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An energy efficient routing scheme in internet of things enabled WSN: neuro-fuzzy approach

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Abstract
The Internet of Things (IoT) has led to the deployment of many battery-powered sensors in various applications to gather, process, and analyze meaningful data. Clusters of sensors provide for more efficient data collection and increased scalability in such contexts. A low-latency, long-lived routing strategy is described for WSNs that can connect to the Internet of Things. In this research, we present a neuro-fuzzy approach to energy-efficient routing (NFEER) for IoT-enabled WSNs. The novelty of the proposed algorithms is the multiple parameters for the routing in IoT-enabled WSN as consideration of CH distance to sink, cluster size, and residual energy of CH. These variables are used to find the most efficient path across the network, which will help mitigate the hotspot issue. During the operation on the condition "consider only those nodes which have energy greater than the pre-defined threshold energy," the NFEER relies on energy thresholds to restrict the set of candidate nodes. Extensive simulations are performed to specify the effectiveness of the NFEER, and it elongates stability period by 27.98%, 13.97%, and 10.91% as compared to existing protocols. The stability duration, residual energy, network lifetime, and throughput are enhanced by the proposed method as compared to PSO-Kmean, BMHGA, and FSO-PSO.

Keywords Neuro-fuzzy · IoT · Clustering · Routing · WSN

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1 Introduction

IoT enable WSN refers to an emerging trend in information and communications technology that involves a global system of machines and gadgets that are able to communicate with one another [1]. The primary goal of the Internet of Things is something that is already present in our regular lives and is dependent on the actions of users. However, the limited energy of sensor nodes is the primary concern that acts as a bottleneck to drive a large number of time-critical applications, which are used for monitoring, tracking, coordinating, and managing in various settings [2]. Sensors in a forest, city, health care, under water, and industrial environment may be interconnected to monitor and regulate environmental variables. Significant sensing work that can revolutionize data collecting and processing may be achieved by linking them over wireless networks [3, 4]. By establishing energy-efficient communication between sensor nodes, the network's operating period may be extended as much as possible.

Traditional routing techniques, when used in a network with homogenous nodes, are unable to save the energy of the nodes. It has been determined that the homogeneous network's nodes, which all share the same capacity, computation, and coverage resources, are ineffective. As data transmission progresses in smaller steps, node energy drops. Heterogeneous network nodes are grouped by their energy source. The algorithm ensures that the method devised for different groups of sensor nodes matches their energy profile. High-energy network nodes serve as a storehouse for other nodes. Because of the significant role they play in the variety of the energy supply, expected battery resources are the ones that see the most widespread use [5].

The reduction of the sensor nodes' overall energy consumption is one of the primary goals that is being pursued by the researchers that are investigating IoT-based WSN [6]. In this context, researchers have developed energy-efficient routing algorithms. These solutions conserve sensor node energy to prolong network life [7]. A novel protocol named NFEER is proposed to solve the shortcomings of prior cluster formation strategies. It considers the CH distance to sink, residual energy of CH as well as cluster size. This is achieved by using convolutional neural networks that make use of fuzzy rules in order to modify the weights of the nodes in the network. Throughout the whole procedure of cluster building as well as cluster-based routing, a reasoning strategy known as fuzzy reasoning was used. These four criteria will be applied to each and every CH that is a part of the proposed network by the non-CH nodes in the system using the fuzzy inference method. In addition to this, the system makes use of the fuzzy inference system and applies the member join principle. The member join principle involves estimating the greatest amount of energy required for connecting a CH. Comparisons are made between the proposed routing mechanism and the protocols that are presently in operation [8–10] so that the efficacy of the proposed mechanism can be evaluated.

Inspired by the conversation, we would like to propose a novel approach that takes into consideration the NFEER in order to locate the routing route in the IoT-based WSN thus that the performance of the network may be achieved.

The following highlights have the most significance:

(a) In order to extend the lifespan of the network, we present a neuro-fuzzy-based method for IoT-based WSNs. This algorithm takes into account three parameters: the cluster size, the distance the CHs are from the sink, and the amount of energy they have left over.
(b) The purpose of this research is to offer an energy-efficient routing system that can be used for single or multi-hop communication and that incorporates the criteria in order to circumvent the issue of hot spots of the network.
(c) The NFEER technique would only consider initialization nodes with energy levels over a certain threshold. Using this criterion accelerated convergence to the indicated optimization technique.
(d) When the performance of the proposed method is compared with the performance of the state-of-the-art optimized routing techniques based on neuro-fuzzy, such as PSO-Kmean [11], BMHGA [12], and FSO-PSO [13].
(e) The proposed NFEER algorithm considers only those nodes for the initialization process which have energy more than the pre-defined threshold energy. This criterion renders the early convergence to the proposed optimization strategy.

The remaining parts of this paper is as follows: The relevant work is presented in Sect. 2, followed by a complete discussion of the suggested algorithm in Sect. 3, followed by a description of the simulation results and a summary in Sect. 4, and finally, the conclusion is presented in Sect. 5 (Table 1).

Table 1 Abbreviations

N	Total number of nodes
E_{tx} (l, d)	The amount of energy that is required to send z bits of data across d
E_{elec}	The energy that is utilized to activate the electronics of both the transmitter and the receiver
E_{efs}	Represent the free space energy model
E_{mp}	The energy that is involved in the multipath energy model
d_o	Threshold distance
E_{rx}	The amount of power required to receive z bits of data
E_{da}	Energy used in the process of aggregating 1-bit data
E_{dx}	During the process of data aggregation, energy is used
E_{Total}	The total energy of the network
CH	Cluster head
$E_{R(i)}$	Residual energy of node i
E(i)	Initial energy of node i
NFEER	Neuro-fuzzy approach to energy-efficient routing
N_NORM, N_ADVN, and N_SUP,	Normal, advance, and super nodes

2 Related work

IoT-enable WSNs have several issues, including extending network lifespan, reducing transmission latency, and ensuring reliable communication with a high data delivery rate. WSNs is a critical part of IoT applications as it is responsible for collecting large amounts of data. As nodes are powered by batteries thus energy consumption is the most studied QoS measure in the literature because it has a direct impact on network lifetime. Using clustering algorithms, several attempts were made to improve the performance and lifetime of the wireless sensor network. They are being used in a variety of applications. Batteries often power sensor nodes in classic WSNs. Efficiency of the battery energy has suited a key concern for WSNs [14] because of the limited collected energy and the difficulty of battery-operated substitution. Several research attempts have been recently committed to designing energy-efficient methods toward extend the lifespan of network, including cluster-based routings. CH is recommended to effectively manage and avoid the needless expenditure of energy collected by sensor nodes, while clustered WSNs are normally formed of the sink and the required number of clusters. On the other hand, the performance measurements utilized in prior research are unsuitable for real-world applications such as remote surveillance systems [15, 16].

Gaikwad et al. [17] introduced an enhanced ABC for large-scale data clustering optimization. The modified ABC is used to construct the cluster, consuming less power. On the other hand, the protocol methodology utilizes a distributed technique to select CHs and fixing the threshold power is utilized for selecting CHs using K-means, according to experimental data. Amiri et al. [18] suggested a novel fuzzy algorithm with enhanced discrete ABC for data clustering.

Betzler et al. [19] presented an IoT technique for round-trip time estimate that uses a backoff factor to incorporate the age factor for retransmission timeouts. Almost all IoT communications are well-suited to this kind of fluidity and flexibility. Another important phase in the clustering process, known as cluster formation, has been emphasized by several studies. Das et al. [20] suggested an improved form of the Ant Bee Colony optimization technique for data clustering. The forgiving features of bees are considered in the updated form and provide a fair chance for untrustworthy and trustworthy bees. The suggested technique uses a probability-based selection mechanism to allocate a set of data in each cyclic rotation. It is combined the suggested approach with GA and PSO algorithms to improve its performance and provide global optimum and diversified solutions [21, 22].

