Energy Efficient Clustering Using Improved Particle Swarm Optimization in Wireless Sensor Networks

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Abstract. The Wireless Sensor Network (WSN) includes many low-cost nodes that have the capacity to perceive, operate, and communicate wirelessly. WSN can spread the information to all around through a cooperative node approach. It also has many advantages in terms of both cost and cooperative intelligence. In a wireless sensor network, nodes have limited energy resources, so their life cycle is considered as one of the main concerns about wireless sensor networks. Energy efficiency grouping and routing are two well-known issues in optimization that have been widely studied in order to increase the lifetime of wireless sensor networks. In this paper, an improved particle swarm optimization (IPSO) clustering algorithm for energy efficiency network management is introduced in order to find a route for creating optimal clusters. To evaluate the efficiency of the proposed clustering algorithm, this algorithm is simulated and compared with the particle swarm optimization(PSO) algorithm based on parameters such as network energy, number of live nodes and network life.

1. Introduction

The Wireless Sensor Network (WSN) consists of numerous low-cost nodes having the capacity to receive, operate, and communicate wirelessly. WSN can distribute the obtained information around itself through a cooperative approach of nodes [1]. As the size of the network and the number of nodes increase, the scalability of the network becomes more important because this subject determines whether the network can be implemented in the real world. In this regard, hierarchical architecture is a proper approach to increase the scalability of the network in efficient manner. In recent years, WSNs have received lots of attention due to their wide range of applications such as national security, military, and environmental monitoring [2].

Sensor nodes are limited in terms of energy, so energy-aware algorithms are an important factor for maintaining their life cycle. Clustering is a standard process for analyzing multi-variable data used for energy efficient communication and to discover the innate structure of data objects. Each cluster has a leader that is called a cluster-head (CH) and is selected or assigned by the network designer in previous. A CH can schedule cluster activities and pool data collected by its cluster sensors. The sensors are randomly organized in such a way to be placed in the range of transmission, which causes certain nodes to go to sleep and this leads to significant energy saving. Each node transmits its information to the cluster-head, which in turn collects the data from the other cluster nodes and compresses and formats them before sending them to the base station (BS). An optimal cluster-head is the node that has the most residual energy and the maximum number of neighboring nodes and is closer to the base station. Therefore, the cluster-based approach has advantages such as developed resource allocation and the ability to use bandwidth again. CH due to the load that it tolerates, consumes more energy than other nodes. The connection route between CH and the base station is guaranteed by the CH position, which indicates its necessity in terms of energy efficiency and efficiency [3].

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A sensor node, despite its limitations in amount of energy, processing capabilities, and memory, is applied with other sensor nodes for displaying the surrounded physical environment, combining the received data, and sending it to the base station. With the ability of these nodes for monitoring and controlling, these networks can provide a proper universal picture of the target area and integral the data collected from multiple sensors that each of them provides a local and global perspective [4].

Due to the fact that these sensor nodes have a limited power supply and do not have the capability of being charged or replaced; Their performance must be efficient in terms of energy. This limited energy per node affects lifetime of the whole network and as a result, energy efficiency is one of the most important design features for wireless sensor network protocols and algorithms [5].

This organization of this paper is this manner: in section 2, previous works are reviewed. In section 3, the proposed solution is presented. In section 4, the evaluation of the proposed solution is discussed. In section 4, the evaluation of the proposed solution, and finally, in section 5, a conclusion from this paper is provided.

