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Research Article

An Improved Energy-Aware Routing Protocol Using Multiobjective Particular Swarm Optimization Algorithm

Zhihao Peng,[1] **Mehdi Sajedi Jabloo**,[2] **Yahya Dorostkar Navaei**,[3] **Morteza Hosseini**,[4] **Rozita Jamili Oskouei**,[5] **Poria Pirozmand**,[6] **and Seyedsaeid Mirkamali**[7]

[1]*School of Software, Dalian Neusoft University of Information, Dalian, China*
[2]*Department of Computer Engineering, Moghadas Ardabili Institute of Higher Education, Ardabil, Iran*
[3]*Department of Computer and Information Technology Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*
[4]*Department of Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran*
[5]*Department of Computer Science and Information Technology, Mahdishahr Branch, Islamic Azad University, Mahdishahr, Iran*
[6]*School of Computer and Software, Dalian Neusoft University of Information, Dalian, China*
[7]*Department of Computer Engineering and IT, Payame Noor University (PNU), Tehran, Iran*

Correspondence should be addressed to Yahya Dorostkar Navaei; y.dorostkar@gmail.com

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The energy of sensor nodes in wireless sensor networks is limited, which is one of the most important challenges due to the lack of a fixed power supply. Because data transmission consumes the most energy of nodes, a node that transmits more packets runs out of energy faster than the others. When the energy of a node comes to the end of a network, the process of network operation may be disrupted. In this case, critical information in the network with the desired quality may not reach the hole and eventually the base stations. Therefore, considering the dynamic topology and distributed nature of wireless sensor networks, designing energy-efficient routing protocols is the main challenge. In this paper, an energy-aware routing protocol based on a multiobjective particle swarm optimization algorithm is presented. In the proposed particle swarm optimization algorithm method, the proportionality function for selecting the optimal threaded node is set based on the goals related to service quality including residual energy, link quality, end-to-end delay, and delivery rate. The simulation results show that the proposed method consumes less energy and has a longer lifespan compared with the state-of-the-art methods due to balancing the goals related to service quality criteria.

1. Introduction

Wireless sensor networks (WSNs) are subsets of wireless networks designed to collect information from the environment using different types of sensors such as cameras, thermometers, and speedometer [1–3]. Due to the widespread use of communication networks as well as the ease of wireless communication, WSNs have received more and more attention. Usability in any environment, without the need for infrastructure and physical communications, as well as the need for environmental monitoring and engineering, which is a unique feature of these networks, has led to the increasing use of wireless networks in various fields [3, 4]. These networks are made up of sensors that are scattered throughout the environment and report data on accidents that occur in these environments for review and necessary actions [5]. On the other hand, in wireless sensor networks, due to the lack of infrastructure such as routers, sensor nodes, in addition to receiving information from the environment, are also used as routers to send data packets [6]. The sensor node receives the energy it needs to sense and collect information from the environment and send and receive this information from the battery connected to the sensor, which cannot be recharged. The duration of use of the limited energy of the power supply determines the life of the sensor node, and therefore, the available energy should be consumed in a balanced way.

The efficiency of a WSN is usually determined by the average amount of power consumption by the wireless sensor nodes in the network which determines the life of the network [6]. The WSN must have the power to control the overall productivity of the network to ensure that data is delivered according to quality of service (QoS) standards. Service quality refers to delay management, packet loss, and power consumption in the network and seeks to provide an appropriate routing protocol to obtain optimal results for these variables [2, 3, 7]. Therefore, it can be said that energy consumption in WSN has the highest role in meeting the criteria related to service quality and overall network performance. Given that the sensor nodes have a constant amount of energy required to sense data and receive data packets, therefore, most of the energy consumption is related to the power required to exchange information between nodes, which energy-aware routing methods can manage average energy consumption and grid life [2, 3]. Providing an optimal routing approach in WSN that improves existing constraints is as difficult and complex as NP-hard optimization issues [8]. Thus, deterministic and traditional search algorithms cannot provide near-optimal solutions at the right time for WSN routing. Meta-heuristic algorithms can be used to target network service quality criteria. They have been able to provide near-optimal solutions for WSN [9]. Therefore, in this paper, an energy-aware routing protocol based on a multiobjective particle swarm optimization algorithm is presented. In the proposed method, particles are considered as spinning nodes whose proportion function has the highest value based on service quality goals including residual energy, link quality, end-to-end latency, and delivery rate for that node. In fact, in each cluster of sensor nodes that are formed in the monitored areas, the node that has the highest value of the target function is selected as the head node and is responsible for sending data packets. Link quality is defined as the energy used to send packets from the source node to the current node, in addition to the estimated cost of sending packets from the next node to the destination. This method uses a multistep routing approach in which the next node is dynamically selected in each step. In order to select the next node in the network, in addition to the value of the proportion function, the distance between the nodes and the distance to the hole is also considered. It is expected that the proposed method will provide global energy-aware routing awareness of the goals of service quality criteria in order to select the optimal local node at any time.

This research is organized into five sections. In the next section, we will review the background of the research. In the third section, we describe the proposed methodology in detail. In the fourth section, we will fully describe the simulation results obtained from the proposed method and also compare results with the state-of-the-art methods. Finally, in the fifth section, we will state the conclusion and explain the future work.

2. Related Works

The wireless sensor network consists of a large number of sensor nodes that are widely distributed in an environment and collect information from the environment. The location of the sensor nodes is not necessarily predetermined. Such a feature makes it possible to place them in dangerous or inaccessible places [10]. WSNs are a combination of fixed and mobile sensors, and the sensors, depending on the nature of the applications, receive information from the environment and, if possible, process the data before sending it, and through the base station to the information hole, and finally, the application will transfer. The processing and transmission of information by the occurrence of specific events take place in an environment where the sensors are configured in response to a user application request.

The various protocols for wireless sensor networks can be classified into two main categories, structure-based and feature-based. Node uniformity has been used to classify network structures. The main feature of this type of protocol is how to connect nodes and transfer data based on the connection framework.

The design of a network is influenced by several factors. These factors include fault tolerance, scalability, production cost, work environment, sensor network topology, hardware constraints, transmission environment, and power consumption [9].

In 2018, Challa et al. [10] investigated the issue of data aggregation in wireless sensor networks using a particle swarm optimization scheme that uses an iterative upgrade process, and optimal node coordination points. Provide others with reliable communication. Also, the energy consumption of the node is determined by various parameters such as distance from the hole, number of factors, and neighbors for neural network training, and finally, it is predicted that it helps to estimate the condition of the node, whether a node can carry duplicate data for the next step or not. These predictions are made based on the energy consumed and the energy required for data transmission by the node. An extensive and comparative simulation study is presented which shows that the proposed approach has performed better than the superior energy-aware routing techniques in wireless sensor networks.

We summarize different methods that worked on energy-aware routing techniques based on their protocol type and name and also the method they use in their techniques in Table 1 [10–17].

3. Proposed Methodology

In recent years, researchers have conducted many studies and proved that clustering is an effective scheme to increase the scalability and longevity of wireless sensor networks. In clustering schemes, there are two types of nodes in one cluster, namely, one cluster head (CH) and several cluster members (CM). Cluster members periodically collect data from the environment and send the data to the cluster head. Headers collect data from their cluster members and send the collected data to the base station (BS). There are two types of

Table 1: A comparison of previous methods.

