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Fuzzy PSO-based algorithm for controlling base station movements in a wireless sensor network

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Abstract: There are strong limitations on the software, energy, and hardware capacities of a wireless sensor network (WSN) and therefore algorithms that increase the lifetime of a WSN are of great significance. In this paper, a mobile base station movement control strategy for WSNs is proposed. This strategy combines fuzzy logic node clustering, fuzzy cluster-head selection, and fuzzy logic control (FLC) of the base station movements. After determining cluster-heads, according to the distance and energy of the heads, the base station moves on a predefined square, triangle, circle, or hexagon shaped path. Direction and speed of the movements are controlled by FLC. In addition, a particle swarm optimization (PSO) algorithm is applied to optimally calculate the number of clusters, path shape and size, and the base station's speed vector amplitude and direction. The proposed strategy is numerically simulated for a WSN with randomly distributed nodes. The fuzzy clustering algorithm of this paper is compared with other conventional clustering methods. Moving the base station by the proposed FLC is also compared with a static base station. Results confirm substantial improvement in the lifetime of the moving base station WSN.

Key words: Mobile base station, wireless sensor network clustering, network lifetime, fuzzy control, particle swarm optimization

1. Introduction

A wireless sensor network (WSN) consists of many sensors (nodes) and one or several base stations (sinks). Sensors collect data from the environment and transfer them to the base station. Wireless sensor networks have many applications in environmental monitoring: robotics [1], medical purposes [2], traffic control [3], and supervision systems.

Sensors of WSNs have limited battery capacity and hardware, and usually they are fed by renewable energy sources to power up their sensors and electronics [4]. Most of the energy consumption is in data transfer with other nodes and the base station where several commutation and network routing algorithms are used [5]. To reduce energy consumption in the network, nodes are clustered and cluster-heads are selected using an optimum criterion. In every data transfer round (DTR), each node sends data to the cluster-head, then cluster-heads collect all the data and forward them to the base station. According to this, the base station repeats the clustering algorithm and selects new cluster members and cluster-heads. Finally, clustering results are transmitted to the nodes. Figure 1 illustrates the data transfer direction in a WSN.

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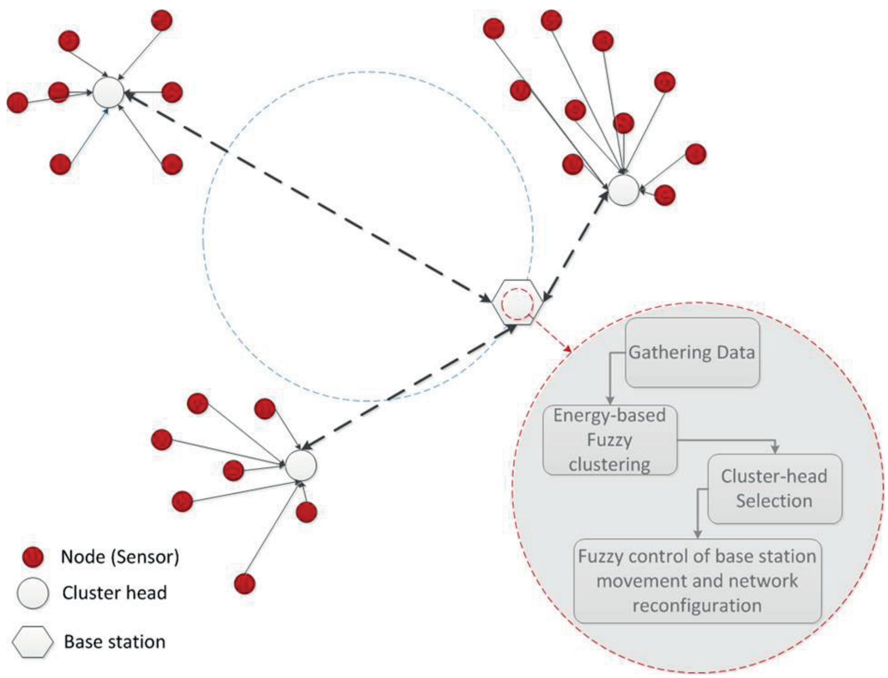

Figure 1. Data transfer direction and base station tasks in a WSN.