2. Related works

In this section, we review the studies in the field of optimal clustering for wireless sensor networks.
In [6], the nonlinear programming structure for clustering problems in WSN is explained. The energy efficiency clustering scheme for WSN is then presented in the alignment of the PSO approach. In the proposed algorithm, the energy consumption of CHs is significantly balanced in order to improve network lifetime. This algorithm is based on derivation of efficient particle coding method and proper function derivative.
In [7], the efficiency of the ant colony optimization approach is enhanced for wireless sensor networks with mobile sinks. The selection of cluster-heads (CHs) is based on the remaining energy in each node, and CH rotation occurs only when the residual energy falls below a specified threshold. Mobile sinks collect data along an optimal route identified by an improved ACO algorithm and establish direct connections with CHs using short-range communications.
In [8], the author introduces a mobile sink clustering algorithm for wireless sensor networks based on particle swarm optimization. This algorithm employs virtual clustering during the routing process, utilizing the particle swarm optimization algorithm. The initial parameters for selecting a cluster-head include the residual energy and node conditions. The control strategy for the mobile sink is carefully designed to efficiently gather data from the selected cluster-head.
In [9], the authors propose energy efficiency routing and clustering algorithms based on particle swarm optimization. In addition, they provide a prevention technique that increases the network lifetime by eliminating traffic loading on entrance routes, which have residual energy that goes beyond a certain threshold value.
In [10], the authors have introduced a scheme for energy efficiency and maximum network lifetime, which is achieved through load balancing that applies the management of subnet networks in a wireless sensor network. Their scheme considers the load balance of each node to maximize network lifetime.
In [11], the study delves into the analysis of balanced energy consumption, presenting a genetic algorithm aimed at preventing the occurrence of unbalanced traffic routes. In essence, the authors enhance the distribution of energy consumption in WSNs through the incorporation of balance loading techniques and genetic algorithms. The proposed algorithm initiates with a set of randomly generated initial solutions forming the initial population. Subsequently, each member of this initial population autonomously explores the optimal solution globally, aided by collaborative search processes.
In [12], the authors introduce the PSO-ECHS (Particle Swarm Optimization-based Energy Efficiency Cluster-Head Selection) algorithm. This algorithm employs an efficient particle coding scheme and function to enhance energy efficiency. The PSO approach considers various parameters such as internal cluster distance, sink distance, and residual energy in sensor nodes. Additionally, a cluster structure is established where non-cluster-head sensor nodes join their respective CHs based on the achieved weighted performance.
In [13], the paper explains the classification of clustering routing protocols in wireless sensor networks and outlines the total performance index of these protocols. An ant colony optimization-based cluster routing algorithm is proposed, with simulations conducted using information on fusion velocities, residual energy, and network lifetime.

In [14], the authors present an energy-efficient clustering protocol for WSNs utilizing the Improved Artificial Bee Colony (iABC). The protocol employs an energy-efficient strategy to select optimal Cluster Heads (CHs) based on a developed search equation and an effective evaluator function.

3. The proposed method

In 1995, James Kennedy and Russell Eberhart introduced the Particle Swarm Optimization Algorithm (PSO), a robust random nonlinear optimization method grounded in the principles of group and motion intelligence, drawing inspiration from the social behavior of birds. PSO operates by having each particle update its position based on various factors, including its current velocity, current position, distance to the best solution found individually, and distance to the best solution found by its neighbor.

In the velocity update equation of the PSO algorithm, optimal velocity information is incorporated at the swarm level, while optimal historical information is utilized for each individual particle. The particle's velocity is a combination of the optimal route in the total population for the current iteration and the optimal historical route for the individual. However, this combination may not always yield the most optimal result, as the best route for the entire population or the historical route for the individual may differ. To address this issue, the authors in paper [15] have enhanced the velocity equation, taking this consideration into account.

Furthermore, the PSO algorithm's inherent ability to escape local optimal solutions is noted, indicating that its efficacy in this regard may not be as robust. Consequently, the advantages of other intelligent algorithms can be leveraged. Paper [45] introduces a novel velocity update equation, addressing this limitation and defining it as follows: [Include the specific definition from the paper].

$$v_1 = \omega(t)v_i(t) + c_1r_1(pbest_i(t) - x_i(t));$$
$$v_2 = \omega(t)v_i(t) + c_2r_2(gbest_i(t) - x_i(t));$$

$$v_1 = \omega(t)v_i(t) + c_1r_1(pbest_i(t) - x_i(t)) + c_2r_2(gbest_i(t) - x_i(t));$$

$$v_i(t+1) = \left\{V_k \middle| \begin{array}{c} f(x_i(t) + V_k) \\ = \max\{f(x_i(t) + V_k).\, j = 1.2.3\} \end{array}\right\}. \tag{1}$$

$$x_i\,(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

The definitions for the parameters are similar to the basic PSO algorithm. Based on (1), it can be seen that the i-particle performs a comparison based on the experiences of individuals, social experiences, and a combination of both of the above experiences, and then updates its mode.