Rani et al. [11] proposed a GA with a dynamic clustering-based technique and frame relay nodes. A mobile sink technique is used for CH selection rather than data gathering; the node's location and residual energy are critical characteristics. In order to choose the preferable sensor node (SN) from a cluster of nodes. Pan et al. [23] developed two enhanced techniques. First, a search model was created using the best-of-random mutation strategy. Second, to develop new solutions, several dimensions were modified. The various optimization approaches were employed to compare HABC against the basic Ant Bee Colony method and two additional modified Ant Bee Colony variants for performance assessment. Based on the results of the studies, their suggested method has resulted in significant gains in optimization performance [24, 25].

Sahoo et al. [26] proposed a hierarchical hybrid technique for distributed clustering in WSNs. There are two stages of clustering: ground-level clustering with GA and upper-level clustering with greater convergence. The method reduced energy usage, which increased the network's lifespan. Mirjalili et al. [27] proposed GWO, a leader selection mechanism based on alpha, beta, and delta wolves, to upgrade and modify the solutions in the archive. A power system mechanism has been added to GWO to improve nondominated solutions.

Agrawal et al. [28] developed the GWO-C method to pick an appropriate clustering technique for transmitting information from the node to the BS and maximizing the network's lifespan. Zahedi et al. [29] proposed a SIF strategy to justify swarm intelligence; it uses an effective clustering method to produce efficient clusters when appropriate CHs are picked. This strategy yields balanced clusters. This routing strategy aims to extend network life [13, 30]. Zhang et al. [31] suggested an effective clustering and topology management routing system.

Renold et al. [32] introduced a MRL-SCSO protocol for efficient data routing. This approach takes into consideration residual energy as well as buffer length. In addition to that, it implements sleep scheduling as a means of energy saving. The most significant problems of this protocol are its significant levels of delay and its unsatisfactory delivery of packets. Guo et al. [33] suggested a routing system that is based on reinforcement learning and in which the forwarder node is chosen based on the amount of residual energy, the connection distance, and the hop count. On the other hand, it has a significant latency and an uneven distribution of energy [12].

To improve the efficiency of food supply management in smart cities, Nagarajan et al. [34] developed an Internet of Things (IoT)-based food supply with dynamic vehicle routing (IFSCDVR) together with a bee colony algorithm. A smart sensor data collection strategy that is based on IoT is utilized, which would improve the efficacy and accuracy of the supply chain network with the minimized size of dataset and the introduction of an algorithm for vehicle routing, as well as the tracing of the contamination sources of infected food that is sold in the markets. Since the IoT model was first developed, it has been discovered that WSNs are the concept's essential enabler. In the Internet of Things, all of the sensor nodes are able to connect to the internet so that they may send and receive information; however, in wireless sensor networks, the nodes do not have a direct connection to the internet. In order to connect to the internet, each node in a WSN has to use a mediator. Over the last several years, a significant amount of research has been done on bridging WSN into IoT. When it comes to connecting the Internet of Things and wireless sensor networks, there are a lot of security holes that need to be fixed [35–38].

Palanisamy et al. [39] present communication trust and energy aware (CTEA) routing protocol that makes use of the proposed trust model to mitigate the effects of badmouth and energy drain attacks. Trust models are the preferred mechanism for securing WSN. The hacked nodes are used to mislead the sensed data and disrupt communication, both of which have the potential to impact the whole of the decision-making system that is reliant on the sensed data. It is also possible to deplete the energy stored in the sensor nodes, which will result in the networks having a shorter battery life [40].

Existing data routing systems does not include numerous criteria for improving network longevity, reducing communication latency, and increasing throughput. Consequently, networks face difficulties including energy holes problem. This paper offers neuro-fuzzy energy-efficient routing technique for IoT-enabled WSNs. This paper suggests a cluster-based routing scheme to balance sensor node load. The deployed node uses energy level, throughput, and network lifespan to identify the ideal route for data transmission. The suggested technique improves QoS and prevents energy holes and network partitions.

3 Network structure of NFEER

In this section, we consider a heterogeneous network that has three different degrees of heterogeneity energy. When processing data, these nodes use up enough energy. In order to limit the amount of energy that is being used, here we explored an energy model. This model utilizes the amount of energy that was utilized in order to form the nodes that are responsible for data transmission for NFEER until it got entirely depleted.

3.1 Radio energy model

NFEER's sensor radio energy paradigm is shown in Fig. 1 as a system structure of the node energy consumption. In this work, we used the initial-order radio energy model. The distance between nodes i and j is denoted by d_{ij}. The amount of energy used by node i to convey l-bit data to node j is

$$E_{tx}\left(l, d_{ij}\right) = \begin{cases} l * E_{\text{elec}} + l * E_{\text{efs}} * d_{ij}{}^{2} for d_{ij} \leq do \\ l * E_{\text{elec}} + z * E_{\text{mp}} * d_{ij}{}^{4} for d_{ij} > do \end{cases} \quad (1)$$

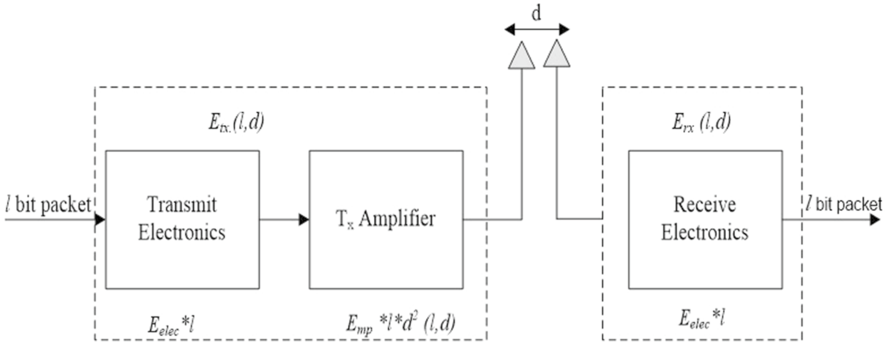

Fig. 1 Radio energy model

where, Eqs. (2) and (3) represent the energy spent by a node in accepting and aggregating z-bit data packets, respectively.

$$E_{\mathrm{rx}}(l) = l * E_{\mathrm{elec}} \tag{2}$$

and

$$E_{\mathrm{ag}}(l) = x * l * E_{\mathrm{da}} \tag{3}$$

Equation (4) calculates the overall energy spent in packet forwarding, processing, and data aggregation.

$$E_{\mathrm{Total}} = E_{\mathrm{tx}} + E_{\mathrm{elec}} + E_{\mathrm{ag}} \tag{4}$$

Radiofrequency (RF) transmissions from high-power sources, such as radio stations, are expected to power sensor nodes. RF-to-DC power conversion circuitry is used to store the received power in a rechargeable battery during energy enable time slots.

