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Energy-Efficient Routing Mechanism for Mobile Sink in Wireless Sensor Networks Using Particle Swarm Optimization Algorithm

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Abstract
One of the most effective approaches to increase the lifetime of wireless sensor networks (WSNs), is the use of a mobile sink to collect data from sensor. In WSNs, mobile sinks implicitly help achieving uniform energy-consumption and provide load-balancing. In this approach, some certain points in the sensors field should be visited by the mobile sink. The optimal selection of these points which are also called rendezvous points is a NP-hard problem. Since hierarchical algorithms rely only on their local information to select these points, thus the probability of selecting an optimal node as rendezvous point will be very low. To address this problem, in this paper, a new method called particle swarm optimization based selection (PSOBS) is proposed to select the optimal rendezvous points. By applying PSO, the proposed method is capable of finding optimal or near-optimal rendezvous points to efficient management of network resources. In the proposed method, a weight value is also calculated for each sensor node based on the number of data packets that it receives from other sensor nodes. The proposed method was compared with weighted rendezvous planning based selection (WRPBS) algorithm based on some performance metrics such as throughput, energy consumption, number of rendezvous points and hop count. The simulation results show the superiority of PSOBS as compared with WRPBS, but it increases the packet loss rate in comparison with WRPBS.

Keywords Mobile sink · Particle swarm optimization · Multi-hop connection · Wireless sensor networks · Clustering

1 Introduction

Wireless sensor networks (WSNs) are consist of a large number of wireless sensor nodes which are deployed in a field to collect data. These sensor nodes are equipped with sensor devices which have limited processing power and wireless communication capabilities.

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WSNs are the best choice to observe the environment, monitoring and security purposes [1–3]. Regarding the existing advances for WSNs, sensor nodes to supply their energies are still depend on low-power batteries. Also, because of employment of WSNs in the inaccessible environments, it is impossible to recharge or replacement the battery of sensor nodes. Due to these constraints, optimal energy management is one of the most important problems in WSNs. Thus, to develop a new protocol in this kind of networks, the network lifetime improvement requirements should be considered [4–7].

Regarding the WSNs literatures, network lifetime is defined as the time at which the first network node runs out of energy to send data. Usually, data generated by sensor nodes are transmitted via multi-hop communication to the sink. In such a network, if a node spends most of its battery power to relay the packets of other sensor nodes, its battery power will be depleted and the node will die. As a result, it will be disconnected from the network which this problem in turn will lead to the loss of network coverage and connectivity. One approach to address this problem, is the use of mobility in the sensor networks, for example, the use of a mobile sink or a mobile agent to collect data from sensor nodes [8].

In the mobile sink based approaches [9–12], the mobile sink moves around the network area and visits some rendezvous points. The selection of optimal rendezvous points for the mobile sink, is one of the challenging problems in wireless sensor networks. As in the hierarchical approaches, these points are only selected based on local information, so the probability of selecting an optimal sensor node as a rendezvous point is very low. This problem can be solved by applying optimization algorithms. Various optimization algorithms such as particle swarm algorithm (PSO) [13], shuffle frog leaping algorithm (SFLA) [14], genetic algorithms (GA) [15] and cuckoo optimization algorithm (COA) [16] have been proposed to solve different optimization problems. In this paper, we have used PSO algorithm to select the optimal rendezvous points.

The main goals of this paper, are to reduce the energy consumption and packet loss rate (PLS) in the mobile sink based WSNs. In the proposed method, a new clustering approach based on PSO algorithm is proposed to cover the entire network and to reduce the end-to-end delay. Our proposed clustering algorithm, determines a set of optimal rendezvous points for the mobile sink. Also, the proposed method tries to minimize the number of rendezvous points for the mobile sink. Briefly, the main contribution of this paper are as follows:

- We made a survey about mobile sink and PSO based routing mechanism for WSNs.
- We proposed an energy efficient PSO based routing scheme for WSNs (PSOBS).
- We performed extensive simulation and comparison with WRPBS scheme.

The rest of the paper is organized as follows. In Sect. 2, an overview of routing mechanisms for static sink and mobile sink based wireless sensor networks are provided. The proposed method is explained in Sect. 3. The simulation results are presented in Sect. 4 and finally Sect. 5 concludes this paper.

2 Related Works

In this section, an overview of existing routing protocols for static sink and mobile sink based wireless sensor networks are described.

2.1 WSNs Based on Static Sink

In wireless sensor networks, to forward the data packets from source node to the sink, a multi-hop connection should be established. As a result, the energy consumption and packet sending time depend on the communication distance. One approach to reduce the communication distance is the use of multiple static sinks [17] and planning the sensor nodes to send their data to the nearest static sink. This approach reduces average length of the path from sensor nodes to the sink and as a result, decreases the energy consumption and delay in comparison with one static sink case. Furthermore, by this method the traffic load will be distributed among the sensor nodes deployed in neighborhood of the static sinks.