The fitness function is also used for evaluating the quality of the PSO solution, depending on the problem to be solved. In this thesis, a clustering algorithm based on improved particle swarm optimization (IPSO) is proposed in order to achieve an energy efficient management of WSNs. The main purpose of the proposed WSN clustering algorithm is that the sensor nodes are initially divided into a number of clusters. To divide the nodes into some clusters, a comprehensive algorithm must use all the solutions to find the optimal clustering scheme. Solving such problems is known as hard NP. This study presents an improved particle swarm optimization (IPSO) clustering algorithm to solve the clustering problem. Optimal cluster-head selection using IPSO method reduces the energy consumption of each sensor node by sending data packets to its cluster-head instead of sending directly to the base station (sink node). In this work, we want to implement the clustering algorithm (cluster-head selection) optimally with IPSO.

3.1. Clustering steps

The clustering operation is performed in two steps: The first step, the optimal cluster-heads selection: Using the IPSO algorithm, the most suitable nodes are considered to play the role of cluster-head. The second step, the formation of cluster-heads: when the cluster-heads are determined, the cluster-heads first send a message across the network in multiple broadcast, and the other nodes after receiving these signals, they connect to the nearest cluster-head based on each received signal intensity and form cluster-heads.

3.1.1. The optimal selection of cluster-heads

In this section, we will select the optimal cluster-heads using the IPSO improved particle swarm optimization algorithm: for this reason, we first describe the particle structure and its fitness function.

A) Particle structure

To determine the cluster-head of each node, we first define the particle structure:

The cluster-head node must have more energy than other nodes, so the first thing to do is to find the node with the most energy. In other words, to select the cluster-heads, initially we obtain the average energy of the network nodes and after that, we select the nodes having more than this average energy as candidate nodes for the cluster-head. Then, we select the number of network nodes in order to cover the network based on an optimal formula as the cluster-head. Next, in order to determine the cluster-heads with the aim of maximizing the network lifetime, we shape the particle in this form using IPSO.

The particle consists of an array. At first, we create this array, which is the length of the number of cluster-heads required for the covering, which is supposed to maintain the indexes of the cluster-heads. As a result, the initial value of the particle is randomly selected with a random numerical value in range of 0 to the number of candidate cluster-heads, meaning that the nodes are selected as cluster-head whose index is selected, and other nodes are considered as remaining normal nodes.

B) Fitness function

The aim of this study is to determine the cluster-heads in such a way that the network has a maximum lifetime. According to the definition of lifetime; it is the length of time that the network can continue to operate without losing a certain fraction of its nodes. To meet this expectation, several points must be considered in the proposed algorithm for clustering:

Firstly: nodes that have more energy are selected for longer deliveries to the sink and more operations. Hence, nodes with less energy have the opportunity to save more energy by sending at shorter distances and consume less energy and have more lifetime in network. As a result, the network lifetime increases.

Secondly: In order to reduce the energy consumption of the nodes in the network, the data should be sent in the network in the shortest possible distance and this task should be done in a hierarchical efficient way, i.e. the cluster-heads are selected to the sink at appropriate distances and then, the rest of the nodes are connected to the nearest possible cluster-head. The sensed data from this network of these nodes are sent to the nearest possible cluster-head, as result, the transmission distance in the network is minimized and network energy consumption is reduced and network lifetime is increased. Therefore, in the field of selecting candidate nodes for cluster-head, we consider the following parameters as the main parameters in cluster-head selection:

- Total energy of CH candidate nodes
- Total transmission distance of cluster members to CHs
- Total transmission distance of CHs to the sink

Similarly, in the fitness function, the particle is scored according to the following items by receiving each particle as input to determine the cluster-heads:

1. The total energy of the nodes, which is selected as the cluster-head should be maximum.

2. The total transmission distances in the network, sending the members to the cluster-heads and sending the cluster-heads to the sink should be minimum.