The proposed NFEER makes use of energy heterogeneous nodes for its operation, and during the course of this network, three levels of energy heterogeneity will continue to be engaged in a wireless sensor network that is heterogeneous and has certain nodes that have an extra energy source. The other nodes on the network rely on the high-energy nodes to serve as repository for their data, which is the primary role of these nodes. Using the neuro-fuzzy approach, these nodes make certain that this function is carried out in an efficient manner. The number of normal nodes, advanced nodes, and super nodes that are being utilized in the network is denoted by N_NORM, N_ADVN, and N_SUP, respectively, in the provided Eqs. (5–11). In this model, the advance node and the super node are both considered to be high-energy nodes since their fractional correspondences by θ and $\mho$ with the total number of nodes, which is represented by n, are both quite high.

$$N\_\mathrm{SUP} = n * \mho \tag{5}$$

$$N\_\mathrm{ADVN} = n * \theta \tag{6}$$

$$N\_\mathrm{NORM} = n * (1 - \mho - \theta) \tag{7}$$

In comparison with standard nodes, super and advanced nodes continue to occupy positions that are two and three times higher inside the field of energy, respectively. Equations (8–11) calculate the total energy of the network, which is represented by (E_T). The energy of the normal node is designated by E_NORM, whereas the energy of the advanced node and the super node are respectively denoted by E_ADVN and E_SUP.

$$E\_\mathrm{SUP} = E_O * (1 + \omega) * n * \mho \tag{8}$$

$$E\_\mathrm{ADVN} = E_O * (1 + \phi) * n * \theta \tag{9}$$

$$E\_\mathrm{NORM} = E_O * (1 - \mho - \theta) * n \tag{10}$$

$$E_T = E\_\mathrm{SUP} + E\_\mathrm{ADVN} + E\_\mathrm{NORM} \tag{11}$$

3.2 NFEER network assumptions

Sensor node attributes affected network framing. We must give importance to the frame characteristics for NFEER sensor nodes, which comprise the following:

a. The network is supposed to be a square-shaped region with a surface area of 200×200 m2, and 500×500 m2 throughout the network's functioning; the sensor nodes and sink remain stationary.
b. The data collection sink is located outside the network since the NFEER application is regarded as hostile and human involvement is impossible.
c. The radio energy model, which is often employed in most cluster-based routing algorithms, is applied to the energy consumption of the sensor nodes.
d. Even though communication between sensor nodes is wireless, physical medium characteristics such as reflection, refraction, diffraction, and signal splitting are ignored.
e. Physical damage to sensor nodes installed in the target region is not considered.

3.3 Proposed method: NFEER

The primary objective of the proposed study is to increase the lifespan of the IoT-based WSN. The proposed neuro-fuzzy method is a decision-making tool that uses a variety of inputs to produce a single, high-quality output. In cluster-based routing protocols like PSO-Kmean, the suggested model operates in several rounds, beginning with the first round, progressing through intermediate rounds, and finishing with the final round. When compared to the current protocols, such as PSO-Kmean, BMHGA, and FSO-PSO, our suggested approach is unique from the beginning. It is important to note that the number of factors that are taken into account while forming the cluster has increased. When a node is in range of two or more CHs, it transmits data to all of them, creating redundancy. As a result, in our research, routing path was influenced by four distinct elements of each significant parameter. In addition, this research uses a Convolution Neural Network (CNN) to build rules for identifying energy-efficient routing as part of a deep learning strategy.

These findings are provided through a single output after being processed via two hidden layers and one input layer, all of which are used by CNN. Hidden layers are employed as convolution layers in this algorithm. Data from previous and current communications is used to train the neural network. In the beginning, the data from the past is utilized for training. The fuzzy inference engine modifies weights using current input and fuzzy rules. As the distance and energy availability from the cluster heads change, so do the cluster members. The convolution neural network is used to analyze the energy consumption and routing patterns of distinct nodes. Rules are developed via the training of convolution neural networks in order to discover the most effective path with the least amount of energy used. Due to the nature of such networks, training takes place at the base station, with rules being communicated only to the sensor nodes. The sensor nodes communicate a collection of data acquired by the sensor nodes in order to do testing. To ensure that the route identified by the suggested routing algorithm is as efficient as possible, this testing was conducted. Using a convolution neural network for deep learning, the suggested routing method is able to offer an energy-efficient routing procedure by learning the node behaviors with regard to communication. The proposed system of neuro-fuzzy-based system shown in Fig. 2.

3.3.1 Neuro-fuzzy based method

This section discusses a neuro-fuzzy-based inference system for locating a sensor node that will serve as the cluster's central node. To feed the next suggested neuro-fuzzy inference system, the fuzzy-based inference system's output is used as

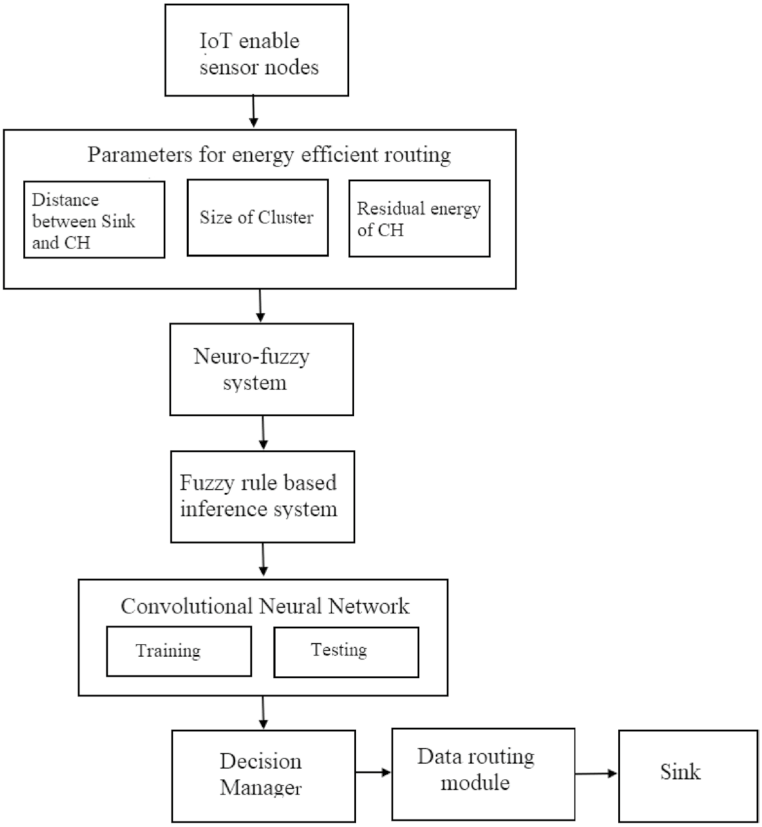

Fig. 2 Neuro-fuzzy rule-based proposed system

input data. The fuzzy-based inference system made use of a Mamdani engine. To determine whether a node may serve as a cluster head, we looked at three metrics: CH distance to sink, cluster size, and residual energy of CH. This is the most plausible criteria for optimal path selection since sensor nodes have a limited amount of power for processing and communication and these battery powers are almost impossible to replenish in nature. If these cluster heads were located distant from the base station, they would waste more energy than necessary. As a result, the distance between the node and the base station is also taken into consideration. Another criterion for determining node density is how far sensors are spread out from the cluster head. Sensor nodes having a restricted number of neighbors in their communication range cannot communicate directly to the cluster head and need intermediate nodes for transmission, increasing communication costs. Consequently. As a result, node density was also taken into consideration.

According to the three metrics, the language variables are as follows: CH distance to sink (adjacent, adjacent distant, medium distant, distant); cluster size (small, medium, highly medium, large); and residual energy of CH (low, average, more average, high). Fuzzy triangle and trapezoidal membership functions were utilized instead of other membership functions (such as Sigmoidal) to achieve superior performance in real-time applications. Trapezoidal membership functions were utilized for residual energy values below and above, node distances adjacent and distant, and node densities insufficient and compact. Figures 3, 4, 5, and 6 show the triangle membership function used for the remainder of the values. Membership function is used as a language variable to describe the likelihood that a sensor node would be allocated the role of optimal path (weakest, weaker, weak, low medium, medium, highly medium, strong, stronger, strongest). Fuzzification needed a total of 16 rules, as indicated in Table 2, due to the fact that we employed three metrics. A set of rules for fuzzy inference was created and placed in the knowledge base of the system. There were only two rules that could be taken to their logical conclusion: To begin with, residual energy of CH value equaled the high, its density was compact, and it was located close to the sink.