In [6], the base station moves toward the cluster-heads, which reduces the clusters' communication load (energy consumption). After clustering and at the beginning of a DTR, each cluster-head sends its position, number of cluster nodes, and energy levels to the base station. Then the base station uses a fuzzy algorithm to determine the cluster-head with the highest priority and moves towards it. After moving to new position, the base station coordination is reported to the network nodes and then cluster-heads transfer new data to the base station. The authors of [7] utilized fuzzy logic to prioritize clusters in each DTR. Then the base station moves toward the cluster-head with the highest priority on a predefined rectangular path. Simulations show that this method increases the network lifetime.

Cluster-heads that are close to the base station have heavier data traffic and therefore, after a while, they lose their energy or, in other words, they die. In this paper, WSN lifetime is defined as the time period over which one of the nodes consumes all its energy. Some studies [8,9] suggested the periodic movement of the base station on a circular path to reduce the energy consumption of nodes. In [10] fuzzy energy-aware unequal clustering (EAUCF) is applied to increase the WSN's lifetime. By using EAUCF, clusters farther from the base station are larger than closer clusters. The authors of [11–14] used fuzzy clustering methods to increase the WSN's lifetime. It should be noted that, besides clustering methods, optimal data transmission path management algorithms such as that in [15] are also used in WSNs to decrease energy consumption.

In this work, a new algorithm is proposed for controlling base station movements. First, a fuzzy logic-based method for selecting cluster-heads based on energy levels and distance from the base station is developed. Then a fuzzy controller is used to manage the direction and speed of the base station movements on a predefined path. Furthermore, a PSO algorithm optimizes the number of clusters, the predefined path shape and size, the direction, and the speed of the base station.

In Section 2, details of the proposed algorithm are discussed. Numerical simulation results are given in Section 3, where PSO is used to determine the optimal path of the base station. Advantages of the proposed algorithm in reducing energy consumption and increasing the network's lifetime are verified by several graphs.

2. Base station movement algorithm

In this section, node clustering, cluster-head selection, and base station movement algorithms are presented. First, by considering K clusters, fuzzy clustering is applied to the network nodes and they are divided into K clusters. Then, in each cluster, by utilizing a proper criterion, cluster-heads are selected. In each cluster, the node with higher energy and shorter distance to the base station has a higher fuzzy chance to be selected as the cluster-head. Nodes send data to the related cluster-heads and they transfer all the collected data to the base station. After head selection, the base station moves one step on a predefined path. Another fuzzy algorithm controls movement parameters. Finally, a PSO algorithm is applied to optimize path shape, path size, movement speed, and number of clusters. The following steps should be done in each DTR until one node loses all its energy.

Step 1 (node clustering): In the beginning of a DTR, the base station runs clustering and cluster-head selection algorithms. The fuzzy C-means clustering method (FCM) is one of the best fuzzy clustering algorithms. Bezdek first derived this algorithm in [16] and it is optimized compared to previous fuzzy clustering methods. In classic clustering methods such as K-means and C-means, each node belongs only to one cluster. However, in FCM nodes belong to clusters with a set of fuzzy membership functions. FCM utilizes the nodes' positions and number of clusters. Then it calculates the fuzzy degree of membership of a node to all clusters.