In most of the works done in the field of clustering, these parameters are considered as the main parameters in clustering. In order to have a uniform and balanced clustering in the network, we also consider the following parameters:

Total distance of CHs from each other: In this way, we try to select the cluster-heads in the network, in such a way that they are scattered in the network, and therefore the nodes that are scattered in the network can be connected to nearest cluster-heads. Therefore, in the proposed method, we try to select this total equals to an appropriate value that makes the cluster-heads scattered in the network.

Therefore, the fitness function is selected as follows:

Since in the IPSO process we decide to choose the particle as the final result having the minimum cost, so the parameters we are trying to reduce should be directly related to the fitness function and the parameters we are trying to increase having an inverse relation with fitness function. By assuming E as the node energy parameter, DistTOsink is considered as the distance from the node to the sink, and DistToCH is considered as the distance between the cluster members and the cluster-heads:

$$\text{Fitness function} \propto \text{DistToSink}$$

$$\text{Fitness function} \propto \text{DistToCH}$$

$$\text{Fitness function} \propto 1/E \tag{3}$$

Since the transmission distance up to a certain threshold depends on power of transmitting the amount of energy consumption related to the second power of the transmission distance and is related to the power of 4 transmission distances at longer distances. In the transmission distance computation between nodes, they are applied at distances more than the intended threshold with power 4 and at shorter distances with power 2. Therefore, the fitness function is as follows:

$$\text{Fitness function} = (\text{DistToSink}+\text{DistToCH})/(E) \tag{4}$$

4. The simulation environment

The proposed algorithm was tested using MATLAB programming and also, the results are plotted using MATLAB (version b 2018) and on an Intel core i7 processor with 2600 chipset, 3.40 GHz CPU, 2 GB RAM running on Windows 7 Microsoft platform.

4.1. The parameters' adjustment

The simulations were performed on different numbers of sensor nodes from 100, 300 and 500. Based on the network density, we select the optimal number of CH cluster heads.

$$\text{CH}=\frac{\text{y\_sink}-\text{Target area}+\sqrt{(\text{y\_sink})^2+(\frac{\text{Target area}}{2})^2}}{2} \tag{5}$$

Where y_sink is the y position of the sink node and target area is the measurement area.

It was assumed that each sensor node had an initial energy of 0.1 joules. In the simulation running, we have used the following parameter values, as shown in Table 1.

Table 1. Network parameters

Parameter	value
The measurement area	200 × 200 m^2
The position of sink node	100-100
The number of network nodes	100, 300 and 500
The energy of sensor node	0.1 joules
E_{elec}	50 nJ/bit
ε_{fs}	10 pJ/bit/m^2
ε_{mp}	0.0013 pJ/bit/m^4
The length of packet	4000 bits

We considered different network scenarios, three of which are presented as follows.

We considered a measurement area of 200 × 200 square meters for all these scenarios. For all three scenarios, the position of the base station was considered to be in the center of the field. That is, it was placed in (100 × 100).

We also considered three different modes of WSN, namely WSN # 1, WSN # 2, and WSN # 3. In WSN # 1, the number of sensor nodes was considered to be 100, 300 sensor nodes in WSN # 2, in WSN # 3, it was equal to 500. We analyze the algorithm efficiency in different modes and different numbers of sensor nodes. We executed the algorithms 30 times and the average of this data sample was considered in order to draw the results. We have tested our algorithm on a variable size of the initial population ranging from 30 to 70, however we used the predefined particle size that equals to 30. Other parameters for implementing our IPSO algorithm are shown in Table 2.

Table 2. IPSO parameters

Parameter	value
The number of nodes	30
C1	2.0
C2	2.0
Wmax	0.9
Wmin	0.4
The maximum repetition	100

4.2. The evaluation criteria

We use the following criteria to measure the performance of the proposed algorithm.

1. Energy consumption: This is the total energy consumption for a certain number of distances, in each of them, CHs collect data, pool it and bring it to BS. It should be noted that as the number of rounds increases, the amount of energy consumption increases.