In [17, 18], the use of multiple static sinks has been proposed by the authors. These static sinks, divide the network into several subnets, each of which with one static sink. One of the challenges by this approach, is the proper placement of static sinks in the network. Vicze et al. [19], have examined this problem and proposed an optimal method to divide the network environment.

By segmentation of sensors field, some advantages of multiple static sinks can be achieved by the use of a single static sink. In the segmentation of sensors filed which is also called clustering, selecting a cluster head in each section (or cluster) is a challenging problem. Clustering can be performed as multi-level hierarchy. In [20], to reduce the amount of data sending to the sink, data aggregation can be performed at each cluster head node. Furthermore, the cluster head selection process can be performed in a random manner [21] or based on deterministic strategies [22].

2.2 WSNs Based on Mobile Sink

To overcome the weaknesses of the static sinks, the use of mobile sinks have been proposed by authors [23]. Usually, a mobile sink follows different mobility patterns in the sensors area including random mobility, fixed/predictable mobility and controlled mobility.

In [8], the main problem is to find a set of RP nodes to be visited by a mobile sink. The main goal of this method, is to reduce the energy consumption by decreasing the number of multi-hop transmissions from sensor nodes to the RPs. The next problem in this method is to determine an optimum tour which visits all the RPs. In this approach, a heuristic is used to find a near-optimal tour which minimizes the energy consumption of the sensor nodes. In [24], the authors presented a PSO based clustering algorithm with mobile sink for WSNs. They used the virtual clustering technique during routing process. To select cluster head, the algorithm uses the residual energy and position of the nodes. In [25], the authors presented cluster-based schemes with multiple mobile sinks for load balancing by a modified multi-hop layered model. For delay-tolerant application, RPs and RNs are utilized to realize the goal of optimal energy consumption through a heuristic algorithm. In [26], the authors proposed a novel tree-based power saving scheme to reduce the energy consumption in WSNs with mobile sink. They used a dynamic sorting algorithm to create a tree-cluster routing structure for the sensor nodes in WSNs. The proposed scheme improved the routing structure based on the location of mobile sink, the distances between the sensor nodes, and the residual energy of each sensor node. In [27], the authors proposed two algorithms for designing efficient trajectory for mobile sink, based on RPs. They used k-means clustering in two proposed scheme and in order to selecting the efficient RPs a weight function proposed by considering several network parameters by ensuring the coverage of the entire network.

3 Proposed Mechanism

The mobility of the sink node in wireless sensor networks, is very valuable, because it makes possible to collect data directly from the sensor nodes. In this case, one of the main challenges is to calculate the optimum route for the mobile sink. In this section, a new algorithm is proposed to determine the path for the mobile sink. This algorithm aims to reduce the tour length to be traveled by the mobile sink and as the result to reduce the end-to-end delay. Furthermore, the proposed algorithm minimizes the number of clusters. In the proposed method, TSP (traveling sales person) algorithm is used to determine the optimal tour in which RP nodes is assumed as cities and edges specifies the Euclidean distance between the RP nodes.

A mobile sink can collect data from the sensor nodes in two real-time or non-real-time modes. In the real-time mode, the mobile sink moves around the network and data is transmitted from current location to the mobile sink. But in the non-real-time mode, before collecting data by periodic visits of the mobile sink, data is buffered in certain nodes.

In our proposed method, the non-real-time data collection is applied, so that by reducing the length of TSP tour, the packet delivery delay is also reduced. The mobile sink travels on a TSP tour and collects data from the sensor nodes which have been selected as a cluster head. A cluster head, buffers the data generated by its cluster members until the mobile sink reaches it. Thus, when the mobile sink arrives, data is transferred to it using a single-hop communication. Figure 1 shows the flowchart of proposed scheme.

3.1 System Architecture

In the proposed method, it is assumed that the sensor nodes are randomly distributed in a rectangular area. There is no assumption about network connectivity or coverage. The sensor nodes have radio transceivers and their buffer capacities are limited. The proposed architecture avoid from multi-hop routing, i.e. the sensor nodes do not produce any routing overhead. The mobile sink moves through a pre-determined path and collects data and recharges its battery if needed, and this process is repeated.

The input of the algorithm is the set of sensor nodes and their radio ranges. A set of clusters and their centers are generated as output. These centers are used to calculate the TSP tour and to obtain the shortest path for the mobile sink. A sensor node located at (x_i, y_i) is covered by a circle with center (x_c, y_c) which the Euclidean distance between these two points should satisfy the condition in Eq. (1).

$$\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \le R \tag{1}$$

where R is the radio range of a sensor node. The proposed method, checks for each node to see whether it is within a circle or not. As this condition is checked for all the sensor nodes, thus ensures that each node will surely be covered by a cluster. When a sensor node is covered by a cluster node, it will be removed from the set of unclustered nodes. As a result, each sensor node will only be located in one cluster, and as a result there will not be any