Metrics used	Advantage	Method	Objective/Target	Protocol name	Protocol type
Grid life, power consumption, CH count	Balanced and reduced energy consumption in each cycle, increasing life expectancy	Use of optimal sliding window, dynamic optimization of CHs	Obtain the desired number of clusters dynamically and energy efficiency	LEACH-SWDN	Classical
Energy consumption, latency, production rate, closed loss rate	Increases network time and performance	Use multicast tree optimization, minimally distributed transmission	Ensure energy efficiency and grid performance	EAODV	
Energy consumption, package delivery ratio, average package delay, throughput, overhead	Low overhead and better network performance	Use of blind sending method, slope maintenance criterion	To enable mobility and robustness in routing	PHASeR	
Package delivery rate, total energy consumption, operating power, average delay	Increased network life, PDR, and low overhead	Fuzzy- and nonfuzzy-based implementation	To increase network life and performance for heterogeneous networks	HEEDML	
FND (death of the first node), HND (death of half of the nodes), LND (death of the last node), success rate	Increase network life time, balanced energy consumption	Genetic combination and thermal simulator, multipurpose fit function	To achieve increased network lifetime and energy savings of SNs	ASLPR	
Average energy consumption, end-to-end latency and throughput	Ensure longer lifetime and reduced energy consumption	Improved mode routing, conscious energy path selection	To ensure an overall reduction in energy consumption	EA-FSR	
Average energy latency and grid life	Energy efficiency and improved latency	Virtual cluster PSO	To achieve energy efficiency and better grid performance	EPMS	Swarm intelligence
FND, energy consumption per cycle, grid life, information received by BS	Better network lifetime, lower power consumption per cycle	Optimization of CHs selection using artificial fish algorithm	Reduce network power consumption	AFSA	
Maximum and standard deviation of distance between clusters, FND, HND, LND, success rate	Save energy and prevent uncertainty during network operation	Use of fuzzy c-means, FA-SA hybrid	To achieve balanced clustering and minimal overall energy consumption	SIF	
Network lifetime and residual energy	Optimal cluster formation leads to increased grid performance and balanced energy consumption	Bee colony optimization, optimal cluster	For a long network lifetime, energy consumption balance	PECE	
Network lifetime, the average residual energy, the remaining energy standard deviation	Network lifetime is increased and energy consumption is reduced	Improved harmony search algorithm	To extend the lifetime of the network	IHSBEER	
Total energy consumption, living nodes, average residual energy	Increase network lifetime	Using the bee mating algorithm	To provide trust based on proper clustering and energy consumption	LWTC-BMA	
Energy consumption, energy efficiency, first dead node, package delivery rate, package loss rate and network coverage	Increase network life, coverage, package delivery ratio	Using the ABC algorithm, based on the cost function	To design a scalable grid and improve energy efficiency	ABC-SD	
Data delivery rate, packet delay, power consumption, energy efficiency, lifetime network	Choose the optimal route	Using the PSO algorithm, based on meta-exploration techniques	To select the optimal route in routing	MOTPSO	
Energy, energy efficiency, lifetime network	Increase network lifetime			ECPSO	

Table 1: Continued.

Metrics used	Advantage	Method	Objective/Target	Protocol name	Protocol type
		Use of PSO algorithm, based on energy and latency	To reduce energy consumption, limited energy clustering		
Price, packet delay, power consumption, network lifetime	Energy efficiency network	Use the PSO algorithm, based on energy and cost	To maximize network lifetime, cluster node organization, optimal location costing	CHSPSO	
Intracluster distance, distance to hole, residual energy of sensor nodes, network lifetime	Effective reduction of energy consumption	Use of PSO algorithm, based on energy and latency	For energy efficiency, efficient particle encoding scheme and proportion function, energy efficiency	PSO-ECHS	
Node residual energy, network life, latency and data accuracy	Energy-limited clustering	Use of PSO algorithm, based on energy and latency	Reduce energy consumption, extend the lifetime of the network, data collection	DAPSO	
Energy consumption, energy efficiency, network lifetime	Effective choice of header	Use PSO algorithm based on distance error function	For data aggregation in wireless sensor networks, optimal point coordination for reliable communication	PSDEO	

communication between cluster head and BS, single-step communication, and multistep communication. In multistep clustering algorithms, the energy consumption of the cluster head includes the energy of receiving, accumulating, and sending data from their cluster members (energy consumption within the cluster) and energy for sending information to neighboring clusters (intercluster energy consumption).

Energy imbalance between nodes is the main factor affecting the life of the network. To balance the energy consumption between nodes, network clustering algorithms with uniform node distribution tend to build headers uniformly, so that the clusters have the same approximate number of members and areas covered. Therefore, the energy consumption within the cluster is almost equal for the clusters, and the energy consumption of the clusters can be balanced. For cluster members, due to the uniform size of the cluster, the maximum communication distance between the cluster members is approximately equal. Therefore, the energy consumption of cluster members can also be balanced. Therefore, the uniform distribution of cluster heads can balance energy consumption between nodes and ultimately extend network life. In networks with uneven distribution of nodes, the mechanisms used to balance energy consumption and extend network life are not always effective. The clusters are evenly distributed so that the clusters have a uniform cluster size so that energy consumption can be balanced among the members of the cluster. However, unbalanced energy consumption still exists among cluster heads due to uneven node distribution [18].

3.1. The Proposed Multiobjective Optimization Model. Node clustering in WSN is one of the most effective ways to reduce energy consumption and distribute the data transfer task to more energetic nodes [19]. One of the first clustering methods in WSN is the LEACH protocol [20], in which the random generation of threaded nodes cannot guarantee the rationality of the threaded position. In other words, the unbalanced distribution of nodes at the head of the cluster means that more energetic and efficient nodes are not selected for data transmission. Also, the headers may not be in the right position relative to the other nodes in the cluster, and long distances can cause high energy consumption in the headers, which will affect the life of the entire network. Therefore, the first step that can improve energy consumption in the WSN is to carefully select the optimal head position and nodes to transfer data between clusters to the cavity. For this purpose, in the proposed method for selecting the threaded node, four parameters are discussed, which are distance to destination, link quality, and total network power consumption. These parameters play a decisive role in the selection of threaded nodes, and improving these parameters will improve other goals in the network. By proposing these parameters as multiobjective optimization algorithms, the proposed method tries to optimize the overall goals of the network, including reducing energy consumption, increasing life expectancy, reducing latency, and increasing the delivery rate in the network. In the following, the following items will be modeled.

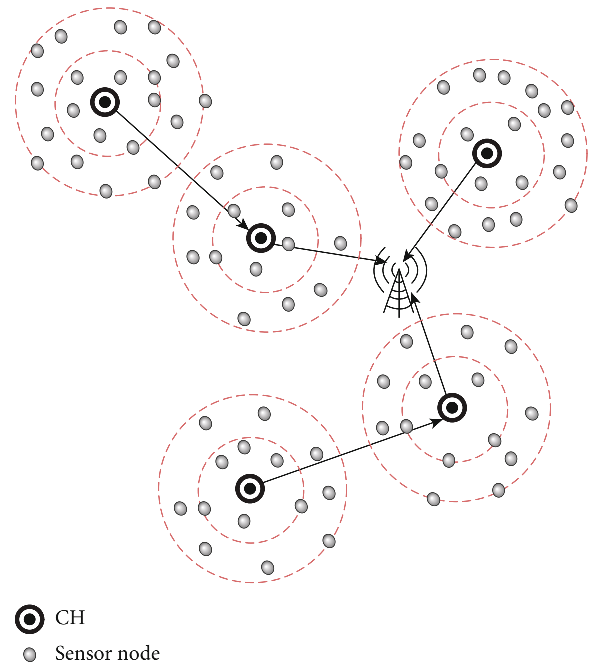

Figure 1: Multistage transfer from the head to the cavity node [20].

3.1.1. Intracluster Distance D_{nc}. In WSN, cluster member nodes must send information to the cluster head node. When the cluster member nodes in each cluster surround the cluster head, this means that the distance between the cluster member nodes and the cluster head node is the closest and the packet transmission distance is the shortest. In fact, when the node is almost in the middle of the other nodes in the cluster, its distance from all nodes will be approximately the same and at least the distance. Thus, transferring data in the shortest distance requires the least amount of energy. The intracluster distance model is expressed in the following equation:

$$D_{\mathrm{nc}} = \min\left(\sum_{m=1}^{M}\left(\sum_{n=1}^{N} d_{\mathrm{ncluster}}\right)\right), \tag{1}$$

where M represents the number of heads of the clusters, N represents the number of members of each cluster, and d_{ncluster} represents the Euclidean distance of the cluster nodes to the cluster member nodes.