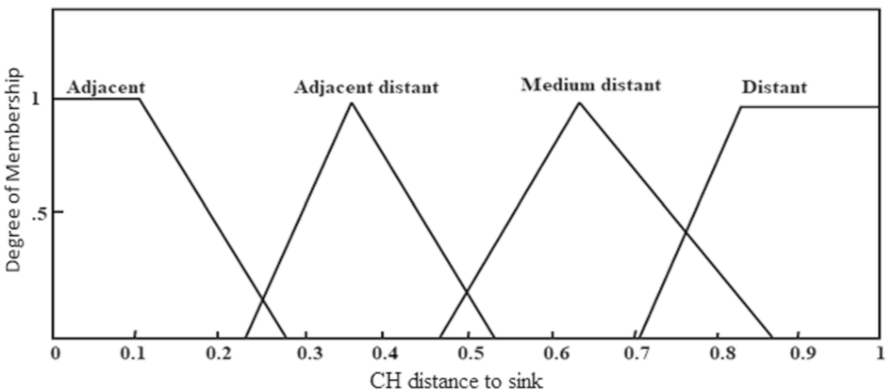

Fig. 3 Linguistic value of CH distance to sink

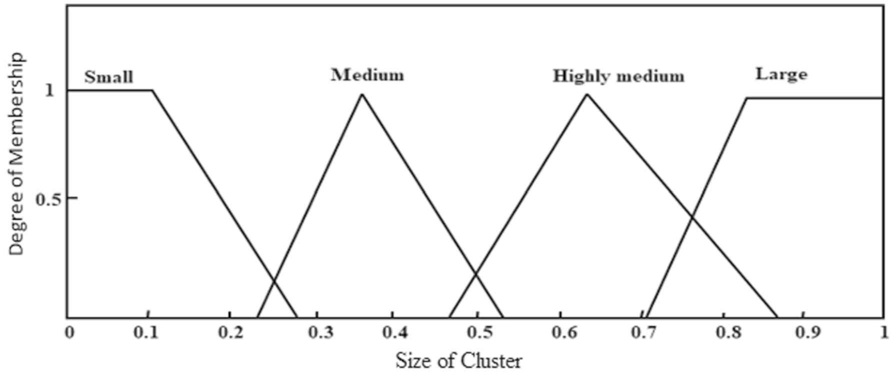

Fig. 4 Linguistic value of cluster size

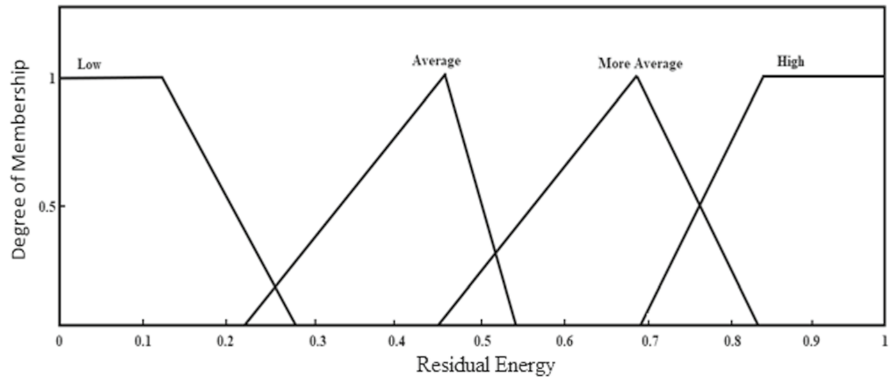

Fig. 5 Linguistic value of residual energy of CH

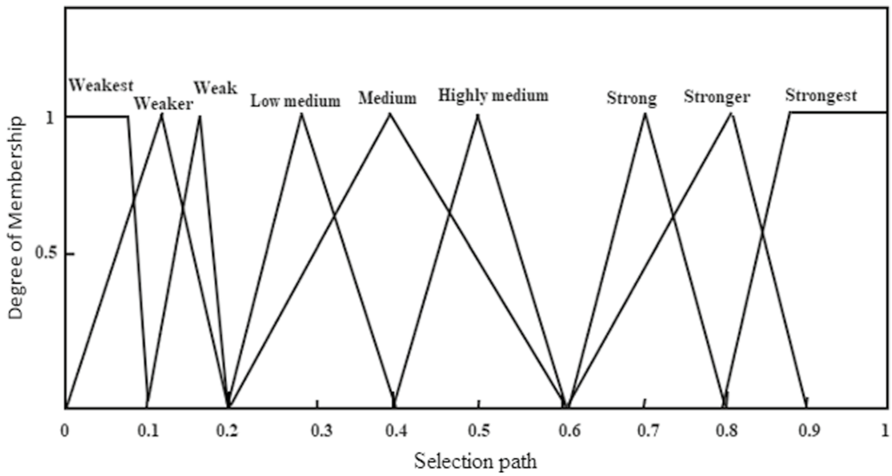

Fig. 6 Membership function for optimal path

Table 2 Fuzzy rule based

CH distance to sink	Cluster size	Residual energy of CH	Membership selection
Adjacent	Small	Low	Weakest
Adjacent	Small	Average	Weaker
Adjacent	Medium	More average	Low medium
Adjacent	Medium	High	stronger
Adjacent distant	High Medium	Low	Weakest
Adjacent distant	High Medium	Average	strong
Adjacent distant	Large	More average	Low medium
Adjacent distant	Large	High	medium
Medium distant	Small	Low	weaker
Medium distant	Small	Average	Highly medium
Medium distant	Medium	More average	Stronger
Medium distant	Medium	High	Strongest
Distant	High Medium	Low	Weak
Distant	High Medium	Average	Strong
Distant	Large	More average	Highly medium
Distant	Large	High	Medium

This gave the node a great probability of being assigned the role of optimal path. Nodes with small cluster size and high residual energy have select an optimal path if they are closer from the sink and CH.

(a) **CH distance to Sink**

CH distance to sink is the significant parameter to find the linguistic values between CHs to sink as per the distance of the network. Linguistic value of CH distance to sink shown in Fig 3.

Cluster size In order to avoid inefficient energy use, it is necessary to maintain the optimum size of the cluster. This might be achieved by ensuring that the cluster's size is always just right. The cluster's energy consumption increases dramatically when the cluster's size is large. The cluster's storage capacity grows as its node count increases. Linguistic value of cluster size is shown in Fig. 4. The second parameter is given in Eq. (12).

$$\mathrm{P}_2 = \frac{N}{\sum_{i=1}^{\mathrm{Tot\_CL}} (N_{\mathrm{SN(i)}})} \tag{12}$$

where, Tot_CL is denoted the total number of clusters in the network and $N_{\mathrm{SN(i)}}$ is denoted as ith number sensor node.

(b) **Residual energy of CH**

A descending sequence is used to list the residual energy of all CHs. As a result, the high-energy CHs are preserved and allowed to communicate their data to the sink. Linguistic value of residual energy of CH is shown in Fig. 5. Hence, the first parameter for the optimal path is given as below

$$P_3 = \sum_{i=1}^{\text{Tot\_CH}} \text{Res\_Energy}_{\text{CH(i)}} \tag{13}$$

where,Tot_CH is denoted the total number of cluster heads and $\text{Res\_Energy}_{\text{CH(i)}}$ is denoted as residual energy of *i*th CH.