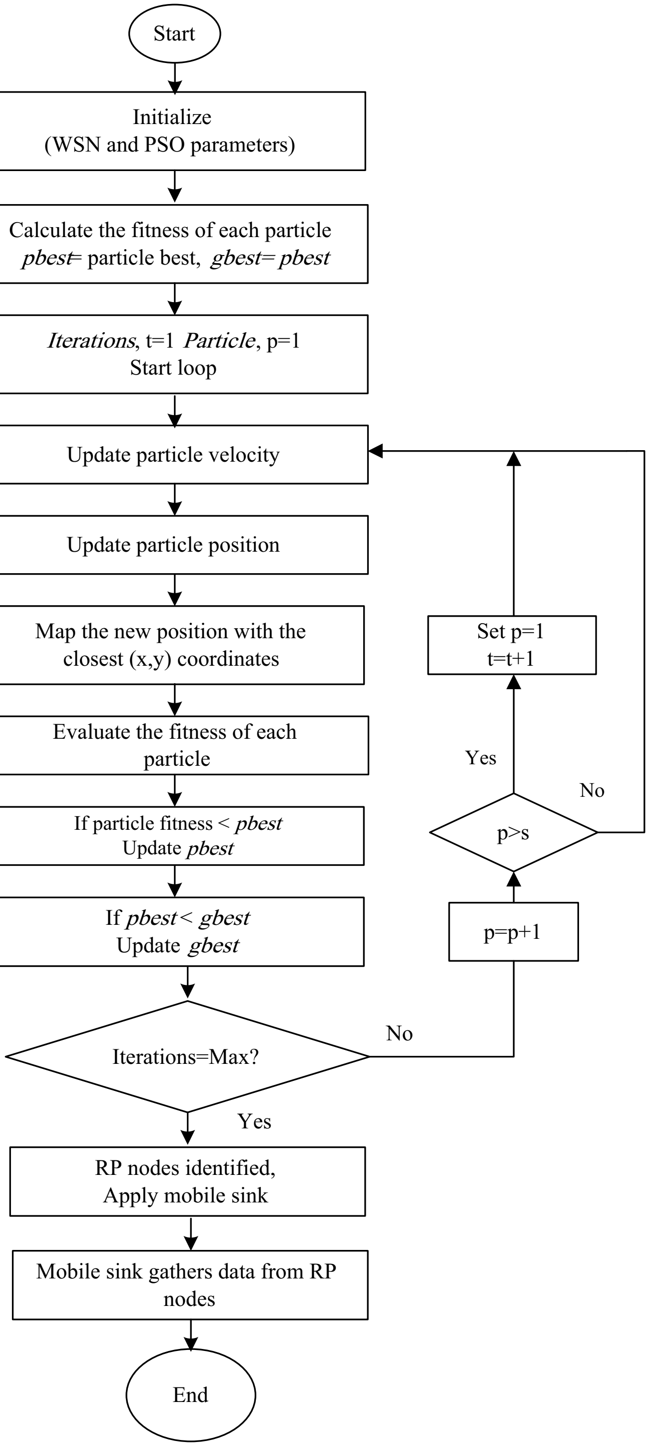


Fig. 1 Flowchart of the proposed scheme

overlapping among clusters. According to this method, data collection steps by the mobile sink are as follows:

- Clusters and their centers are obtained.
- The cluster centers form a TSP tour.
- The mobile sink starts from a point on the tour and visits cluster centers which are rendezvous points.
- At each rendezvous point, the mobile sink communicate with sensor nodes which are within that cluster, collects their data and moves on.
- When the mobile sink comes back to the starting point, it will recharge its battery, if needed.

A model diagram for an RP based data collection by the mobile sink is presented in Fig. 2.

3.2 Proposed Method Based on Mobile Sink

In the proposed method, a new clustering algorithm based on the particle swarm optimization algorithm called PSOBS is proposed to select the RP nodes. It is assumed that the sink is aware of the location of all sensor nodes (through GPS or by sending a message containing location information from sensor nodes to the sink). In this case, the sink can determine the distance between any two nodes and it can also identify the neighbors of each node by using the nodes transmission ranges. Accordingly, the sink will be able to create the TSP tree without sending any message between nodes and also to establish the shortest path from one node to another.

On the other hand, to compute a weight value for each sensor node, the number of neighbors of each sensor node (i.e., one-hop children) is required. In the proposed method, the sink can calculate the weight of each sensor node without any need to exchange specific information. So, the weight of node i is calculated using Eq. (2):

$$W_i = e^{-(|NFD - Sigma|)} \tag{2}$$

where sigma shows the optimal number of nodes that each node can ideally communicate. Also, NFD shows the number of packets that each node receives from its children

