calculated for all PSO particles. In this paper, objective function is to maximize network lifetime.

c) In this stage, the particles are determined based on best response.

d) In this block, it is considered whether the algorithm has reached a predetermined number of iterations. If yes, the algorithm goes to step *f* otherwise goes to step *e*.

e) In this stage, based on the objective function, the particle updates is done.

f) In this stage, the particle with best response and optimal value of objective function is determined.

6. Simulations and Results

In this section, we evaluate the performance of proposed algorithm via simulations. For evaluation, we used MATLAB and tested proposed algorithm and other algorithm, such as EA-MCS-UDG [4] and DEBB [8] in terms of network lifetime and backbone size. Then, we define different scenarios and compare performance of the proposed algorithm in these scenarios with EA-MCDS-UDG using simulations.

6.1. Simulation Setup of Experiment I

The simulations are carried out with a random network topology with sensor nodes randomly distributed in the monitoring area with the size of 100m × 100m. The simulation network size is 100-250 numbers of nodes in increments of 50 nodes respectively. All parameters of simulations are shown in Table 1.

Table 1. Simulation Parameters of Experiment I

Parameters	Values
Network size	100m ×100m
Number of nodes	100 to 250
Transmission range	20 m
Data packet size	512 Bytes
Broadcast packet size	250 bits
Initial energy of nodes	1.5 to 2 J
E_{elec}	50 nJ/ bit
ε_{fs}	10 pJ/ bit/ m^2
ε_{amp}	0.013 pJ/ bit/ m^4
number of particle of PSO algorithm	20
Number of iterations of PSO algorithm	20
C_1	1.5
C_2	2.5

6.2 Simulation Results of Experiment I

Backbone size: Backbone size is the number of network nodes included in the backbone. The backbone size is inversely proportional to the radio transmission range. Communication cost is directly proportional to the backbone size [8].

Figure 3 shows backbone size of proposed algorithm in comparison with EA-MCS-UDG and DEBB. To show the impact of the network size on the backbone size, the number of nodes changes from 100 to 250. Numerical results show that the backbone size increases as the number of nodes increases. As shown in Figure 3, the backbone size of the proposed algorithm is almost the same as EA-MCS-UDG. From the results shown in this figure, it can be seen that when the network size is small, the network backbone constructed by DEBB is smaller than those created by the proposed algorithm and EA-MCS-UDG; but with different

number of nodes, backbone size of proposed algorithm has less steep compared to DEBB. With increasing network size, the network backbone constructed by the proposed algorithm is smaller than that created by the DEBB.
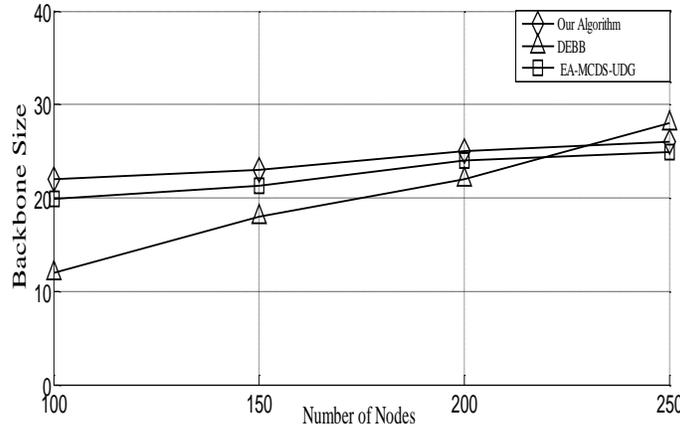

Figure 3. Backbone Size versus the Number of Nodes

Network lifetime: Network lifetime is defined as the duration of the network until the first node depletes its energy. So, the network lifetime effectively ends with the first node death (FND) [3].

Figure 4 shows the network lifetime of proposed algorithm in comparison with EA-MCS-UDG and DEBB. It is clear from Figure 4 that the proposed algorithm has better performance than other algorithms in terms of network lifetime. Figure 4 also shows that the network lifetime decreases as the network size grows.
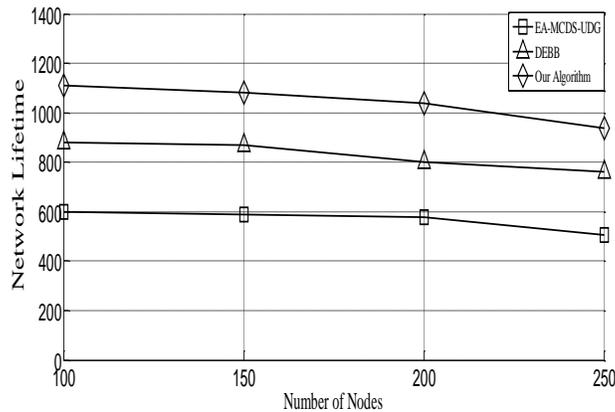

Figure 4. Network Lifetime per Round

6.3. Definition of Different Scenarios

In this section, we define different scenarios according to the needs of the network to describe the network lifetime. Performance of the proposed algorithm in these scenarios and EA-MCDS-UDG using simulation results will be shown.

Scenario (1): Given a wireless sensor network environment where it is installed, leaving even a single node may lead to the lack of desired service and disrupt network performance. In these situations, in each round, the backbone nodes are determined so that leaving of the first node is delayed as much as possible. So in this case, our aim is to determine backbone so that leaving of the first node occurs after the maximum time possible.

Scenario (2): In some situations, the maximum number of nodes in each round may be desirable. In these conditions, the backbone nodes are determined so that maximum number of nodes remain alive in each round. So, the objective function is defined as the total number of live nodes in each round.