2. Network lifetime: As mentioned earlier, we consider the length of the network as the number of rounds until the last death of node, usually it is called LND. The longer the network lifetime, the better the network efficiency.

3. Number of alive nodes: After each implementation period, alive nodes in the network are counted.

4.2.1. The efficiency measurement in terms of energy consumption

First, we implemented the algorithms in order to compare the total energy consumption of the network by changing the number of sensor nodes from 100 to 500 and the number of optimal cluster-heads according to the formula 1-5. The results of the proposed method comparison (Proposed IPSO) with PSO are shown in Figures 1, 2 and 3.

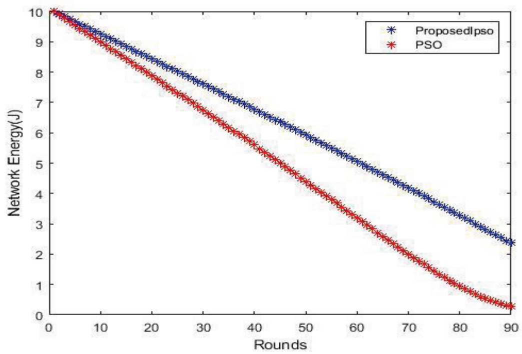

Fig. 1. The efficiency comparison in terms of network energy consumption with 100 nodes

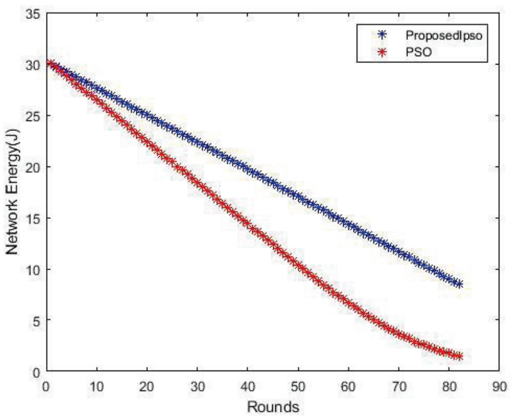

Fig. 2. The efficiency comparison in terms of network energy consumption with 300 nodes

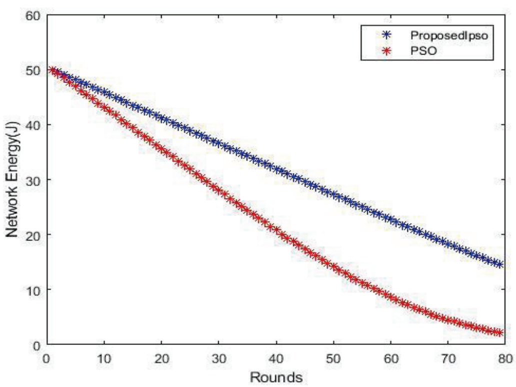

Fig. 3. The efficiency comparison in terms of network energy consumption with 500 nodes

Figures 1 to 3 depict the first scenario wherein the base station is centrally positioned in the field, and the number of sensor nodes is set at 100. The results illustrate the superior performance of our proposed method over PSO concerning total energy consumption. This advantage arises from the optimal assignment of sensor nodes to their nearest Cluster Heads (CHs), resulting in reduced energy consumption and, consequently, lower total network energy consumption. This outcome is attributed to our fitness function, which effectively addresses energy consumption by minimizing the distance between sensor nodes and their respective CHs.

As the network size expands, the efficacy of existing algorithms diminishes, as evident in Figures 2 and 3. The vertical axis in these figures represents energy consumption, while the horizontal axis indicates the number of simulation rounds. The observed trend in Figures 2 and 3 highlights the consistently superior efficiency of our proposed method across the three scenarios when compared to the PSO algorithm.

With the progression of rounds, there is a decrease in the residual energy of sensor nodes. The selection of Cluster Heads (CHs) becomes crucial in mitigating energy consumption, and our algorithm employs a fitness function to meticulously choose CHs, ensuring optimal selection and subsequent reduction in energy consumption.