(c) **Membership function for optimal path**

This research uses convolutional neural networks to train IoT-based WSN sensor nodes and communication architecture. This approach uses neuro-fuzzy principles to find the shortest path between nodes, cluster heads, and the sink node. The NFIS uses a convolutional neural network with triangular and trapezoidal membership functions to make decisions. Membership function for optimal path is shown in Fig. 6. The neuro-fuzzy rule system uses fuzzy membership functions, defined by Eqs. (14) and (15).

$$\mu_A(x) = \begin{cases} \frac{x-\alpha 1}{\alpha 2-\alpha 1}, \alpha 1 < x \leq \alpha 2 \\ \frac{x-\alpha 2}{\alpha 3-\alpha 2}, \alpha 2 < x \leq \alpha 3 \\ 0, otherwise \end{cases} \tag{14}$$

$$\mu_{\overline{A}}(x) = \begin{cases} 0, otherwise \\ \frac{x-\beta 1}{\gamma 1-\beta 1}, \beta 1 < x \leq \gamma 1 \\ 1, \gamma 1 < x \leq \delta 1 \\ \frac{\alpha 4-x}{\alpha 4-\delta 1}, \delta 1 < x \leq \alpha 4 \end{cases} \tag{15}$$

3.3.2 Selection of optimal path

Here we discuss the neuro-fuzzy-based path selection to construct the paths among the CHs for the sink. Let *NCH(i)* be the *i*th neuron and *N* is the number of neurons, and each neuron is represented by a bit frame structure or vector. The size of the frame is equal to the number of CHs. The frame consists of ID of the CHs and the neurons are differ by the order of CHs. The pseudo code of the algorithm is given in Algorithm 1. The input to the algorithm is the *N* number of randomly created set of neurons, denoted by *NCH(i).* The output of the algorithm is best solution which consist the order of CHs by the sink. Calculate the membership function value using Eqs. (14) and (15). Next, node-collected data should be routed via the CHs using the shortest path discovered in step 3, as well as the fuzzy rules. If the user has specified a maximum number of iterations, the procedure will continue until that number is reached. Algorithm 1 illustrates the NFEER algorithm's pseudocode. For the suggested algorithm, we focused its inputs and outputs and the terms used to express.

Algorithm - 1. NFEER Algorithm for optimal path selection.

Input: Training dataset {CH distance to sink, cluster size, residual energy of CH}
Output: Optimal routing path

1. **Begin**
2. use the Euclidean distance to arrange the nodes into clusters using the distance between them
3. with the sink acting as a coordinator, choose the CHs for each cluster based on the distance between sink and CH, size of cluster, and residual energy.
4. **While** *round* <= *itermax* **Do** /*Loop to check termination */
5. Calculate the membership function value using equation (14) and (15)
6. Node-collected data should be routed via the CHs using the shortest path discovered in step 3, as well as the fuzzy rules.
7. Collect the data at the sink
8. Check the node's energy if energy <=0 then stop the process
9. Else step-4 continue upto maximum rounds
10. **End while**
11. **End**

3.4 The operational process of NFEER

After the set-up phase is over, the NFEER will begin to perform the communication between CH and the sink in this phase. Because the NFEER is a responsive protocol, it handles the concept of a hard threshold in addition to a soft threshold in the same manner that the TSEP protocol implements it. This is functionally equivalent to the TSEP procedure. In the end, the transition's outcomes determine whether a hard or a soft threshold is implemented. The node will send intra-cluster data to the CH if the value indicated by (C(V)) exceeds a certain threshold. If the difference between the current value and the previous value is greater than the predetermined soft threshold, the subsequent round of contact will be established. In the event that this does not take place, the data transfer process will proceed at a slower pace. In addition to this, in the event that the node is removed, and its associated energy is drained, the connections between the deceased nodes would strengthen by a factor of 1. Despite this, there is still an aggregation of data for CH since the data were supplied in accordance with CH and then, after that, an essential data aggregation was sent to the sink from CH. The same procedure is carried out until all of the

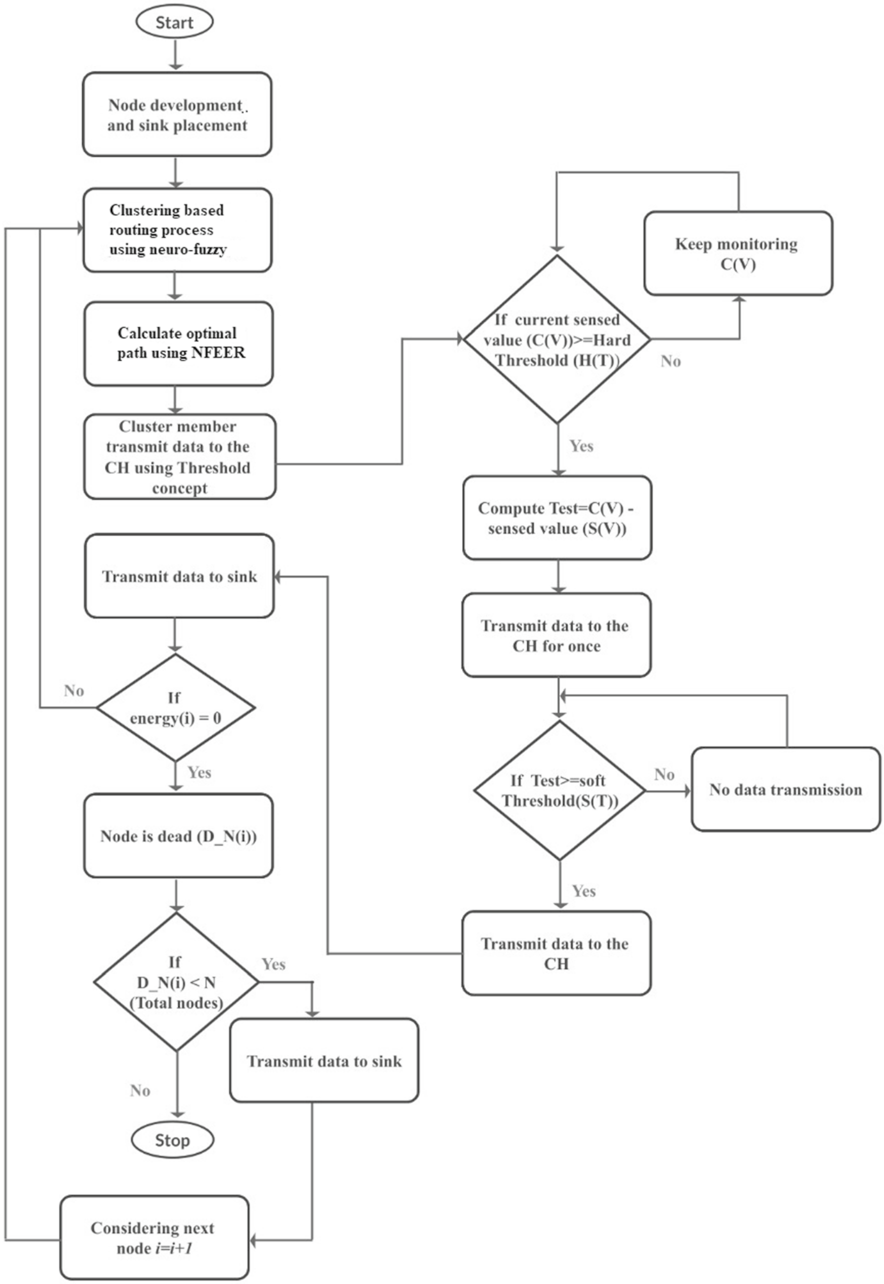

Fig. 7 Overall flowchart for data transmitting of NFEER Protocol

nodes in the network have perished, at which time it is recognized that the network has, in effect, ground to a stop. At this point, the process is considered to be complete. The overall flowchart shown in Fig. 7.