3.1.2. The Distance between the Threaded Node and the D_{cs} Hole Node. In clustering-based protocols, the threaded node combines the information on the received information and sends it to the hole node. In fact, in the threaded node, a processing step is performed on the data to eliminate incomplete and duplicate information. The remaining information is then sent to the hole node as useful information. In the initial protocols, nodes were sent from the header to the hole in a single step, and information was sent directly from each header node to the hole. Such a strategy would waste too much energy on a branch. Therefore, using multistep data transfer is a solution to solve this problem, which is used in the proposed method. As shown in Figure 1, threaded nodes send data to the destination through other threads to transfer information to the hole.

As shown in Figure 1, threaded nodes use a multistep approach to transmit information. In this case, the shorter the distance between the threaded node and the hole node, the shorter the duration and transmission distance. As a result, energy consumption is lower. The distance model between the threaded node and the hole node is expressed in the following equation:

$$D_{\text{cs}} = \min \sum_{m=1}^{M} d_{\text{csink}}, \tag{2}$$

where M represents the number of threaded nodes of the clusters and d_{csink} shows the Euclidean distance from the cluster node to the hole node.

3.1.3. Energy Consumption. The energy consumption model in WSN is divided into two general parts, which we will review and model in the following.

(1) Total Energy Consumption of Energy1 Network. The total energy consumption of the network in the clustering stage is such that in the first stage, the cluster node broadcasts a message that informs the rest. Also, the table of nodes in the cluster is updated and the information of this table is distributed among the nodes of the cluster. The value of the transmitted data is equal to t-bits. The energy consumption of a cluster node when it sends information is calculated using the following equation [21].

$$E_{\text{cn}}(t, d_{\text{cn}}) = \begin{cases} t\left(E_{\text{elec}} + \tau_f d_{\text{cn}}^2\right), & d_{\text{cn}} < d_{\text{c}}, \\ t\left(E_{\text{elec}} + \tau_m d_{\text{cn}}^4\right), & d_{\text{cn}} \geq d_{\text{c}}, \end{cases} \tag{3}$$

where E_{elec} represents the energy consumption by the threaded node for the transmission of 1 bit of data and τ_f and τ_m represent the signal amplifier energy consumption when transmitting 1 bit of data per unit distance in open space and the model, respectively.

Multiple fades. d_{cn} shows the Euclidean distance of the members of the current cluster to the ecliptic node.

Threshold $d_0 = \sqrt{\tau_f/\tau_m}$ is for conversion between communication channel models.

Then, the cluster member node receives the t-bit information and the cluster table from the cluster node and sends the data t-bit to the cluster node according to the same table to verify the cluster node identity.

In this process, the energy consumption of the cluster member nodes is calculated using the following equation:

$$E_{\text{non-cn}}(t, d_{\text{cn}}) = \begin{cases} t\left(E_{\text{elec}} + \tau_f d_{\text{cn}}^2\right) + t \times E_{\text{elec}}, & d_{\text{cn}} < d_{\text{c}}, \\ t\left(E_{\text{elec}} + \tau_m d_{\text{cn}}^4\right) + t \times E_{\text{elec}}, & d_{\text{cn}} \geq d_{\text{c}}. \end{cases} \tag{4}$$

Finally, the energy consumption of the process for the clustered node is to accept the nodes of the cluster member and to send them a packet that is calculated through the following equation:

$$E_{\text{cn}}(td_{\text{cn}}) = tE_{\text{elec}} \times \left(\frac{N}{M} - 1\right). \tag{5}$$

The total energy consumption of the Energy1 grid in the clustering phase is summarized in the following equation:

$$\text{Energy1} = \begin{cases} \min\left(tE_{\text{elec}} \times \left(\frac{N+2}{M} - 1\right) + \tau_f d_{\text{cn}}^2 \times \left(\frac{N}{M} - 1\right)\right), & d_{\text{cn}} < d_{\text{c}}, \\ \min\left(tE_{\text{elec}} \times \left(\frac{N+2}{M} - 1\right) + \tau_m d_{\text{cn}}^4 \times \left(\frac{N}{M} - 1\right)\right), & d_{\text{cn}} \geq d_{\text{c}}. \end{cases} \tag{6}$$

(2) Balance of Energy Consumption of Energy2 Network. The grid energy consumption balance consists of two parts, D_{no} and D_{en}. The variance of the number of node members in each D_{no} cluster is as follows. The smaller the value, the higher the average number of nodes per cluster, meaning that the load on each head is more balanced [22].

$$D_{\text{no}} = \frac{\sum_{i=1}^{m} (v_i - u)^2}{m}, \tag{7}$$

where v_i is the number of node members of the cluster in cluster i and u is the average number of nodes of each cluster in the network.

The variance of energy consumption is the states of a cluster member in each D_{en} cluster. The smaller the value, the higher the average energy consumption in the clusters; it is calculated from the following equation:

$$D_{\text{en}} = \frac{\sum_{i=1}^{m} (E_i - u_e)^2}{m}, \tag{8}$$

where E_i is the total energy consumption in clusters i and u_e is the average energy consumption of each cluster.

In summary, the grid energy balance is calculated from the following equation:

$$\text{Energy2} = \min\left(D_{\text{no}} + D_{\text{en}}\right). \tag{9}$$

Thus, to optimize energy consumption in WSN, it is possible to select a suitable head node that improves the service quality criteria and the mentioned factors.

3.1.4. Link Quality. Link quality in WSN is considered as a criterion for estimating the cost required to transfer data between sensor nodes. Link quality with a criterion called ETX (expected transfer) is used to indicate the estimated cost between a threaded node and its potential cluster member nodes at the time of aggregation, and to estimate the cost required between the threaded node and the hole node. In other words, for a clustered node, ETX is the estimated total cost of collecting data from the cluster member nodes that belong to it and transferring the aggregated data to the hole in several steps. In calculating ETX, the number of steps required to send packets from one cluster member node to a clustered node, followed by the hole node as well as the distance between nodes, is important. Since in WSN, the main source of cost is energy consumption, and in the proposed method, the goal is to reduce energy consumption, after a new parameter called EETX (energy-aware ETX) to measure the quality of the link between the selected threaded nodes. And we call it the estimated amount of energy required to collect data from the nodes of the cluster and transfer it to the hole. Obviously, the lower the EETX for a threaded node, the better the link quality. Link quality modeling is shown in the following equation.

$$\mathrm{ETX}(k, d) = \min \sum_{i=1}^{n} \sum_{j=1}^{K} \left(\varepsilon_e * n_i * d_{ij}^2 \right) + \left(K - 1 * D_{jK}^2 \right), \tag{10}$$

where ε_e is the energy consumption constant for sending data, n_i is the number of members of the i^{th} cluster, d_{ij}^2 is the distance within the cluster, K is the number of clusters, and D_{jK}^2 is the estimated distance of the cluster from other clusters.

In the proposed method, the threaded nodes are used according to the mentioned parameters as evaluation criteria in the fit function related to the multiobjective particle swarm algorithm. In the following, we will explain the proposed multiobjective particle swarm algorithm.

3.2. Multipurpose Particle Swarm Optimization Algorithm. Particle swarm optimization (PSO) algorithm was proposed in 1995 by Kennedy and Eberhart [23]. The PSO algorithm mimics the behaviors of fish school flocks. The goal of the PSO is to find the optimal solution in the search space of a target function, just as a flock of birds' searches for the best food source. In PSO, a collection of randomly generated particles, they search for the best solutions. Particles search by adjusting their direction and flight speed, using the following equations, respectively.