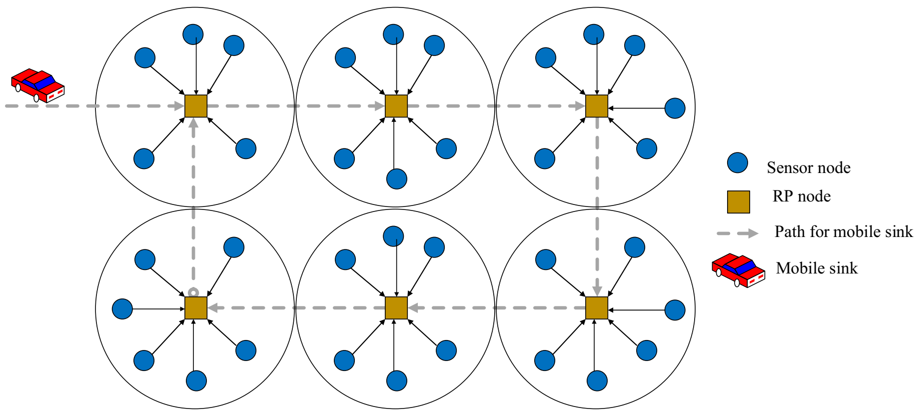


Fig. 2 WSNs with mobile sink and RP

according to TSP tree. In the proposed algorithm, the sink or base station node, runs PSO algorithm, specifies the RPs and by sending a packet to each node, it also specifies nodes type (whether RP or not). Furthermore, it determines the path from each node to the closest RP. To do this, the sink node advertises intermediate nodes *IDs* along the path by sending a packet to each node.

3.3 Particle Swarm Optimization

In PSO algorithm, a set of solutions are randomly generated in which each solution represents a bird or a particle in the problem space. Each solution is defined as an array which its length is equal to the number of sensor nodes in the network. For example, Fig. 3 shows a random solution in the proposed algorithm, where number 1 and 0 stands for the RPs and member nodes, respectively. In this figure, the total number of nodes is equal to 7 (N = 7) and nodes 1, 5 and 6 are selected as RPs.

After generation of random solutions, a fitness value is calculated for each one. In the proposed method, each particle is assigned a fitness value which is calculated using an objective function. The objective function of particle *p* in the proposed method is defined using Eq. (3):

$$\begin{gathered} Fit_p = c_1 * \left(\frac{\sum_{i=1}^{NRP} W_i}{NRP} \right) + c_2 * e^{-(|RPR-NRP|)} + c_3 * e^{-\left(\left|L_{max}-P_{cost}\right|\right)} \\ |c_1| + |c_2| + |c_3| = 1 \end{gathered} \tag{3}$$

where NRP is the number of RPs in the random solution and RPR is the expected number of RPs which is calculated using Eq. (4):

$$RPR_p = \frac{n}{sigma} \tag{4}$$

where n shows the total number of network nodes. Also, in relation (5), L_{max} is the maximum tour length and Pcost is length of the route passing through randomly selected RPs which is calculated by using TSP algorithm.

Each particle or solution in PSO algorithm, is updated using two values. The first value is the best position that the particle has ever experienced. This value is called the best personal experience or Pbest. The second value is the best position ever achieved in the population. This second value is called the best global position or Gbest. When these two values were found, the position and speed of each particle are updated by Eqs. (5) and (6), respectively:

$$V_i(t+1) = wV_i(t) + c_1 r_{1,i}(t)\left(P_i(t) - X_i(t)\right) + c_2 r_{2,i}(t)\left(P_g(t) - X_i(t)\right) \tag{5}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{6}$$

Fig. 3 An example of a random solution in the proposed algorithm

1	2	3	4	5	6	7
1	0	0	0	1	1	0

a	b	c	d	e	f	g	h	i	j	Current position
0	1	2	3	4	5	6	7	8	9	best personal experience
A	B	C	D	E	F	G	H	I	J	best global position among all birds

a	b	c	3	4	5	6	H	I	J	Offspring1
A	B	C	d	e	f	g	7	8	9	Offspring2
0	1	2	D	E	F	G	h	i	j	Offspring3

Fig. 4 Uniform crossover

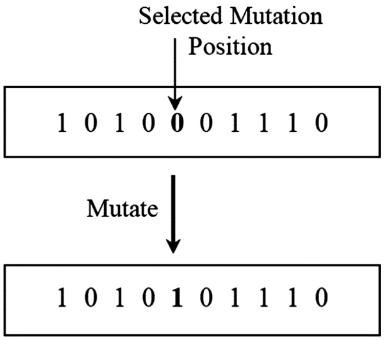


Fig. 5 A solution before and after mutation

In the above equations, t represents the number of iterations and c_1, c_2 variables are learning factors. In PSO algorithm, the particle population is initialized randomly and until the termination condition is reached, fitness of the solutions are calculated repeatedly and Gbest, Pbest, speed and position of the particles are updated, accordingly. Finally, the Gbest solution and its fitness will be considered as the output. In the proposed method, Gbest determines the RP nodes.

The relationships (6) and (7), are used to improve the position of a particle in the continuous optimization problems. As clustering is a discrete optimization problem, has to improve the position of each particle in the proposed method, a genetic algorithm operator called uniform crossover is used.

In PSO algorithm, to improve the position of a particle three values are considered: (1) the current position of the particle, (2) the best position that the particle has ever experienced and (3) the best position obtained among all particles. Thus, to perform crossover, we need to use a crossover operator which includes the above three values. One of the most known types of crossover, is called uniform crossover. This operator is an extension to single point crossover. For n parents, by choosing $n-1$ displacement points and selecting the genes between these points, the offspring chromosomes are created. For example, this process for $n=3$ is shown in Fig. 4.