4.2.2. The efficiency measurement in terms of network lifetime

Next, we put algorithms in place to compare the lifespan of the network in terms of rounds when there were 100, 300, and 500 sensor nodes, respectively. Figures 5.4, 5.5, and 5.6 demonstrate the superiority of the suggested technique over PSO. The rationale is that the suggested method's CH selection takes the sensor nodes' remaining energy into account. In actuality, it uses more energy as a CH than traditional sensor nodes.

As a result, they use less energy than traditional sensor nodes. Low-energy sensor nodes have a higher chance of dying fast, which can shorten the lifespan of the network. To increase the network's length, we choose CH using the suggested way from traditional sensor nodes with higher residual energy. The following figures demonstrate the outcomes of our implementation of the algorithm, which involved increasing the number of sensors from 100 to 500. The lifetime is shown by the vertical axis in the figures, while the number of simulation rounds is represented by the horizontal axis. Based on all three numbers, it is possible to determine that the suggested algorithm's network lifetime is greater when the base station is in the center of the target field

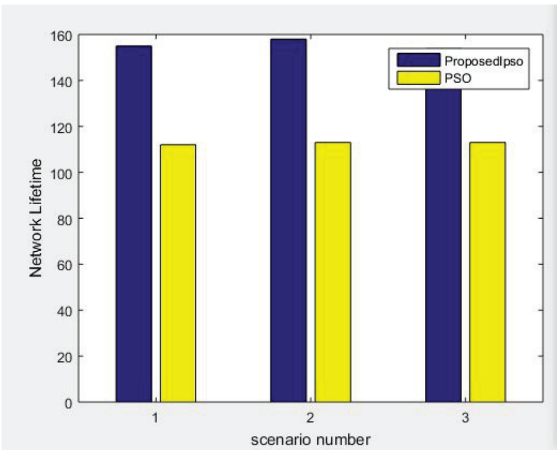

Fig. 4. The efficiency comparison in terms of network lifetime with 100 nodes

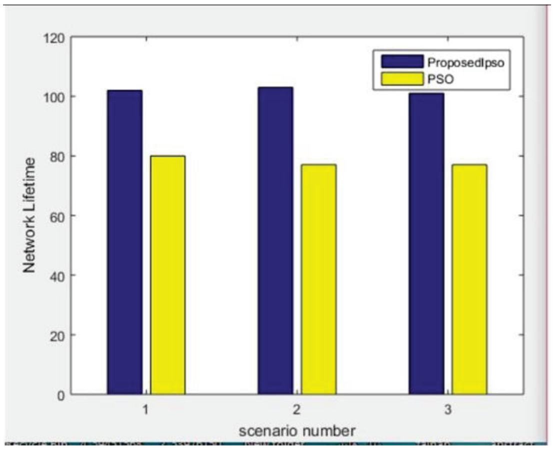

Fig. 5. The efficiency comparison in terms of network lifetime with 300 nodes

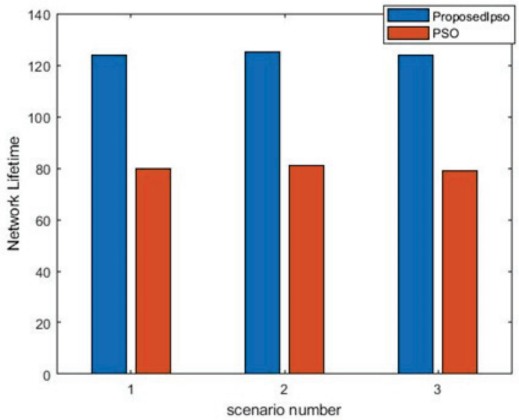

Fig. 6. The efficiency comparison in terms of network lifetime with 500 nodes

4.2.3. Performance measurement in terms of the number of alive nodes

Finally, we implemented the algorithms to compare the number of alive nodes with different numbers of sensor nodes from 100 to 500. Here, the number of alive nodes of the proposed clustering algorithm and PSO clustering algorithm are analyzed in the number of different nodes of 100, 300 and 500 with energy of 0.1 joule. A count of the network's live nodes is conducted following each implementation phase. Nodes with lower energy levels are eliminated from the network because, as in the suggested algorithm, only nodes with higher energy levels are selected as cluster-head candidates. Furthermore, similar to the energy comparison results in the cluster-head selection phase, the clusters are chosen based on their energy and distance, enabling the nodes to choose an appropriate cluster-head that uses less energy. The lifetime of the nodes is directly affected by efficient energy use. Below, the comparison results in different scenarios with 100, 300 and 500 nodes are shown in Figures 7, 8 and 9, respectively. In the figures, the vertical axis represents the number of alive nodes and the horizontal axis represents the number of simulation rounds.