Time Complexity: The computational complexity of the method's ability to be implemented in real-time execution. The overall computational complexity of the proposed algorithm is O ($\text{Round}_{max} \times N$), where N is the total number of nodes and Round_{max} is the maximum number of rounds. The complexity of the process may be expressed as an exponential function.

4 Simulation and results

This section provides more information on the simulation settings, performance metrics, and state-of-the-art approaches that were utilized to compare performance. All the simulations were run using MATLAB R2019a, with the machine configured to have 8 gigabytes of RAM, one terabyte of hard drive space, and an Intel i5 CPU. The table below provides a summary of the simulations' utilized network parameters as well as the sensor radio energy paradigm. During the experiments of our simulation, a total of 200 nodes were dispersed at random across an area of (200 m × 200 m) and (500 m × 500 m) using a network of various energy nodes. The placement of network nodes should consider initial energy and incorporate heterogeneity nodes. Super nodes may last longer than advanced nodes, while advanced nodes are better than normal nodes. It is standard practice to provide a number between 0 and 1 to each node that represents the initial energy. Table 3 continues to provide a summary of the three levels of sensor nodes, as well as the energy percentage nodes and parameters.

It has been revealed that its nodes may be classified into a wide variety of subgenres on the basis of the original energy resources they had as well as the unique IDs

Table 3 Simulation parameters of NFEER

Parameters	Values
WSN#1 size of the area	200 m × 200 m
WSN#2 size of the area	500 m × 500 m
Nodes (N)	*100, 200*
Sink	*1*
Heterogeneous nodes	*N_NORM, N_ADVN, and N_SUP node*
N_SUP (Ʊ), N_ADVN (θ)	Ʊ=*1 Joule, θ=2 Joule*
Essential transceiver energy (E_{el})	*50nJ/bit*
Threshold-distance (d_o)	*86 m*
Packets size	*4000bits*
E_{efs}	*10pJ/bit/m²*
E_{mp}	*0.0013pJ/bit/m⁴*
E_{da}	*5nJ/bit/signal*
Simulation run	*20*

that had been created. However, because of the radical data transmission, the energy of the node will eventually decrease. The developed algorithm is structured in a way that allows it to adapt to the energy profiles of different types of sensor nodes.

4.1 Performance metrics

The suggested NFEER performance is validated using standard performance indicators. Four performance metrics of two networks are taken into consider: (a) network stability, (b) network lifespan, (c) throughput, and (d) network's remaining energy. The state-of-the-art algorithms are used to compare the proposed NFEER's performance to the state-of-the-art algorithms now in use, such as (a) PSO-Kmean [11], (b) BMHGA [12], and (c) FSO-PSO [13]. We choose this choice of algorithms for the following reasons: These algorithms (a) make use of neuro-fuzzy approaches, and (b) provide a valid comparison with existing methods, demonstrating that the achieved results are not only attributable to neuro-unique fuzzy's qualities.

4.2 Experiment results discussion and analysis

The experimental result explores further into the simulation environment, the measurements used to measure performance, the state-of-the-art methodologies used to compare those metrics, that follows.

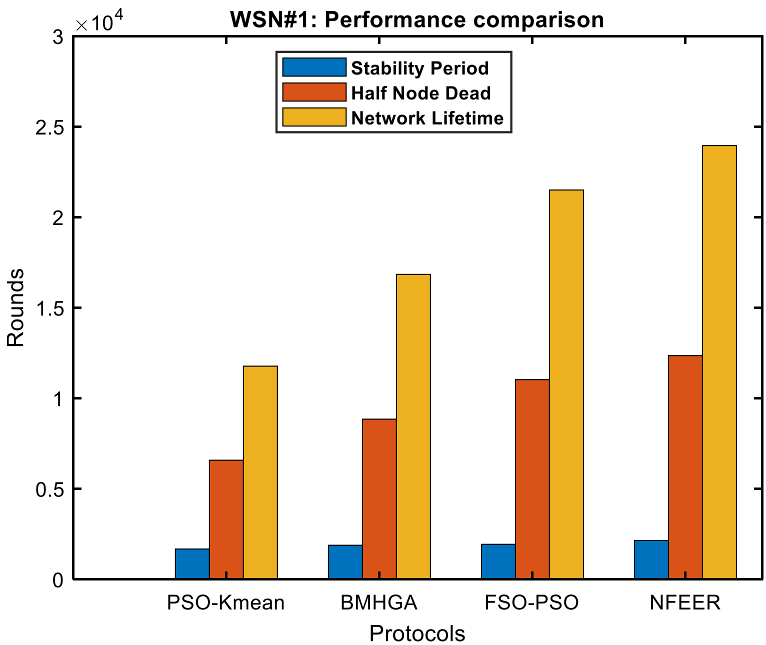

Fig. 8 Comparative analysis of WSN#1

4.2.1 Stability period

It can be observed that the first node in NFEER has died after 2145 rounds, however in the cases of PSO-Kmean, BMHGA, and FSO-PSO, there are still only 1676, 1882, and 1934 rounds remaining, respectively, as shown in Fig. 8. The knowledge that NFEER improves stability period in accordance with 27.98%, 13.97%, and 10.91% when compared to the protocols PSO-Kmean, BMHGA, and FSO-PSO, respectively, is the most essential item. The unification of these three parameters ensures that energy is conserved even when the process of data transmission is taking place, and improvements like a longer stability period and HND are examples of such unifications. As a result, the distance between the nodes and other nodes, as well as the distance between the sink and other nodes, is effectively lowered.

From the point of view of the networks, it is possible to understand that NFEER protocols have a better stability period than the state-of-the-art protocols. This increase in stability period may be attributed in large part to the integration of energy-efficient fitness parameters into the fitness function.

In WSN#2, Fig. 9 shows the NFEER protocol, the First Node Dead (FND) occurs after 721 rounds, but in the PSO-Kmean, BMHGA, and FSO-PSO protocols, the FND occurs after 278, 473, and 507 rounds, respectively.