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \tag{11}$$

$$\begin{aligned} v_{id}(t+1) = w * v_{id}(t) + r_1 * c_1 * [p_{id}(t) - x_{id}(t)] \\ + r_2 * c_2 * [g_d(t) - x_{id}(t)], \end{aligned} \tag{12}$$

where d is the number of dimensions, w is the weight of inertia that controls particle exploration, r_1 and r_2 are random numbers between 0 and 1 ($r_1, r_2 \in [0, 1]$), c_1 and c_2 are the acceleration constants that are best used to control the effect of individual and global particles are used, p_{id} indicates the best personal position for a particle (p_{best}), and g_d indicates the best global position found by neighbors (g_{best}).

Certainly, PSO demonstrates the ability to converge at high speeds in single-target problems, which is a good choice for multiple targets. The proposed algorithm uses Pareto dominance to generate a set of leaders that control the particle flight direction and optimize the search process. Also, the dominant solutions found are stored in external global memory (called a repository), which is later used by particles as global leaders. The global guide is selected using a roulette wheel selection based on extra cube scores. Besides, the proposed algorithm adopts a geography-based strategy to maintain the diversity of solutions. In essence, the external "archive" repository consists of two parts: the controller and the network. The purpose of the controller is to decide whether to add a new solution to the archive or not. Updating or pruning an archive depends on the dominant relationship. However, whenever the archive is full, an adaptive network method is called. In contrast, networking is used to promote diversity between solutions. In principle, the target space is divided into areas called transcubes. Transcubes are geographical areas that consist of some solutions that are created according to the objective functions. Each meta-cube is assigned a proportional function based on the number of particles in it. Therefore, meta-cubes with a large number of particles have a lower fit value. Figure 2 shows an example of a cube with a large number of particles.

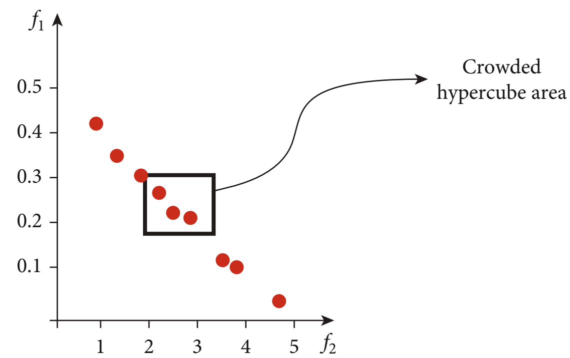

Figure 2: Meta-cube representation of the proposed algorithm.

As shown in Figure 2, f_1 corresponds to the error rate and f_2 is the number of attributes. The roulette wheel selection method is used to select a cube. After selecting a meta-cube, a random particle is selected from it. The network facilitates the selection process of solutions located in sparsely populated areas in the target space compared to samples located in crowded areas [11].

The following steps summarize the process of selecting particles [11]:

(1) Initialize the population $POPi$, where $i = [1, 2, \cdots, N]$ and N is the population size

(2) Initialize the velocity of each particle $VELi$

(3) Evaluate each particle and assign it to a value of the fit function

(4) Save particle positions that represent the dominant solutions in the external archive (REP)

(5) Create meta-cubes and adjust particles using meta-cubes as system coordinates

(6) Initialize the memory of each particle and save the initial positions as the best particle positions available

(7) Calculate the velocity of each particle using Equation (7)

(8) Calculate the new positions of each particle using Equation (5)

(9) Keep particles within the limits of search space constraints

(10) Particle evaluation

(11) Update REPs and meta-cubes by inserting new dominant solutions, which remove previous non-dominant solutions. However, when the REP is full, particles have a higher priority in secluded areas

(12) Update memory with the best personal positions of each particle if the current position is better than the current position in memory using Pareto dominance

(13) If the stop condition is met, stop; otherwise, return to step 7

$$\begin{aligned} v_{id}(t+1) = w * v_{id}(t) + r_1 * c_1 * [p_{id}(t) - x_{id}(t)] \\ + r_2 * c_2 * [\mathrm{REP}(h) - x_{id}(t)], \end{aligned} \tag{13}$$

where $\mathrm{REP}(h)$ is a dominant solution for reservoir selection in which the h-index is selected based on the value of the fit function of the meta-cubes.

3.2.1. Proposed Fit Function. In order to formally define the evaluation function in the proposed method, we assume that the node is represented by index i, and the member nodes are represented by index j. For this purpose, considering the modeling of multiobjective optimization methods in WSN, we consider the following limitations in the proposed multiobjective particle swarm optimization algorithm.

(i) The sum of the distances within the cluster should not be more than a fixed value. This limit is set so that the size of the clusters is not too large. If the distance threshold within a very large cluster is selected, all the nodes in the network may be in one cluster, which greatly affects the performance of the proposed method. The distance of the threaded nodes from each other should not be less than a threshold value. Due to this limitation, the proposed method tries to avoid creating more than one header within a cluster

(ii) The initial energy of the nodes is equal to and not more than a fixed value. Given that the main focus of the proposed method is on reducing the energy consumption of the nodes in the WSN, therefore, the nodes must have the same constant energy in order to compare with other proposed methods

(iii) The number of steps to send data between headings should not exceed the number of headers. This constraint prevents loops in the WSN and ensures that the proposed method finds the shortest path in the network to transfer data from the sensor node to the node

(iv) The total delay of packet transfer on the route should not be more than a fixed value. Critical messages on the network must reach the nodes within the time frame they have. Failure to do so may result in disruption to WSN applications

Since the goals in the network may be contradictory and improving one goal reduces the optimization of the other goal, standard criteria for WSN are insufficient, so multiobjective criteria are considered to find the right path from the source node to the hole node. In the proposed particle swarm optimization method with multiobjective criteria, an attempt is made to create a balance between the goals in the network that may be contradictory or compatible, so that the optimality of all goals is considered. Therefore, the mentioned parameters are considered for multiobjective performance in order to find the most desirable path between the source node and the hole node. Finally, the cumulative evaluation function is shown in the following equation:

$$\begin{aligned} F = \min \; & \sum_{i}^{n}\sum_{j}^{k} D_j - d_i + \left(tE_{\mathrm{elec}_i} \times \left(\frac{N+2}{M} - 1\right) \right. \\ & \left. + \tau_f d_{\mathrm{cn}_j}^2 \times \left(\frac{N}{M} - 1\right)\right) + \left(D_{\mathrm{no}_j} + D_{\mathrm{en}_j}\right) \\ & + \left(\left(\varepsilon_e * n_i * d_{ij}^2\right) + \left(K - 1 * D_{jK}^2\right)\right) \\ \text{s.t.} & \sum_{j=1}^{k} D_j \geq \alpha \\ & \sum_{i=1}^{n} D_i \leq \beta \\ & \sum_{i=1}^{k} E_{\mathrm{cn}} + D_{\mathrm{no}_i} + D_{\mathrm{en}_i} \leq \gamma \\ & \sum_{i=1}^{k} \mathrm{ETX}_i \leq \delta. \end{aligned} \tag{14}$$

According to Equation (14), in each round of updating the proposed particle swarm optimization algorithm in the path selection step, the node that minimizes the value of the F function within the cluster is selected as the header node, and the data transfer process assumes the nodes of the cluster to the node of the hole. During several stages of the upgrade, the value of the objective function may be minimal for a node and the header may not change over several steps, but as time goes on and packets are sent, the header energy decreases and the header must be replaced. The path selected based on balancing the WSN network targets the shortest path that will create the shortest distance between nodes with the least amount of latency. A flowchart of the proposed method is presented in Figure 3.