FCM attempts to partition n nodes, $S = \{s_1, s_2, \ldots, s_n\}$, to c fuzzy clusters with respect to a given criterion. FCM returns a set of cluster centers, $C = \{c_1, c_2, \ldots, c_c\}$, and a weight matrix $W = [w_j(s_i)]$, $i = 1, 2, \ldots, n$, $j = 1, \ldots, c$. $w_j(s_i) \in [0 \;\; 1]$ gives the membership degree of s_i to c_j. FCM has an iterative nature and it begins by assigning each node a random degree of membership to clusters, $w_j(s_i)$. Then it calculates the center of each cluster (c_j) via weighted averaging [16]:

$$c_j = \frac{\sum\limits_{s_i} w_j^m(s_i) s_i}{\sum\limits_{s_i} w_j^m(s_i)}. \tag{1}$$

The degree of membership of each node, $w_j(s_i)$, is inversely related to the distance of s_i from c_j. FCM repeats calculations of centers and degree of memberships until they stay almost constant in two consequent iterations. Finally, FCM assigns a node to the cluster with the largest membership and returns the final $w_j(s_i)$ and c_j.

Step 2 (selecting cluster-heads): Cluster-heads gather and combine all data from cluster nodes and forward them to base station. There are many methods for cluster-head selection; however, optimal methods reduce energy consumption in the WSN. In this paper, a fuzzy logic-based method is proposed to select cluster-heads. In this method, nodes with higher energy and smaller distance to the base station have a higher chance of being selected. Inputs to the fuzzy system are the normalized value of the nodes' energy and distance to the base station. The output is the priority of the nodes. Five triangular membership functions for inputs and output are used, which are defined in the domain $[0 \;\; 1]$. A singleton fuzzifier and center average defuzzifier are used. Table 1 shows the rule-base of the fuzzy system. Nodes with higher energy and smaller distance have a higher chance to be selected as the head.

Step 3 (data transfer and energy calculation): After clustering and selecting cluster-heads, the base station sends clustering information to the cluster-heads and consequently to the nodes. Then each node sends new collected data and its energy level to the head through a data packet with length L. Cluster-heads transmit the data to the base station, and all nodes calculate their current energy and update their status. Energy consumption of a node in a DTR (E_{TX}) depends on data packet length and the node's distance from the cluster-head:

Table 1. Fuzzy clustering rule-base. Input 1: Energy. Input 2: Distance. Output: Priority of the node. VL: Very large. L: Large. M: Medium. S: Small. VS: Very small.

Input 1	Input 2	Output	Input 1	Input 2	Output	Input 1	Input 2	Output
VS	VS	M	S	VL	VS	L	M	L
VS	S	V	M	VS	L	L	L	M
VS	M	S	M	S	L	L	VL	M
VS	L	VS	M	M	M	VL	VS	VL
VS	VL	VS	M	L	S	VL	S	VL
S	VS	M	M	VL	S	VL	M	L
S	S	M	L	VS	VL	VL	L	M
S	M	S	L	S	L	VL	VL	M
S	L	S						

$$E_{TX} = \begin{cases} L * E_{elect} + L * E_{fs} * d^2 & \text{if } d < d_0 \\ L * E_{elect} + L * E_{mp} * d^4 & \text{if } d >= d_0 \end{cases}, \tag{2}$$

where E_{elect} is consumed energy per bit, d is node distance from the cluster-head, and E_{fs} and E_{mp} are two energy constants. d_0 is the square root of E_{fs}/E_{mp}. The initial energy of a node is 1 J, $E_{elect} = 50nJ/bit$, $E_{fs} = 1$, and $E_{mp} = 1.3 \times 10^{-3}\, pJ/bit/m^4$. While energy consumption during data reception is not small, it is not considered in the literature. In this paper, energy consumption of a node for receiving data (E_{TX}) is taken into account as:

$$E_{TX} = L \times E_{elect}. \tag{3}$$

Step 4 (fuzzy control of base station movement): When the base station receives the new data and energy levels of the nodes, it moves to a new location. In this paper a fuzzy controller is developed, which manages the base station movements on a predefined path with a constant speed and in the proper direction. The lifetime of the WSN with a mobile base station is improved compared to a WSN with a static base station. Fuzzy controller inputs are the distance of the base station from each cluster-head and the energy of the cluster-heads. The output of the fuzzy system is the priority of cluster-heads. Inputs and outputs have 5 triangular membership functions, which are defined in $[0 \;\; 1]$. Nodes with lower energy and longer distance from the base station have a higher priority. The fuzzy controller uses a singleton fuzzifier, a center average defuzzifier, and the rule-base given in Table 2.