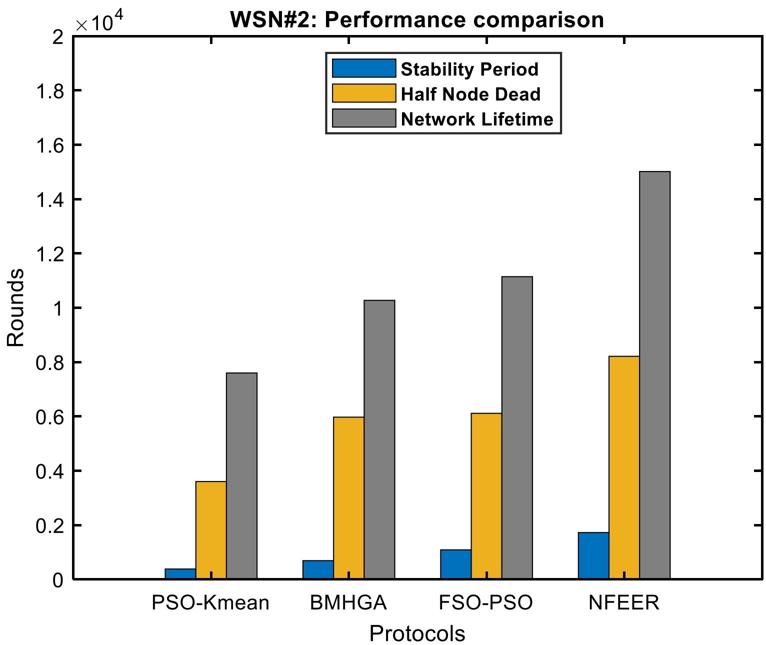

Fig. 9 Comparative analysis of WSN#2

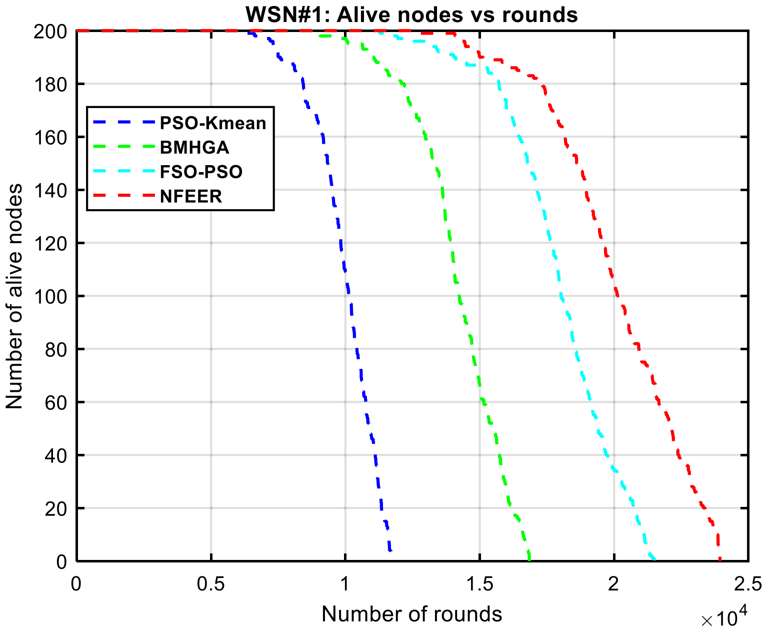

Fig. 10 Alive nodes vs rounds of WSN#1

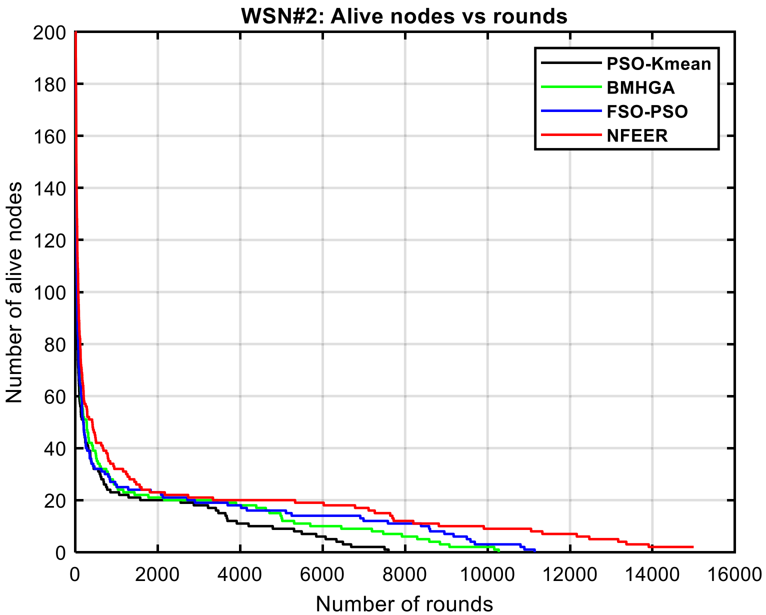

Fig. 11 Alive nodes vs rounds of WSN#2

4.2.2 Network lifetime

It can be noted that in NFEER, the process is finished after 23,952 rounds, but the network lifespan for merely the PSO-Kmean, BMHGA, and FSO-PSO has been seen on 11,771, 16,837, and 21,497 rounds, respectively. This can be seen in the results. According to the findings of the research, the NFEER protocol covers 12,183 rounds, 7115 rounds, and 2455 rounds more than the PSO-Kmean protocol, the BMHGA protocol, and the FSO-PSO protocol, respectively, as shown in Fig. 10. As a result, the overall energy of the network is preserved, which increases its longevity. As a result of this, a standard distance between a node and a CH is lowered to a great extent when there is a high number of surrounding adjacent nodes (Fig. 11).

4.2.3 Network's remaining energy

The NFEER protocol reduces the network's energy consumption while transferring data. Observers monitored networks' leftover energy by counting rounds following an increase. NFEER achieves better results than PSO-Kmean, BMHGA, and FSO-PSO because it uses more rounds and improves data transfer (see Fig. 12). NFEER's dual-hop communication uses less energy per round than competing protocols. NFEER's improved performance compared to PSO-Kmean, BMHGA, and FSO-PSO is due to its optimum selection of CH. The distance and the amount of energy