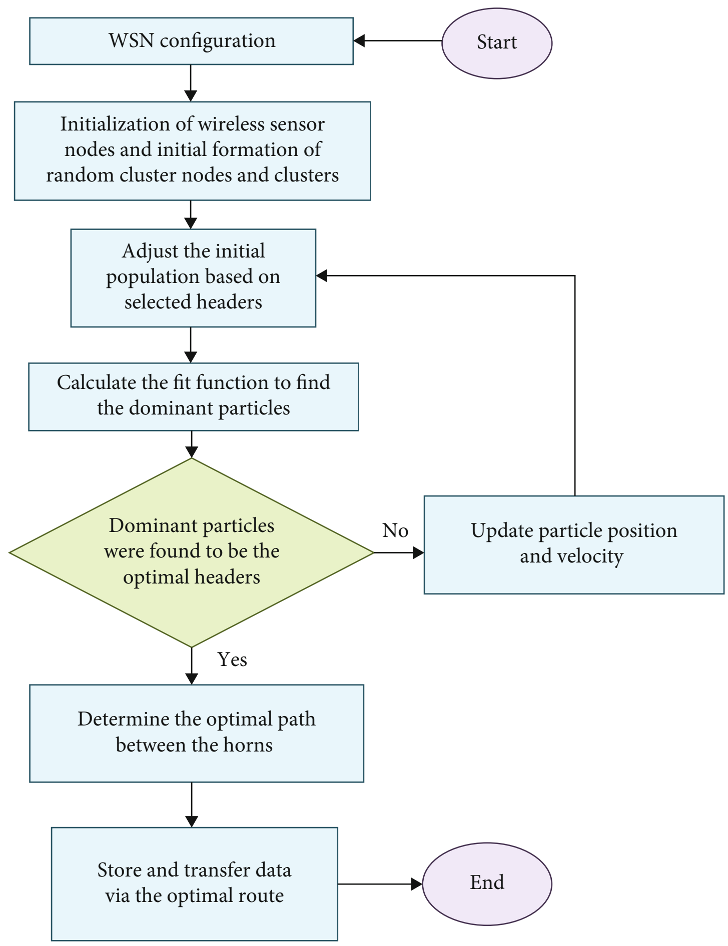

Figure 3: Flowchart of the proposed method.

4. Simulation and Evaluation

We start the implementation of the proposed method with the initial configuration of wireless sensor nodes and the distribution of nodes in the monitored environment in MATLAB software version 2019. The LEACH toolbox is used to simulate the wireless sensor network. We consider the monitored environment to be a 100 $*$ 100 space in which 100 sensor nodes are randomly scattered. The number of sensors can be adjusted according to different scenarios and this number can be changed to compare the proposed method with other methods available in publications. Other parameters related to network configuration are considered according to the standards mentioned in the publications. The parameters related to the proposed wireless sensor network are shown in Table 2. Figure 4 also shows the initial configuration of the wireless sensor network based on the proposed scenario.

As shown in Figure 4, the wireless sensor network is formed according to the random distribution of nodes and based on the values of the parameters in Table 2. The grid consists of 100 sensor nodes with the same initial energy equal to 0.5 joules, shown in the figure with small blue circles. Also, a hole node has been installed in the center of the monitored area to make it easier for wireless sensor nodes to access this hole. The initial energy of the cavity node is considered to be higher than the other nodes and equal to 10 joules. Since the hole node is constantly in contact with other nodes, it is natural to consume more energy, and for this purpose, the initial energy of the hole node is considered more.

In the first step of the hole node simulation, by sending a routing package in the form of a “Hello” message, it tries to obtain information about wireless sensor nodes in the network. Each of the sensor nodes that receive this message immediately sends the RREP routing response packets to begin the process of clustering the nodes on the network. The hole node then randomly selects some threaded nodes in the network. Given that, in the first step, no connection is made and the initial energy of all nodes is equal, so all nodes have an equal chance of being selected as the hub node. The hole node, as a centralized controller, collects information about the locations of sensors in the network and selects several random head nodes based on this information. Figure 5 shows the selection of the primary threaded nodes in the wireless sensor network.

As shown in Figure 5, the threaded nodes are randomly selected and marked with a black cross (×). In the next step, the wireless sensor nodes are joined to form clusters based on their distance from the eclipse nodes. Nodes that are closer to the hole are prevented from clustering in a header node, and

Table 2: Basic parameters of the proposed sensor network.

Parameters	Value
Network dimensions	$100 * 100$
Hole node coordinates	$(50, 50)$
The initial energy of the nodes	0.5
The initial energy of the cavity node	50
Energy consumption coefficient in data transmission	$5 * 10^8$
Energy consumption coefficient in data reception	$5 * 10^8$
Energy consumption coefficient in sending routing packets	$1 * 10^8$
Energy consumption coefficient in sending routing packets	$13 * 10^{13}$
Energy consumption coefficient in data aggregation	$5 * 10^9$
The initial probability of selecting the sensor node as a header	0.01
Maximum number of rounds	3500
Data package length	4000
Number of packets sent per step	10
Length of routing package	100
Radio board	5000

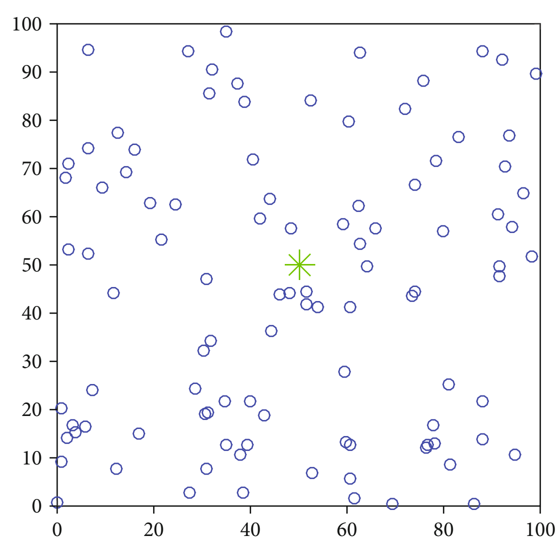

Figure 4: Initial configuration of the proposed wireless sensor network.

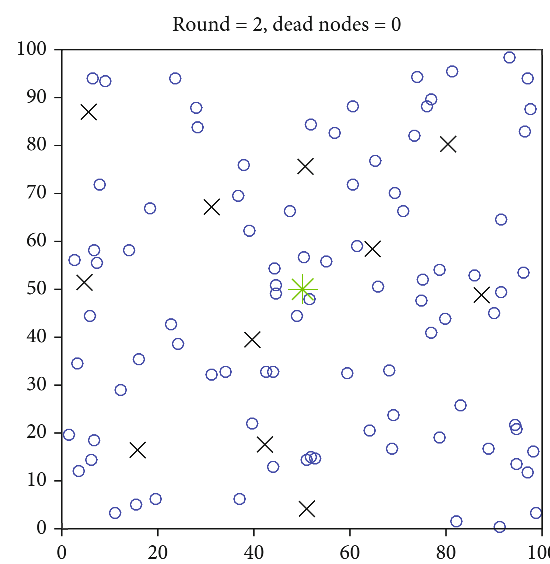

Figure 5: Selection of initial random headers.

these nodes will send their information directly to the header. After the formation of the cluster and the information about the nodes of the cluster, the member is transferred to the clusters, and through this, the factor of the average distances within the cluster can be calculated in order to find the optimal cluster nodes in the next steps. Figure 6 shows the transfer of initial information from cluster member nodes to clusters. Table 3 also shows the indices for the initial random headers.

As shown in Figure 6, the sensor nodes are clustered according to their distance to random headers, and each sensor node sends its information to the nearest header. Also in Figure 6 are nodes that do not belong to any cluster because the distance between these nodes and the hole node is less than the distance of the nearest head. Therefore, these sensor nodes can communicate directly with the hole to transmit information.