Table 2. Fuzzy controller rule-base. Input 1: Energy of cluster-head. Input 2: Distance from base station. Output: Cluster-head priority. VL: Very large. L: Large. M: Medium. S: Small, VS: Very small.

Input 1	Input 2	Output	Input 1	Input 2	Output	Input 1	Input 2	Output
VS	VS	M	S	VL	VL	L	M	S
VS	S	M	M	VS	S	L	L	M
VS	M	L	M	S	S	L	VL	M
VS	L	VL	M	M	M	VL	VS	VS
VS	VL	VL	M	L	L	VL	S	VS
S	VS	M	M	VL	L	VL	M	S
S	S	M	L	VS	VS	VL	L	M
S	M	L	L	S	S	VL	VL	M
S	L	L						

After calculating the priorities, the base station moves toward the head with the highest priority on the predefined path and then starts a new DTR. The proposed fuzzy controller decreases energy consumption of cluster-heads and therefore the network lifetime increases.

3. Numerical simulations

In this section, through MATLAB simulations, the advantages of the proposed algorithm are investigated and it is compared with other conventional methods. A WSN with static nodes is considered where nodes are randomly distributed in a 150×150 rectangle. The initial energy of nodes is 1 J. Movements of the base station on a rectangle, circle, triangle, and polygon are investigated. The lifetime of the network is defined as the time in which the first node loses all its energy. Figure 2 is related to the circular path shape with a diameter length from 10 to 70. In the following figures, the horizontal axis is the number of DTRs, and the vertical axis is the lowest energy of nodes. Based on Figure 2 and Table 3, diameter length 30 has the longest lifetime.

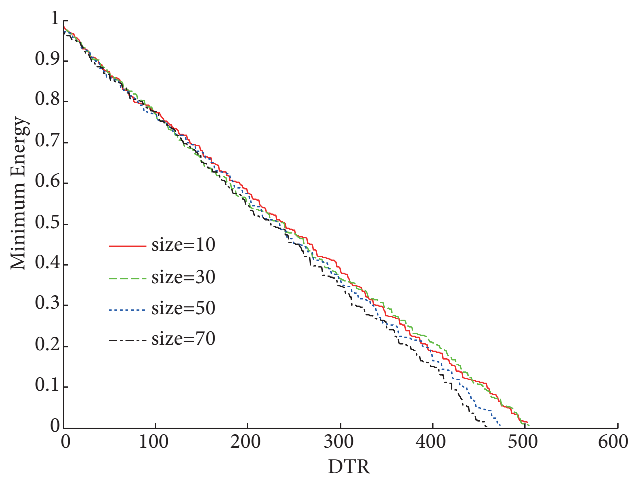

Figure 2. Energy variations of WSN with circular path shape of diameters 10, 30, 50, and 70.

Table 3. Network lifetimes for circular path shape of diameters 10, 30, 50, and 70.

70	50	30	10	Path size
459 DTR	473 DTR	505 DTR	503 DTR	Lifetime

In Figure 3, the base station speed under consideration moves on a circular path of diameter 30. Here, the speed is the distance that base station moves in each DTR to get closer to a selected cluster-head. Results are presented in Table 4. Speed 10 has the longest lifetime.

Similar simulations were repeated for rectangle, triangle, and hexagon shaped paths. Based on Tables 5 and 6, the optimal movement of base station is for the rectangle with side length 30 and speed 10. Tables 7 and 8 show that for a triangle shaped path, an equilateral triangle with sides of length 10 and movement speed 5 yields the longest lifetime of the network. In addition, an equilateral hexagon of side length 10 and movement speed 5 has the best result for a hexagon shaped path; see Tables 9 and 10.