6.4. Simulation Setup of Experiment II

The experiments are assumed to be performed in a square field of 200m×200m, in which nodes are randomly dispersed as shown in Figure 5.
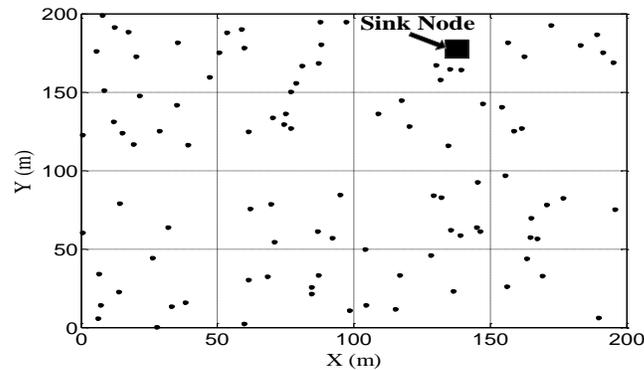

Figure 5. Nodes Deployment in the Network

The parameters used in these simulations are shown in Table 2.

Table 2. Simulation Parameters of Experiment II

Parameters	Values
Network size	200m ×200m
Number of nodes	100
Transmission range	40 m
Data packet size	2000 Bytes
Broadcast packet size	250 bits
Initial energy of nodes	0.1 J
E_{elec}	50 nJ/ bit
ε_{fs}	10 pJ/ bit/ m^2
ε_{amp}	0.013 pJ/ bit/ m^4
Number of particle of PSO algorithm	20
C_1	1.5
C_2	2.5

6.5. Simulation Results of Experiment II

It should be noted that during the simulation, the network lifetime will be increased approximately 50% to 90% using proposed algorithm. Table 3 shows results of the mentioned scenarios in simulations.

Table 3. Simulation Results of Experiment II

Algorithm	Coefficient of minimum residual energy	Coefficient of maximum effective degree	First Node Dies	Last Node Dies	Total number of live nodes
EA-MCDS-UDG	-	-	26	167	7146
Scenario 1	0.2305	0.9358	50	168	6037
Scenario 2	0	0.7910	27	168	7837

As shown in Table 3, in scenario1 that objective function has been intended First Node Dies (FND), proposed algorithm has better performance than EA-MCDS-UDG.

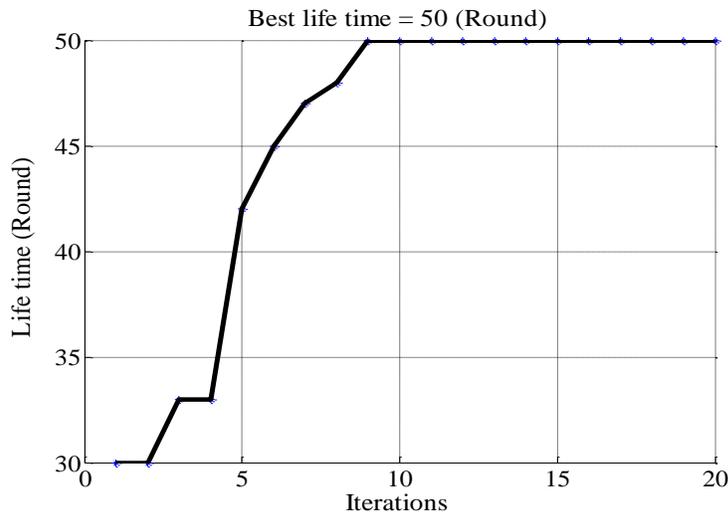Figure 6 shows the convergence of PSO algorithm in this scenario.

Figure 6. Convergence of PSO Algorithm in Scenario 1

It is obvious from Table 3 that in scenario 2, proposed algorithm has better performance than EA-MCDS-UDG in terms of total number of live nodes.

Figure 7 shows the total number of nodes that remain alive over the simulation runs in mentioned scenarios and EA-MCDS-UDG.
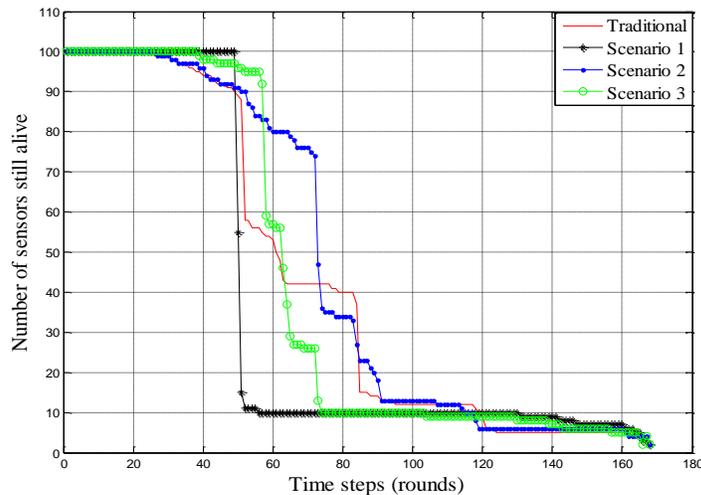
Figure 7. Number of Live Nodes per Round in Different Scenarios and EA-MCDS-UDG

7. Conclusion

In this paper, we proposed an energy efficient backbone formation algorithm to effectively preserve the energy of nodes in order to extend the network lifetime. The main goal of proposed algorithm is to determine the degree and energy constraint of dominating set (DS) nodes to extend the network lifetime. For this reason, we used particle swarm optimization (PSO) algorithm to determine optimal coefficients of maximum effective degree and minimum residual energy of nodes. When constructing the DS in proposed algorithm, we prioritized selecting the nodes that have more energy than coefficient of minimum residual energy and less degree than coefficient of maximum effective degree. Simulation results demonstrate that the proposed algorithm has better performance than EA-MCS-UDG and DEBB in terms of network lifetime.

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