In the next step of implementing the proposed method, the selected headers are entered as the primary particles into the proposed multiobjective particle swarm algorithm. The initial population initially has a velocity and space of zero, and by evaluating the initial particles, the velocity and position values of the particles will be updated. In the first step of the proposed genetic algorithm, the initial population is evaluated according to randomly selected thread nodes. For this purpose, the cumulative evaluation function shown in Equation (13) seeks to minimize two general groups of objectives, the first objective is based on distances within clusters and distance to the cavity and the second objective is the least energy consumed and the most energy remaining in the

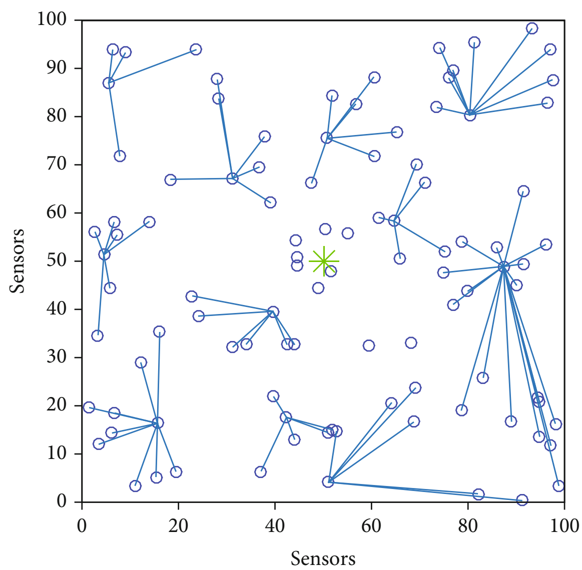

Figure 6: Transfer of cluster member node information to random headers.

Table 3: Index related to primary branches.

Header no.	12	11	10	9	8	7	6	5	4	3	2	1
Node index	99	94	85	77	68	59	36	28	25	14	13	6

nodes, which is applied to primary particles. The proposed proportionality function evaluates the headers according to energy factors, intercluster distances, distance to the hole, and link quality, and calculates the suitability value of each header. Accordingly, Table 4 shows the value of the primary particle fit function.

According to Table 4, it can be seen that the values of the fit function for each of the threaded nodes are calculated as primary particles. Given that data transfer has not yet taken place in the primary population, the initial energy of all cluster nodes and cluster member nodes is equal; hence, the value of the second target, which represents the energy factor in the wireless sensor network is equal for all particles. Thus, the suitability of wireless sensor nodes in the first step is determined based on the average distances within the cluster and the distance from the hole, but in the next steps, considering the optimal paths and information transfer and energy consumption, the residual energy factor will also affect the selection of optimal thread nodes and new particles.

In Table 4, it can be seen that some of the primary particles have lower proportional function values but some have higher proportional function values. Therefore, in the next step, the optimal particles are selected and stored in the archive of expert solutions. The location and velocity of the particles are updated based on expert particles in the archive, and other particles are moved to the optimal particles.

The results show that expert particles are shown as dominant particles in the figure with red star dots. It can be seen that these particles have the lowest proportion function among their generation. However, due to the same amount

Table 4: Values of the particle proportionality function.

Header no.	Node index	First goal value	Second goal value
1	6	0.0283	0.0999
2	13	0.0207	0.0999
3	14	0.0199	0.0999
4	25	0.0164	0.0999
5	28	0.0216	0.0999
6	36	0.0543	0.0999
7	59	0.0185	0.0999
8	68	0.0364	0.0999
9	88	0.0627	0.0999
10	85	0.269	0.0999
11	94	0.0186	0.0999
12	99	0.0232	0.0999

of initial energy of the nodes and the function of the second target, these particles are placed horizontally on the same line. In the next step, according to the dominant particles, new particles are produced with a tendency towards the original particles, and the target values are updated as a function of proportion, velocity values, and particle locations. In the proposed method, new particle populations are selected as new spinning nodes that evaluate the values of the minimum function. The new population is obtained by replacing the nondominant particles in the original population with new particles that have a better fit function value. After selecting the new particles as the new cluster nodes, the fit function is again calculated for the new population and the dominant expert particles in the Pareto space are selected in the search space. Table 5 shows the values of the evaluation functions in the new population relative to the original population.

As shown in Table 5, the values of the fit function are calculated according to the stated targets for the new particle population. According to Table 5, it can be seen that some of the particles that were selected as the dominant particles in the initial population have remained and improved, and some other nondominant particles in the initial population have given way to serious particles with optimal proportion function values. Figure 7 shows the replacement of new particles as new spinning nodes with previous spinning nodes.

As shown in Figure 7, the new threaded nodes have replaced the previous threaded nodes, and the connections between the threaded nodes and the hole node have been made through these new threaded nodes. The values of the fit function for the new and dominant particles at this stage are created, and based on this function, in this step, particles with the minimum values of the targets are selected as the dominant particles. New threaded nodes have been selected as the proposed solution for transferring information from sensor nodes and aggregating data and sending them to the node. However, due to the distances of the threaded nodes from the hole node, if a threaded node sees another threaded node in the direct path to the hole, send packets instead of direct transfer to the hole through the multistep transfer process between threaded nodes. It will be a hole until it reaches the node. Table 6 shows the probability of choosing the path

Table 5: Function values of the new population.

Header no.	Node index of the previous header	The value of the previous first objective function	The value of the previous second objective function	Node index of new header	The value of the new first objective function	The value of the new second objective function
1	6	0.0283	0.0999	10	0.0108	0.0998
2	13	0.0207	0.0999	31	0.0280	0.0998
3	14	0.0199	0.0999	51	0.0145	0.0998
4	25	0.0164	0.0999	52	0.0218	0.0998
5	28	0.0216	0.0999	59	0.0169	0.0998
6	36	0.0543	0.0999	62	0.0219	0.0998
7	59	0.0185	0.0999	66	0.0201	0.0998
8	68	0.0364	0.0999	71	0.0483	0.0998
9	88	0.0627	0.0999	93	0.0224	0.0998
10	85	0.269	0.0999	94	0.0223	0.0998
11	94	0.0186	0.0999	95	0.0218	0.0998
12	99	0.0232	0.0999	100	0.0205	0.0999

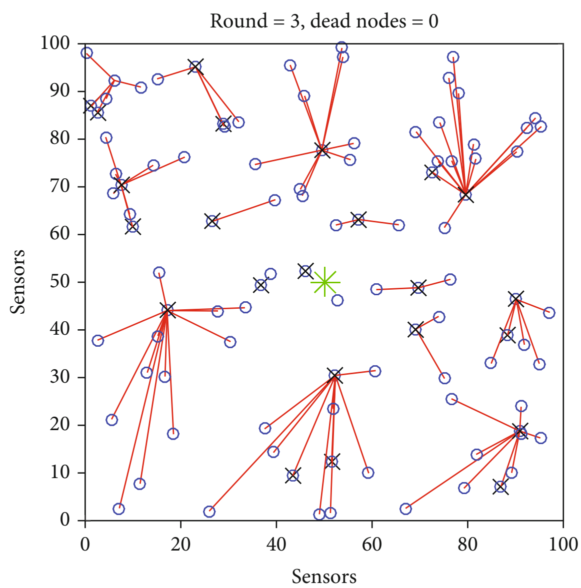

Figure 7: Replacement of new headers.

Table 6: Suggested route with the probability of success of each hop in the route.