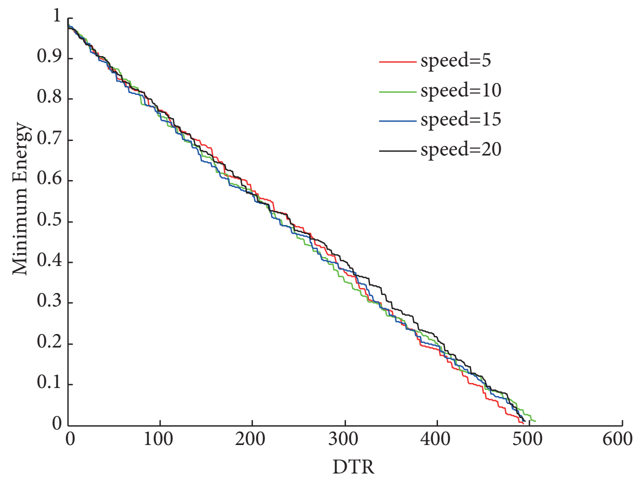

Figure 3. Energy variations of WSN with a circular path (of diameter 30) by speeds 5, 10, 15, and 20.

Table 4. Network lifetimes for circular path (of diameter 30) by speeds 5, 10, 15, and 20.

20	15	10	5	Speed
496 DTR	494 DTR	507 DTR	494 DTR	Lifetime

Table 5. Network lifetimes for rectangle path shape of diameters 10, 30, 50, and 70.

70	50	30	10	Path size
435 DTR	455 DTR	507 DTR	494 DTR	Lifetime

Table 6. Network lifetimes for rectangle path (of side length 30) by speeds 5, 10, 15, and 20.

20	15	10	5	Speed
481 DTR	474 DTR	513 DTR	511 DTR	Lifetime

Table 7. Network lifetimes for triangle path shape of diameters 10, 30, 50, and 70.

70	50	30	10	Path size
454 DTR	483 DTR	502 DTR	506 DTR	Lifetime

Table 8. Network lifetimes for triangle path (of side length 10) by speeds 5, 10, 15, and 20.

20	15	10	5	Speed
500 DTR	502 DTR	500 DTR	505 DTR	Lifetime

Table 9. Network lifetimes for hexagon path shape of diameters 10, 30, 50, and 70.

70	50	30	10	Path size
475 DTR	480 DTR	493 DTR	499 DTR	Lifetime

Table 10. Network lifetimes for hexagon path (of side length 10) by speeds 5, 10, 15, and 20.

20	15	10	5	Speed
499 DTR	500 DTR	505 DTR	507 DTR	Lifetime

In the following, the effects of network area size on the proposed method are investigated. Naturally, networks that have nodes farther from each other yield shorter lifetimes. This is shown in Table 11 where a 50 × 50 network has a longer lifetime. Comparison of Tables 3–10 (for a mobile base station) with the third column of Table 11 (for a static base station) shows a 6%–10.5% improvement in WSN lifetime.

Table 11. Lifetime versus network size for static base station.

200 × 200	150 × 150	100 × 100	50 × 50	Network size
350 DTR	464 DTR	576 DTR	597 DTR	Lifetime