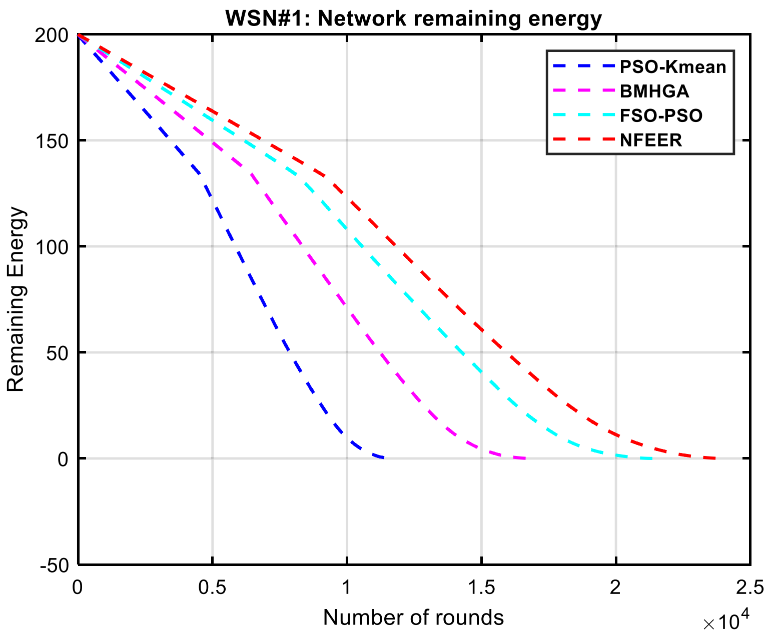

Fig. 12 Comparative analysis of network's remaining energy of WSN#1

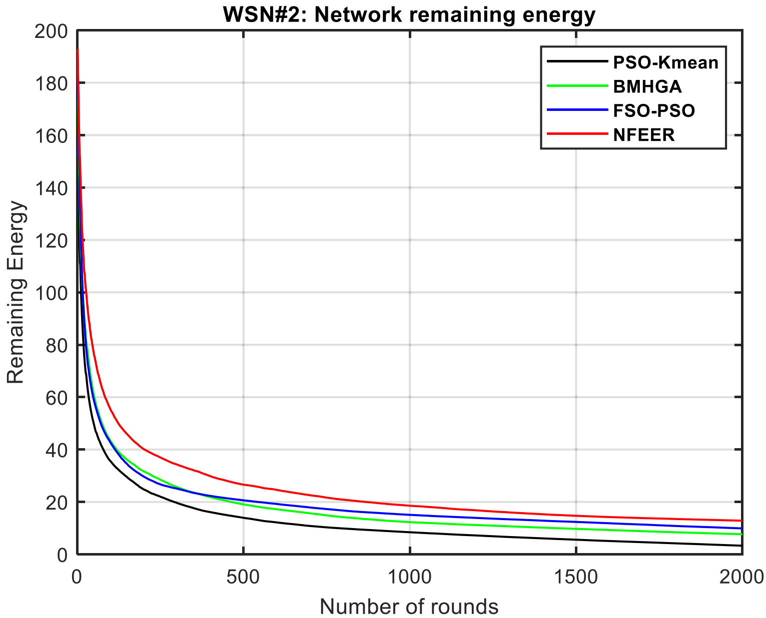

Fig. 13 Comparative analysis of network's remaining energy of WSN#2

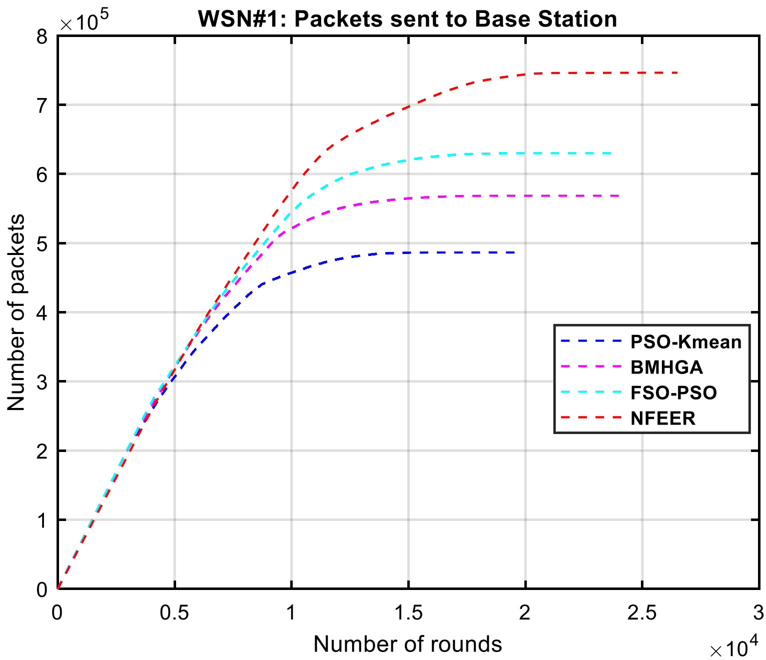

Fig. 14 Comparative analysis of throughput of WSN#1

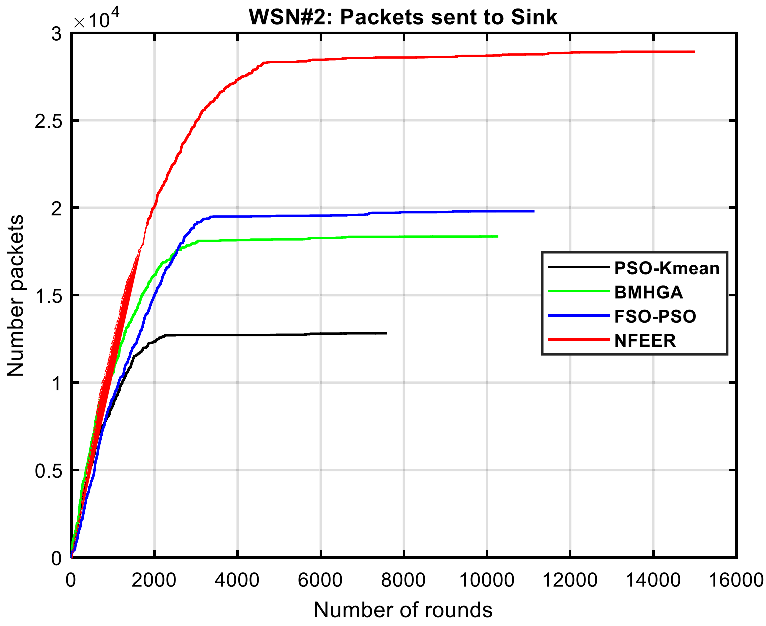

Fig. 15 Comparative analysis of throughput of WSN#2

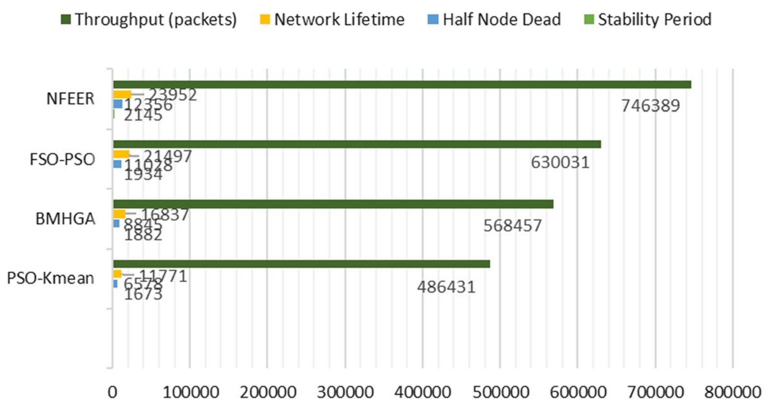

Fig. 16 Comparative analysis of WSN#1 in different metrics

left over both contribute to the relevance of inclusion. The distance factor, which enables the selection of the node that is geographically located closest to the sink, is what ultimately determines the routing route. As can be seen in Fig. 13, as soon as the NFEER operation starts, the network starts using energy, and as the energy of the node's declines, it performs an increasing number of rounds.

4.2.4 Throughput

Throughput is increased methodically as a result of the fact that it effectively communicates 746,389 data packets for NFEER, even though PSO-Kmean, BMHGA, and FSO-PSO transmit 630,031, 532,836, and 486,431 data packets, respectively. This is shown in Fig. 14. When compared to PSO-Kmean, BMHGA, and FSO-PSO protocols, respectively, it has been shown that NFEER increases throughput by 18.39%, 40.04%, and 53.32%, respectively. This was discovered via a comparison of throughput. Throughput has grown so drastically it is virtually unidentifiable during the transmission of data packets that were successfully forwarded due to a drop in loss reported and with a choice of better routing in the proposed protocol.

Figure 15 shows that, the NFEER sends 28,919 packets to the sink, whereas PSO-Kmean, BMHGA, and FSO-PSO 12,818, 18,534, and 19,794 packets to the sink, respectively.

In a nutshell, the NFEER evaluation performance summary, which states that there was an improvement, is described in Fig. 16. According to the comparison study, the performance of NFEER demonstrates that it is much superior to that of other protocols in terms of a variety of performance indicators.

5 Conclusions

In this research, we suggest using NFEER with three important parameters: CH distance to sink, cluster size, and residual energy of CH. The mathematical modelling of these parameters has been completed, and they have been included into the fuzzy inference system. A variety of performance criteria were used in order to make an assessment of NFEER's level of effectiveness. It has been discovered that using NFEER extends the lifespan of a network by 103.5%, 142.25%, and 11.42%, respectively, as compared to using PSO-Kmean, BMHGA, and FSO-PSO. The increase in the stability period may be related to the preservation of energy, which can be attributed to the residual energy of CH components. This is the primary cause for the enhancement. All of these features not only made dual-hop communication more energy-efficient, but also led to a more even allocation of workloads among clusters. We found that NFEER converges at a quicker rate when compared to other approaches already in use. In addition, the use of a number of different sinks has to be done, since this is yet another essential factor that requires optimization. This study may be expanded in future to include the mobility of sinks in the network, which will result in an improvement in the Quality-of-Service characteristics of the network.

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Data availability All data generated or analyzed during this study are included in this paper.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent Not applicable, all data generated or analyzed during experimental work are included in this paper.

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