This cluster head 10 is selected by probability 0.89179
This cluster head 31 is selected by probability 0.97196
This cluster head 51 is selected by probability 0.95471
This cluster head 52 is selected by probability 0.97815
This cluster head 57 is selected by probability 0.83032
This cluster head 62 is selected by probability 0.97806
This cluster head 66 is selected by probability 0.9799
This cluster head 71 is selected by probability 0.95172
This cluster head 93 is selected by probability 0.97557
This cluster head 95 is selected by probability 0.97766
This cluster head 5 is selected by probability 0.97821
This cluster head 100 is selected by probability 0.9795
The optimal path is 57 10 71 51 31 93 95 62 52 94 100 66

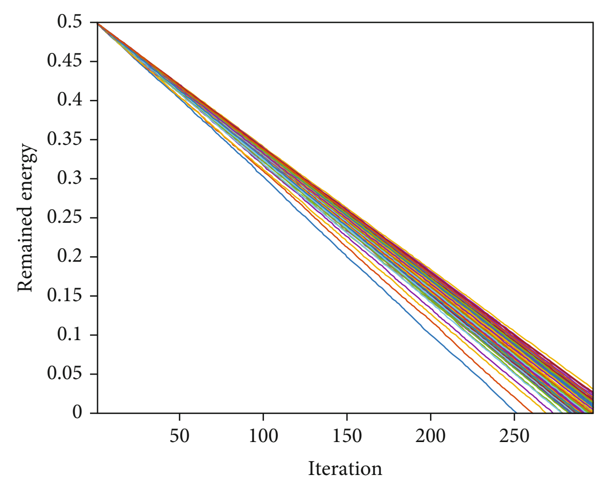

Figure 8: Residual energy of the wireless sensor nodes by increasing the steps of data transmission in the network.

between the threaded nodes with the values of the probability of success of each of these nodes in the path.

As shown in Table 6, the proposed path is determined according to the distances of the threaded nodes from the hole, and in this step of sending information, the sensor nodes send their information to the nearest thread and, based on the mentioned sequence, the clusters send data packets to the hole. At each step of the data transmission, the amount of energy of the wireless sensor nodes, especially the threaded nodes, is reduced to the point that the amount of energy of the nodes is exhausted and the network performance is disrupted. The proposed scenario identifies the optimal head nodes by finding expert particles on the Pareto front at each step of the data transmission, and the information transfer is done in order to aggregate the data. With the transfer of information in the network, the energy of the nodes naturally becomes less and less, and finally, the energy of the nodes is exhausted. In Figure 8, from the 1400 iteration onwards, it can be seen that in the simulation environment, some of the nodes are shown as small red dots that represent dead

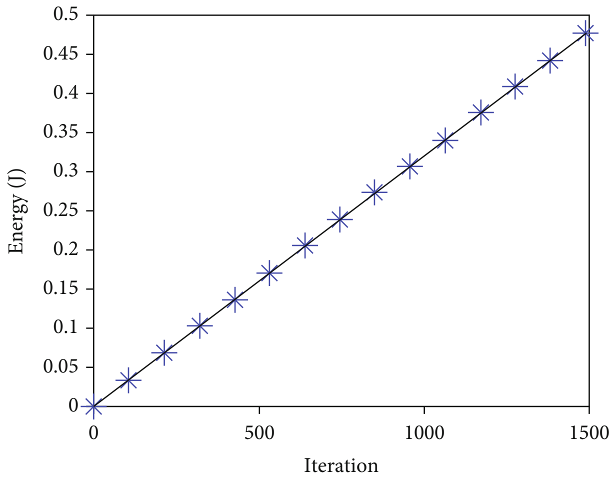

FIGURE 9: Average energy consumption in the proposed wireless sensor network.

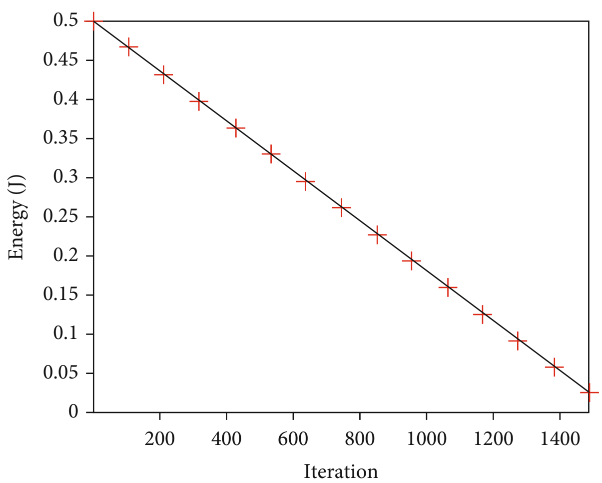

FIGURE 10: Average residual energy with increasing data transfer steps in the proposed method.

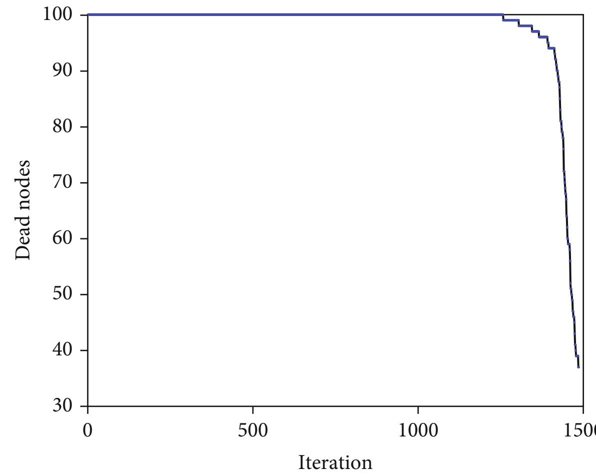

FIGURE 11: Death process of sensor nodes in the network.

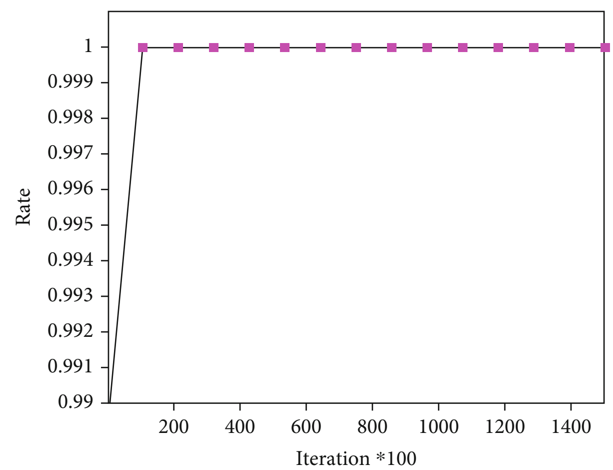

FIGURE 12: Throughput ratio in the network.

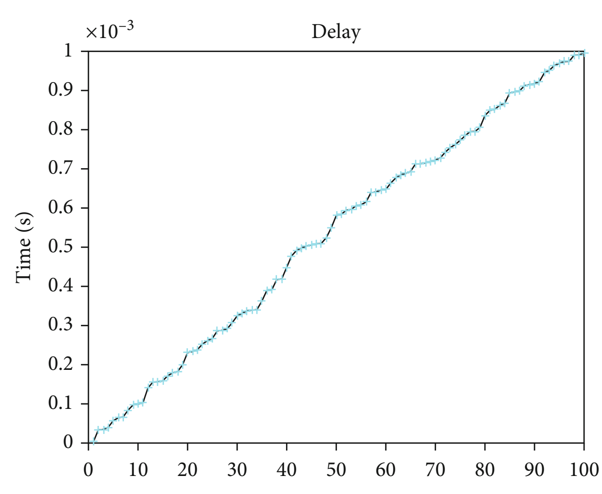

FIGURE 13: Diagram of the cumulative end-to-end delay of 100 nodes in the network.

nodes; their energy is exhausted. Finally, in round 1487, the proposed scenario was not able to aggregate data from the entire network and the network performance was disrupted. Due to the meta-exploratory nature, the proposed method has tried to learn the network factors and the tendency towards the optimal point. Therefore, we made the convergence of the multiobjective particle swarm optimization algorithm towards the optimal point. As shown in these results, the multiobjective particle swarm optimization algorithm reduces the value of the objective function in each step to converge to the optimal point, given that the proportion function used is of the minimization material. In the following, we will evaluate the proposed method.