The proposed fuzzy cluster head selection method is compared with the low-energy adaptive clustering hierarchy (LEACH) clustering algorithm [17,18]. LEACH is a hierarchical protocol in which most nodes transmit data to cluster-heads, and clusters-heads aggregate and compress the data and forward them to the base station. In the LEACH algorithm it is supposed that each node has a wireless communication system that is able to communicate with the base station or cluster-head. The communication system is the main energy consumer source in a node. Each node uses a stochastic algorithm at each DTR to determine whether it will become a cluster-head in this DTR or not. Each node s determines a random number between 0 and 1. If the number is less than a threshold $T(s)$, the node becomes a cluster-head for the current round. The threshold is set as follows:

$$T(s) = \begin{cases} \frac{P}{1-P\times\left(r \mod \frac{1}{P}\right)} & s < G \\ 0 & otherwise \end{cases}, \quad (4)$$

where P is the desired percentage of cluster-heads. Nodes that have been a cluster-head cannot become a cluster-head again for P DTRs. Thereafter, each node has a $1/P$ probability of becoming a cluster-head in each DTR. At the end of each round, each node that is not a cluster-head selects the closest cluster-head and joins the corresponding cluster. The cluster-head then creates a schedule for each node in its cluster to transmit its data. This algorithm ensures that every node becomes a cluster-head exactly once within $1/P$ rounds [19].

In Figure 4, a static base station is used and the proposed fuzzy cluster-head selection method is compared by LEACH and random cluster-head selection methods. An almost 14% improvement was seen in the network's lifetime for the proposed fuzzy clustering method compared to the LEACH method.

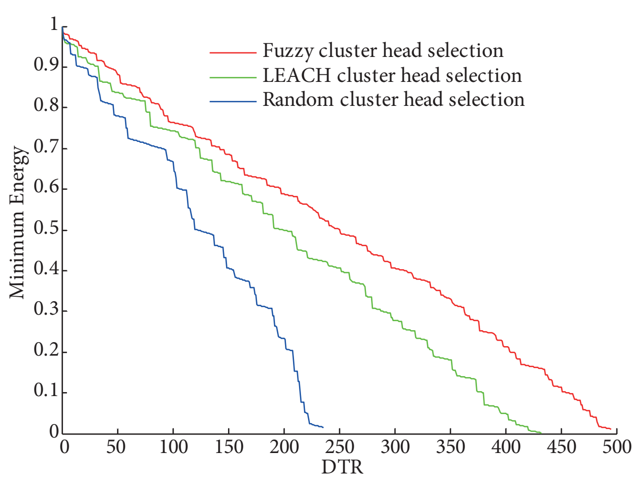

Figure 4. Network lifetime comparison of fuzzy, LEACH, and random clustering methods (in a static base station).

In order to gain the optimal parameters for clustering and base station movement, a PSO algorithm was applied to the fuzzy controller. The PSO and its modification are widely used for optimization of multiobjective cost functions [20,21]. This algorithm optimizes cost function by iteratively improving the last solution. In this paper, a 150 $\times$ 150 WSN using fuzzy clustering and a fuzzy controller for a base station with 100 nodes is considered. The number of clusters, base station path shape, path size, and movement speed are optimized. In PSO, 50 possible solutions or WSN parameter sets are considered, the algorithm is repeated for 50 iterations, and the inverse of the WSN lifetime is the cost function. In the first iteration of PSO, solutions (particles) are chosen randomly. In the consequent iterations, based on previous value of particles (especially their position and speed), PSO formulations, cost function, proposed fuzzy controller, and fuzzy clustering algorithm, particles are updated in each iteration to yield better performance. Iterations are repeated until the stop condition is satisfied. The final value of the particles is a good approximate of the minima of the cost function. Note that the PSO is offline and it has a large computation cost; however, it should be applied only once during the WSN parameter design phase. Optimization reduces energy consumption and increases the lifetime of the WSN. Simulation results are given in Figure 5. The left side of the figure shows the results of 2500 different solutions (particles) that are investigated by PSO. The vertical axis is the WSN lifetime. The right side of the figure shows the best particle during each of the 50 iterations of PSO. The best lifetime is 531 DTRs and it is related to 9 clusters, a hexagon path shape with side size 15, and optimal base station movement speed of 9. Optimal control of the mobile base station in the WSN yields almost 14% longer lifetime than the static base station of Table 11.