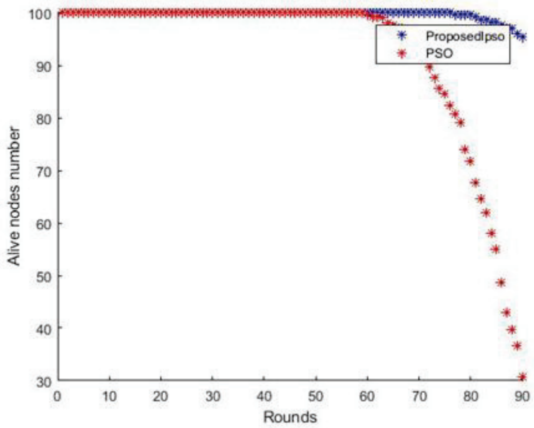

Fig. 7. The efficiency comparison in terms of the number of alive nodes with 100 nodes

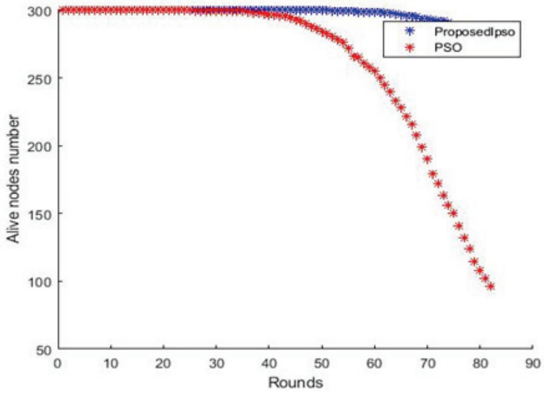

Fig. 8. The efficiency comparison in terms of the number of alive nodes with 300 nodes

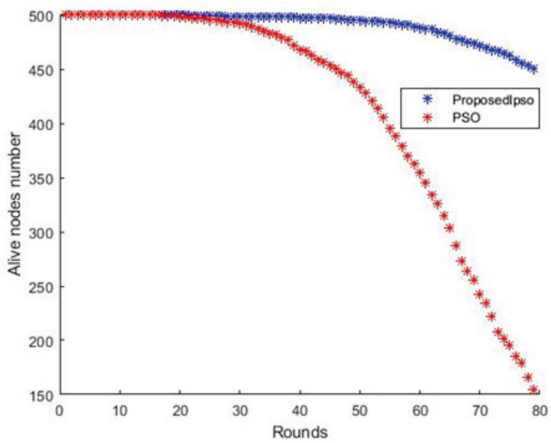

Fig. 9. The efficiency comparison in terms of the number of alive nodes with 500 nodes

5. Conclusion

We primarily address the CH selection problem in this paper, and we suggest an approach based on enhanced particle swarm optimization (IPSO). The suggested technique chooses CH among regular sensor nodes in an effective manner. Initially, we suggested a method for the CH selection problem using linear programming (LP). We then went on to discuss the IPSO-based solution for this issue. We also presented the phase of cluster creation. A particle coding program that is effective is used to develop the suggested IPSO algorithm. To make the IPSO technique based on energy efficiency, fitness performance is also attained by taking into account different distance and residual energy characteristics. The enhancement in the PSO algorithm lies in the particle velocity formula when compared to its predecessors. This improvement involves a comparison that takes into account individual experiences, social experiences, and a combination of both, subsequently updating the particle's status. The algorithm's performance superiority over other existing algorithms has been verified through rigorous testing. The experimental results clearly demonstrate the superior efficiency of the proposed method in comparison to the traditional PSO algorithm.

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