4.1. Evaluation of the Proposed Method. Evaluation criteria in wireless sensor networks vary according to different network applications. Since, in this paper, we seek to reduce energy consumption, increase grid life, reduce latency, and increase grid throughput, we will suffice with these four criteria. We first evaluate the residual energy of the wireless sensor nodes

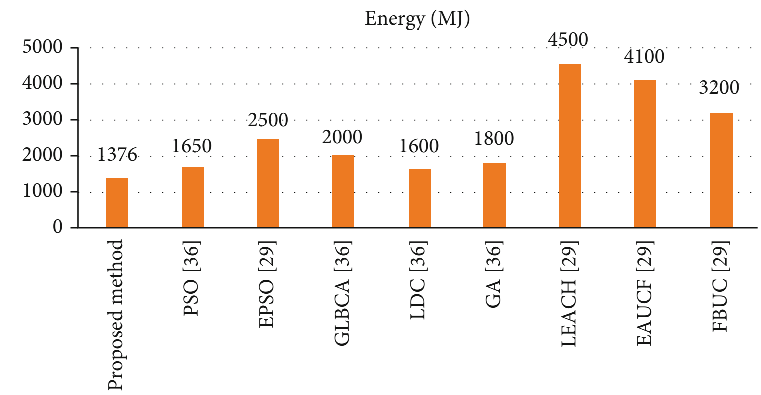

FIGURE 14: Comparison between the proposed method and previous methods in terms of energy consumption.

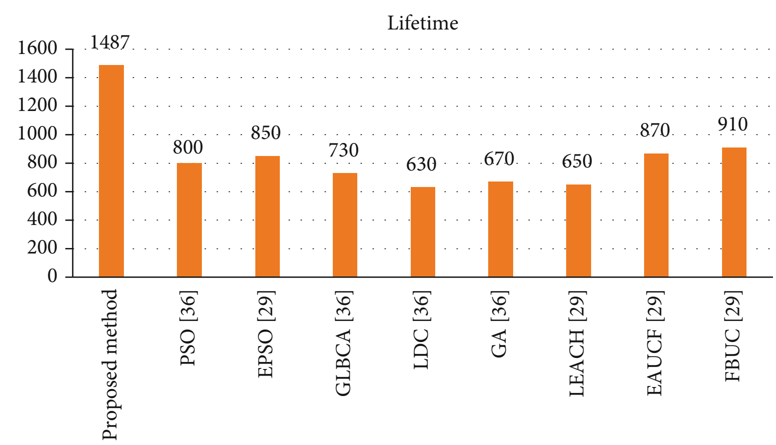

FIGURE 15: Comparison between the proposed method and previous methods in terms of network life.

by increasing the steps of data transmission in the network. The result of this test is shown in Figure 8.

The residual energy of the wireless sensor nodes decreases regularly for all nodes, indicating a balance of energy consumption in the proposed wireless sensor network. In contrast, residual energy is consumed, which can be achieved by subtracting residual energy from the primary energy.

As shown in Figure 9, the average energy consumption in the proposed wireless sensor network increases in a balanced way according to the multiobjective particle swarm optimization method. Moreover, the average residual energy with increasing data transfer steps in the proposed method is shown in Figure 10. This figure shows the proposed balanced energy consumption in wireless sensor networks by providing a linear curve. Thus, it can be said that in the proposed method, the balance of energy consumption is established and the energy of some nodes does not end earlier than others and the energy consumption will be the same in all nodes.

Network lifetime refers to the period that the network is available during a time that does not interfere with the aggregation of network data. Therefore, the life of the network can be considered as the time of energy depletion of some nodes in the network where the network is not able to continue the operation with the remaining nodes. Figure 11 shows a diagram of network life.

As shown in Figure 11, in the proposed network, the network life reaches 1487 cycles and the death of the first node occurs after 1259 repetitions. In wireless sensor networks, with the death of a node, all the paths leading to this node are deadlocked and have to be redirected, and the task of collecting information from the area covered by that node is on the shoulders of its neighboring nodes. The knot falls. This increases the energy consumption of neighboring nodes and increases the likelihood of their death. Thus, as shown in Figure 11, after the death of the first node, the death rate of the other nodes also increases.

Another criterion that has been used to evaluate the proposed method is the throughput criterion in the proposed sensor network. The pass rate is the rate of packets sent per unit of time received at the destination. In other words, the rate of data collected that has safely reached the hole per unit time in a wireless sensor network is called network throughput.

Further, we made the passing criteria of the proposed method. As shown in Figure 12, the proposed method tries to escape the bottlenecks and create a safe path to send data to the whole node w.r.t optimal routing. Therefore, the throughput rate in the proposed network is high and its average is 99.93%.

The last criterion used in the proposed method for evaluation is the end-to-end delay of nodes in the network. Given that the transfer time coefficient of a packet is for fixed nodes, the main reason for the delay in the end-to-end transfer is the distance between nodes. Since in the proposed method the transfer between the sensor nodes and the cluster node takes place, the shorter distance between the cluster nodes and other nodes means accurate clustering and the average distances within the cluster are less, which is one of the objectives. The objective function is proposed in the proposed multiobjective particle swarm optimization algorithm. Moreover, diagram of the cumulative end-to-end delay of 100 nodes is shown in Figure 13. This diagram shows that the proposed method for 100 nodes has an average delay of 1 millisecond per cycle. This small value indicates the small distance between the cluster nodes and the cluster member nodes, which is obtained thanks to the meta-innovative nature of the multiobjective particle swarm optimization algorithm.

4.2. Comparative Analysis with Previous Works. The energy constraints of wireless sensor nodes have led many researchers to optimize methods to find the optimal path to reduce energy and other routing factors in these types of networks. So, wireless sensor networks are becoming more and more popular. In the continuation of this part of the paper, we compare the proposed method with the previous methods in terms of energy consumption and network life. For this purpose, we compare the proposed method with the basic methods of PSO, GLBCA, GA, LDC, EPSO, LEACH, EAUCF, and FBUC algorithms mentioned in [10, 17]. Figure 14 shows a comparison between the proposed method and previous methods in terms of average energy consumption in the network.

As shown in Figure 14, the proposed method has a lower average energy consumption than the other previous methods.

Figure 15 also compares the proposed method with previous methods in terms of network life.

As shown in Figure 15, the proposed method has a longer lifespan than other previous methods. The longer life of the proposed method indicates the balance of energy consumption in this method and the later death of nodes, which results from accurate clustering and observance of the main factors of the network. The proposed method has significantly improved in comparison with previous methods in this field by achieving a balance between several goals in network routing.

5. Conclusion

In this paper, an energy-aware routing protocol based on a multiobjective particle swarm optimization algorithm is presented. In the proposed method, particles are considered as eclipse nodes whose proportionality function has the highest value based on service quality goals including residual energy, link quality, end-to-end latency, and delivery rate for that node. In fact, in each cluster of sensor nodes that are formed in the monitored areas, the node that has the highest value of the target function is selected as the head node and is responsible for sending data packets. Link quality is defined as the energy used to send packets from the source node to the current node, in addition to the estimated cost of sending packets from the next node to the destination. This method uses a multistep routing approach in which the next node is dynamically selected in each step. In order to select the next node in the network, in addition to the value of the proportion function, the distance between the nodes and the distance to the hole is also considered. The simulation results of the proposed method show that the proposed method, in addition to having lower average energy consumption than other previous methods, also has a longer lifespan than other previous methods. The lower average energy consumption and longer life of the proposed method indicate the balance of energy consumption in this method and the later death of nodes, which originates from accurate clustering and observance of the main factors of the network. The proposed method by achieving a balance between several goals in network routing has been able to achieve the desired results, which has significantly improved compared to previous methods in this field. In our future work, we try to use density-based clustering methods to cluster wireless sensor nodes in the network. We believe that this method would improve the clustering of network nodes more efficiently.

Data Availability

The simulation and all proposed data are included in the paper, so there is no need of more data collection.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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