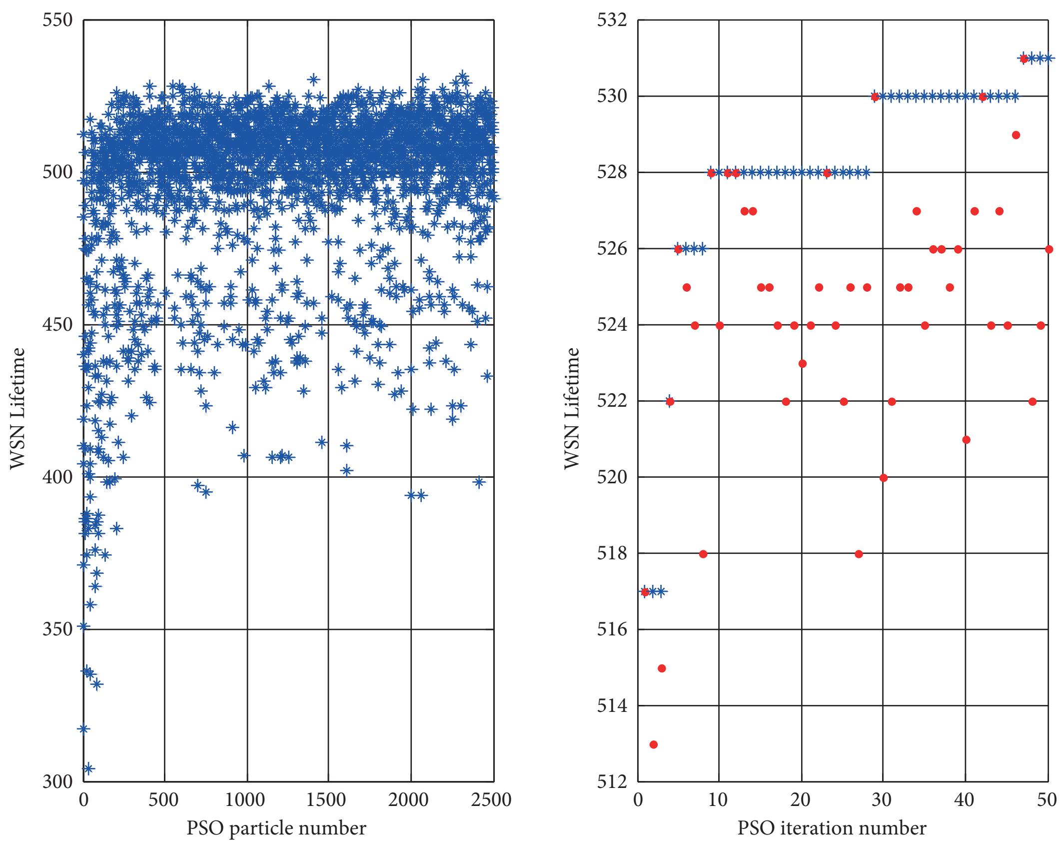

Figure 5. PSO algorithm results. Left: Horizontal axis is particle number, vertical axis is WSN lifetime. Right: Horizontal axis is PSO iteration number, vertical axis is WSN lifetime.

4. Conclusions

Nodes in a WSN measure data and transmit them to the base station. There are restricting limitations on the nodes' energy and hardware resources. Therefore, managing the data transmission path, the control of the base station movements, and the structure of the nodes' clusters is critical. In this work, fuzzy clustering, a proposed fuzzy cluster head selection, and mobile base station movement algorithms are used to reduce energy consumption and to improve WSN lifetime. The proposed fuzzy controller manages base station movements, speed, and direction on a predefined path. For extra increment of the lifetime, a PSO algorithm is utilized to calculate WSN optimal parameters such as base station path shape, path size, movement speed, and number of clusters. The proposed algorithms are simulated in several scenarios and they are compared with conventional methods. Results show improvement in the lifetime of the optimally designed WSN with mobile base station and fuzzy cluster-head selection.

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