After performing crossover, the mutation operator is applied on solutions (particles). This operator selects a gene from a particle randomly and changes its content. For example, in Fig. 5, the mutation operator is applied to the fifth gene and changes its value to 1. After mutation, the generated solutions are considered as new offspring and are passed to the next generation.

3.4 Energy Consumption Model

In WSNs, the energy is consumed for sensing, data processing and communication. In this paper, we only considered energy consumption during data communication and we used the first order radio model as energy consumption model. Based on the distance between sender and receiver nodes (d), a free space or multipath fading channel model will be used for energy consumption. The energy consumption to send K bits of data to distance d is calculated by Eq. (7) [28]:

$$E_{tx}(K,d) = \begin{cases} K \times E_{elec} + K\varepsilon_{fs} \times d^2 & d < \mathrm{d}_0 \\ K \times E_{elec} + K\varepsilon_{mp} \times d^4 & d \geq \mathrm{d}_0 \end{cases} \tag{7}$$

where E_{elec} is the required energy for circuit's activation, ε_{mp} and ε_{fs} are the energy model of relay activation for multi-path channels and empty space, respectively. d^2 power loss is for a free space and d^4 power loss is for multipath fading. In Eq. (7), d_0 is constant value whose value can be calculated from Eq. (8) as follow:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{8}$$

Also, the required energy to receive K bits of data is calculated as follows by Eq. (9):

$$E_{Rx}(K,d) = K \times E_{elec} \tag{9}$$

It is assumed that at each period, each cluster head receives only one packet from its cluster members. Also, after receiving all packets from its members, the cluster head combines their useful information into a single packet and reports it to the sink using a multi-hop communication. The energy consumption for combining data at each cluster head node is calculated using Eq. (10):

$$Eda_V = \mathrm{NM}_v \times \mathrm{k} \times \mathrm{EDA} \tag{10}$$

where NM_v is the number of members of cluster head v and EDA is the cost of combination per one bit of data.

4 Simulation Results

In this section, the performance of the proposed PSOBS algorithm is evaluated and compared with WRPBS [8] algorithm. For this purpose, we have considered number of rendezvous points, average memory consumption, number of hops, packet loss rate, standard deviation (SD), throughput, and energy consumption metrics for comparison. Both PSOBS and WRPBS [8] algorithms have been implemented using MATLAB. In the implementation, following assumptions have been considered:

- The network topology is a rectangular area, sensor nodes are randomly distributed, and there is not any obstacle in the area.

- Each sensor node has limited capacity to buffer the data until the mobile sink reaches it and data production at each node follows a Poisson distribution.
- As a sensor node transmits its data to the mobile sink through a one-hop communication, thus there is no need to routing and relaying the data.
- Mobile sink has enough buffer capacity for at least one round trip, also it can recharge its battery, if needed.

The simulation parameters used to analyze the performance of the above mentioned algorithms are listed in Table 1.

4.1 Number of Rendezvous Points

To guarantee the scalability and to increase the network throughput, the entire network should be divided into several clusters such that the number of clusters are minimized. Thus, the algorithm which is capable of clustering the network with less number of rendezvous points, will achieve better performance in term of different performance metrics. Regarding Fig. 6a, b, the proposed algorithm generates less number of clusters (i.e., less RPs) as compared to WRPBS [8] algorithm. As a result, with reducing the number of hops, the tour length will also be reduced.

4.2 Number of Hops

A lowest number of hops, show that the algorithm has better performance in term of scalability, packet delay, and consequently reducing the probability of packet loss at the RP nodes. In the proposed method, it is assumed that the hop count value for RP nodes is equal to 0, for the child of the RPs is equal to 1 and etc. According to Fig 7a, b, for the node number of 20 or 30 and maximum tour length of 100 or 150, the proposed algorithm achieves better performance than WRPBS [8] algorithm.

Table 1 Simulation parameters

Parameter	Value
Number of nodes (N)	20, 30
Transmission range (R)	30 m
Mobile sink speed (V)	1 (m/s)
Tour length (TL)	100 m × 150 m
Initial energy	0.5 j
E_{elec}	50 nj/bit
ε_{fs}	10 pj/bit/m^2
ε_{mp}	0.0013 pj/bit/m^4
Distance threshold (d_0)	$\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$
Packet size	512 byte
C_1, C_2, C_3	0.4, 0.3, 0.3
Simulation area	100 m × 100 m

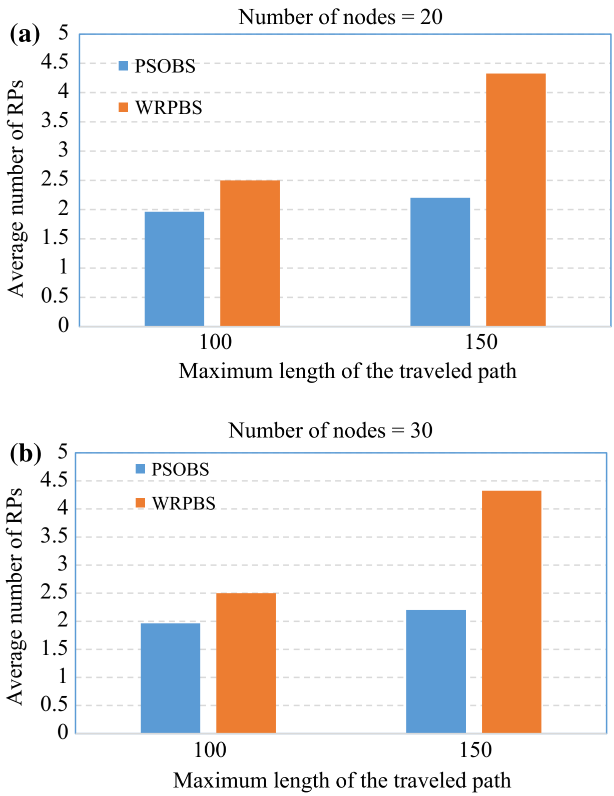


Fig. 6 Number of RPs versus Maximum tour length

4.3 Packet Loss Rate (PLR)

Packet loss rate depends strictly on some factors such as the number of hops and the number of RP nodes. Figure 8a, b shows the packet loss rate for the node number of 20 and 30 for both PSOBS and WRPBS [8] algorithms. Although, the proposed algorithm has fewer number of hops, but it shows relatively poor performance than WRPBS [8] in term of number of unserved packets. It is due to the reason that WRPBS [8] selects more number of RPs than our proposed algorithm.

4.4 Standard Deviation (SD)

SD metric which is used to determine the imbalance between the energy consumption of sensor nodes, is calculated as follows:

$$SD = \sqrt{\frac{\sum_{i\in V} (EN[i] - \mu)^2}{|V|}} \tag{11}$$

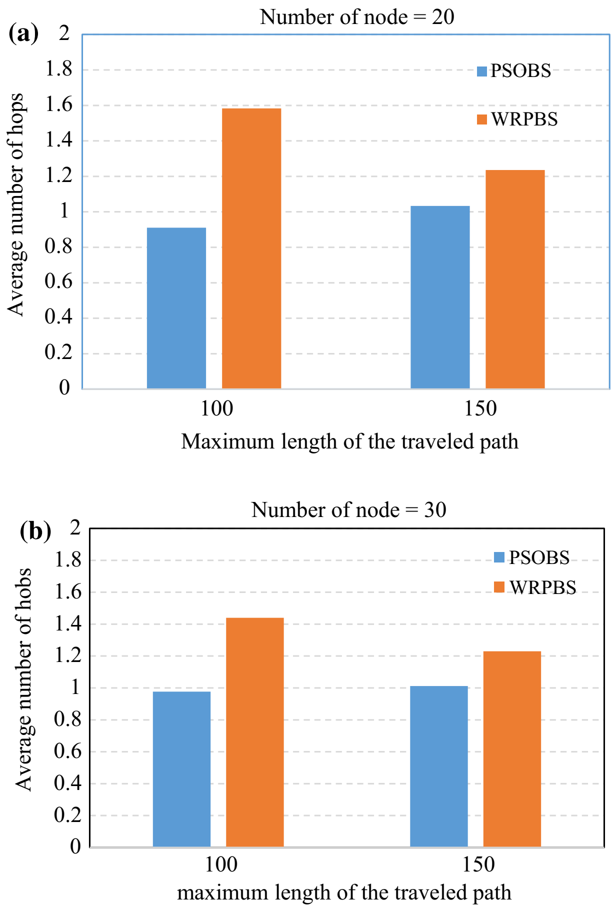


Fig. 7 Number of hops versus maximum tour length

where EN[i] is the energy consumption of node i, μ is the average energy consumption by all the sensor nodes and |V| is the number of nodes in the network. Lower values for SD indicates better performance in term of load balancing. According to Fig. 9a, b, the proposed algorithm achieves better SD as compared to WRPBS [8] algorithm.

4.5 Throughput

Throughput is usually defined as the number of delivered bits or sometimes as the number of data packets received per unit of time. According to Figs. 10 and 11, our proposed algorithm outperformed WRPBS [8] algorithm in term of throughput.

4.6 Energy consumption

The main goal of WSNs is to prolong the lifetime of the network. This is possible by reducing the energy consumption of the sensor nodes. A clustering algorithm is capable

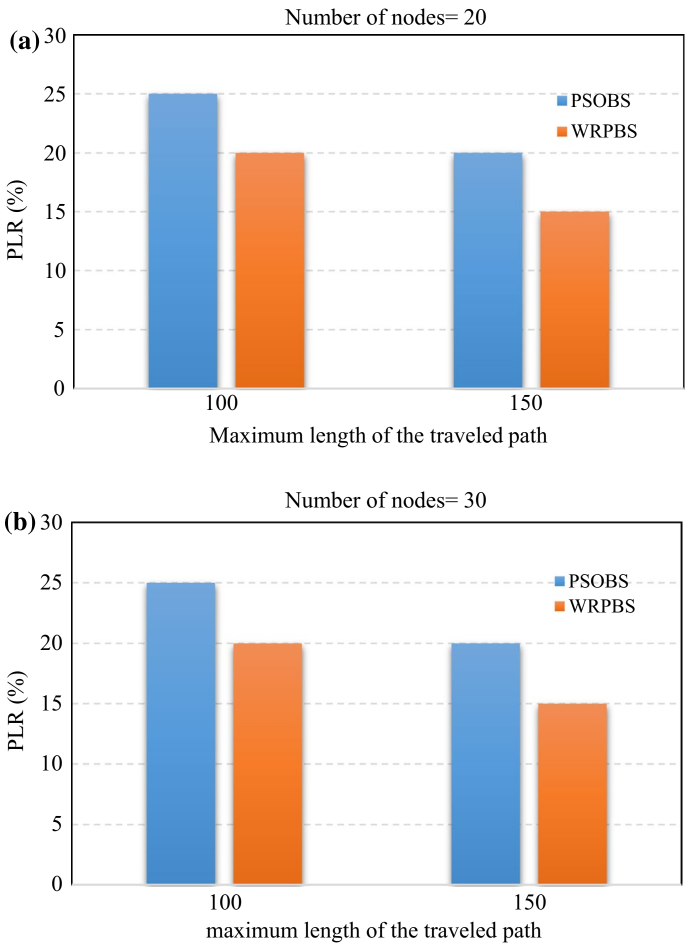


Fig. 8 Comparison of Packet Loss Rate (PLR)

of reducing the energy consumption only when it can balance the traffic load between the cluster head nodes. According to Figs. 12, 13, 14 and 15, the proposed method has less energy consumption as compared to WRPBS [8] algorithm. Although, WRPBS [8] algorithm generates more RPs, but the proposed method still achieves better performance in different node numbers and tour lengths.

5 Conclusion

Recently, the use of a mobile sink have been widely studied by researchers to balance the time and energy consumption in the wireless sensor networks. In most of these studies, a static base station has been used as the sink node. By this approach, the energy of sensor nodes located in the neighborhood of sink node will be depleted faster. To address this weakness, the use of a mobile sink can be very effective and efficient. In this paper, a new method based on particle swarm optimization (PSO) was proposed to support the mobile

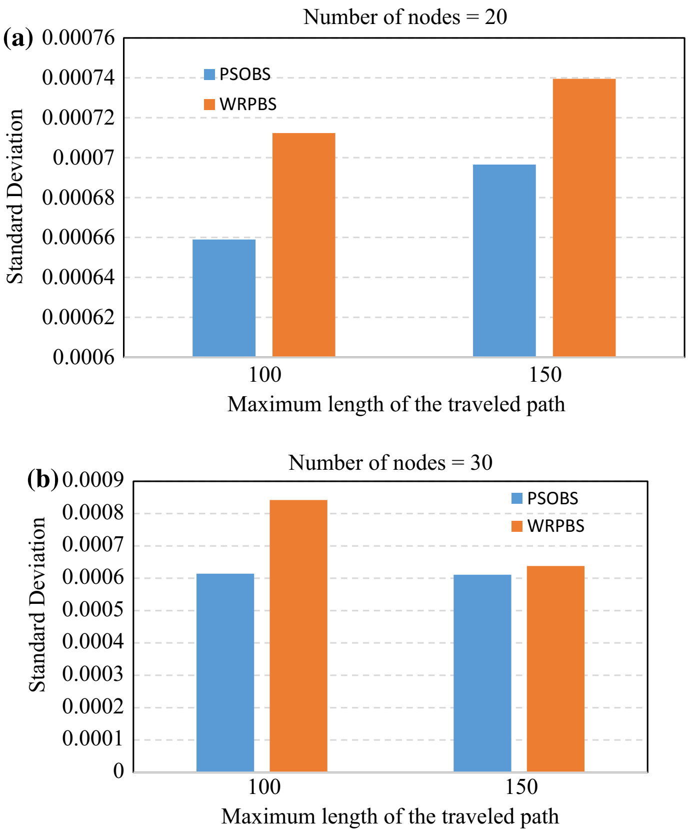
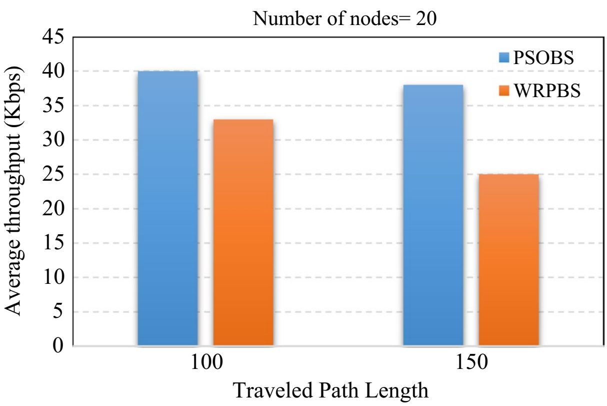


Fig. 9 SD versus maximum tour length

Fig. 10 Throughput versus maximum tour length



sink. The proposed method consists of two main phases. In the first phase, the optimal rendezvous points are selected and in the second phase, the optimum route is calculated through these rendezvous points. The proposed algorithm was compared with WRPBS [8]

Fig. 11 Comparison average throughput

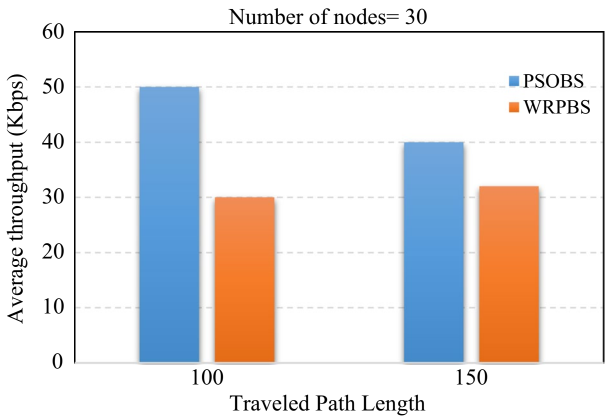
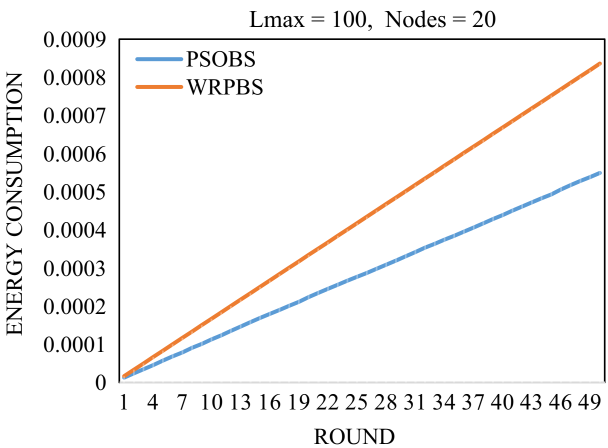


Fig. 12 Energy consumption for number of nodes = 20 and tour length = 100



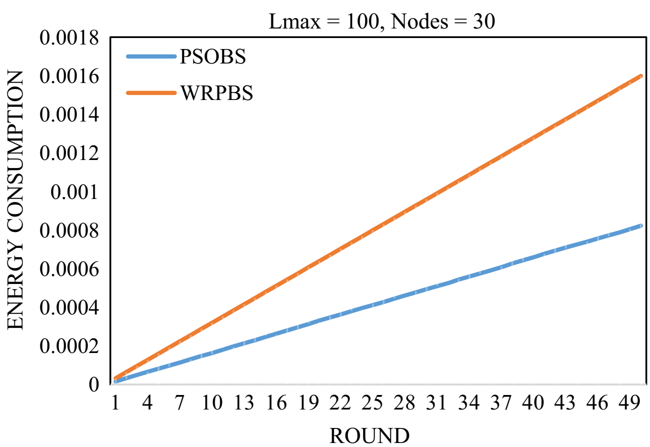


Fig. 13 Energy consumption for number of nodes = 30 and tour length = 150

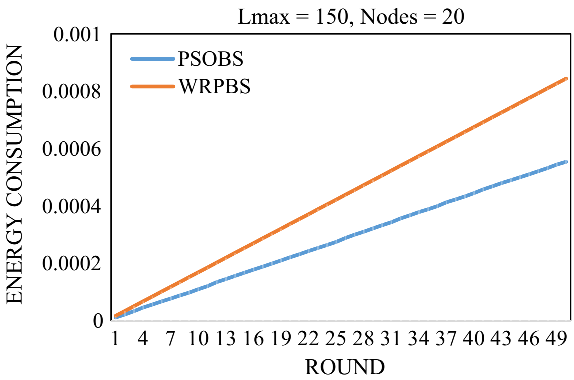


Fig. 14 Energy consumption for number of nodes = 20 and tour length = 150

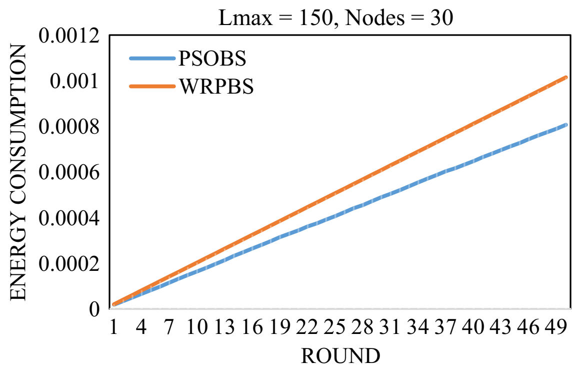


Fig. 15 Energy consumption for number of nodes = 30 and tour length = 150

algorithm based on different parameters such as throughput, energy consumption, rendezvous points and hop count. The simulation results show that the proposed method achieve better performance as compared to WRPBS [8]. In the future, we will use other optimization algorithms such as firefly for improving the proposed scheme.

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