Mathematics

AIMS Mathematics, 8(4): 8310–8331.
DOI: 10.3934/math.2023419
Received: 13 November 2022
Revised: 15 December 2022
Accepted: 27 December 2022
Published: 02 February 2023

http://www.aimspress.com/journal/Math

Research article

A fuzzy logic and DEEC protocol-based clustering routing method for wireless sensor networks

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Abstract: Power-efficient wireless sensor network routing techniques (WSN). Clustering is used to extend WSNs' lifetimes. One node act as the cluster head (CH) to represent the others in communications. The member nodes are less important than the cluster hub (CH) in the clustering procedure. Fuzzy techniques based on clustering theory may provide evenly distributed loads. In this study, we provide a fuzzy-logic-based solution that factors in distance to base station (BS), number of nodes, remaining energy, compactness, distance to communicate within a cluster, number of CH, and remaining energy. Fuzzy clustering has a preliminary and final step. First, we select CH based on distance to the base station (BS), remaining node vigor, and node compactness. In the second phase, clusters are created by combining nodes that aren't already in a CH, using density, outstanding vigor, and detachment as limitations. The proposed solution increases load balancing and node longevity. This work provides a unique hybrid routing technique for forming clusters and managing data transfer to the base station. Simulation findings confirm the protocol's functionality and competence. Reduced energy use keeps network sensor nodes online longer. The framework outperforms Stable Election Protocol (SEP), hybrid energy-efficient distributed clustering (HEED), and Low Energy Adaptive Clustering Hierarchy (LEACH). Using the nodes' energy levels to create a grid pattern for the clusters gave four clusters. In addition, the proposed method has a 4347%, 41.46%, 39.26%, 37.57% and 35.67% reduction in average energy consumption when compared with the conventional algorithms. The proposed technologies could increase the network's lifetime, stability interval, packet transfer rate (throughput), and average energy. The suggested protocol is at least 50% better in every statistic that was looked at, such as network lifetime, stability interval, packet transmission rate (throughput), and average energy use.

Keywords: wireless sensor networks; energy efficiency; fuzzy logic; DEEC; clustering; routing; network lifetime

1. Introduction

Healthcare, environmental sensing, and industrial monitoring are just a few of the industries where wireless sensor networks (WSN) are used [1,2]. A WSN is made up of dual parts: a base station (BS) and numerous dispersed device bulges that connect with the situation by detection certain physical characteristics. These devices are necessary for transmission, initial data processing, and sensing. Data collection, processing, and delivery to the termination user for decision-making are the responsibilities of the BS [3]. WSN nodes only get power from the batteries they have on board, which can't be charged or changed.

The storage, memory, and CPU processing capacities of device bulges are also constrained [4]. Energy-efficient direction-finding approaches are important for dropping vigor ingesting and extending the lifespan of networks since sensor nodes and BS exchange packets via wireless radio signals [5]. More energy is used when transmitting the same data to the BS directly than when sending it in stages over smaller distances. As a result, researchers have paid attention to clustering. Direct communication between each node and the Cluster Head (CH) Then, the CH sends the gathered, compressed, and sent data to the BS or another CH nearby [6].

Clustering algorithms can be categorized as either distributed or centralized methods. While local information is used to create clusters in distributed systems, the clustering algorithm in centralized approaches makes use of the network's global knowledge. The first method for CH election to be based on a probabilistic strategy is called the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol [7]. Every single bulge in the system generates a random number, and if that amount falls below a particular verge, the node in question will declare itself to be the group head and will send an advertisement message to every single other node in the network. The power of the announcement communication is taken into consideration by each non-CH receiving node in the network before reaching a conclusion on which CH it will establish a connection with.

A crucial objective of WSN is the creation of an energy-efficient communication protocol. To solve this problem, several energy-efficient routing techniques were suggested. They all use the strategy of chaining or grouping sensor nodes to permit broadcast to the BS through several hops. Gathering makes it possible to perform operations such as multi-hop broadcast, data aggregation, information density, and the elimination of jobless information. The usefulness of clustering is contingent on the efficiency with which the parameters used are implemented and the precision with which the gathering algorithm operates. In contrast to dispersed gathering procedures, which are carried out by separate device nodes using only the information available to them locally, the centralized clustering algorithms that are carried out by the BS make it possible for optimal clustering solutions to be found. This is because the BS has access to the entire perspective of the WSN. [8]

Clustering techniques in WSN are affected by a wide variety of variables, two examples of which are the quantity of energy that is still present in the sensor nodes and the distance that those nodes are from their respective BS. Nevertheless, if one examines the problem in question properly, one can think about other factors to consider. To find the optimal clustering solution, each parameter will need to have a weight assigned to it that is proportional to the effect that it has on the amount of energy that is lost and the longevity of the network. The determination of this study is to offer an energy-efficient fuzzy-based centralized clustering algorithm that can be applied to WSN routing protocols. The proposed technique of clustering uses fuzzy logic to determine which CHs should be used and mandates a minimum distance of separation between each CH to ensure that CHs are distributed evenly across the covered region. The separation distance is adaptively established [9,10] by considering the number of live nodes that are still present, the size of the area that is still being occupied by these bulges, and the proportion of CHs that are still needed.

There are some limitations to HEED, including the use of tentative CHs that do not become final CHs, which results in some uncovered nodes. According to HEED implementation, these nodes are forced to become CHs, which may be in the range of other CHs or may not have any members associated with them. As a result, more CHs are generated than expected accounting for unbalanced energy consumption in the network.

A flexible route that saves energy FL-DEEC protocol is proposed to reduce energy costs when choosing and prioritizing a forwarder list under opportunistic routing and increase the lifetime of a network. It uses more than one path. FL-DEEC has two types of power models: ones that can't be changed and ones that can. Simulations show that FL-DEEC is better than ExOR in terms of energy use, packet delivery, throughput, loss ratio, and delay.

To rank the CH election alternatives for sensor nodes, the fuzzy model that was proposed uses these five characteristics. This includes the amount of energy that is still available in the device bulge, the detachment to the base station, the density of nearby device nodes (which would probably form the current sensor node's cluster if it were selected as a CH), the packing of nearby device nodes, and the site appropriateness, which is determined by averaging the local energy consumed by nearby nodes. A supplementary contribution that we provide to this work is our suggestion to use the Gini index for the energy poise assessment that the WSN clustering procedure performs among the nodes. Therefore, clustering will be more effective if the procedure uses more energy-affecting parameters. An effective modelling method for combining parameters for better parameter integration outcomes is the fuzzy inference system (FIS). In this research, we investigate a specific class of clustered routing protocols—those like the energy efficient protocol for heterogeneous WSNs (DEEC) protocol—that are designed to work with networks that contain both homogeneous and heterogeneous nodes. In a natural setting, the sensor nodes' starting levels of energy will vary. So, when making a direction-finding procedure for WSN, energy heterogeneity should be one of the main things to think about.

The following contributions are made in this paper:

(1) Suggest direct communication between nearby nodes and the base station to improve the performance of the root cluster.

(2) Every cluster contains a vice cluster head in addition to the cluster head, which reduces data loss.

(3) The proposed method is a robust and enhanced version; it reduces the energy consumption of

sensor nodes and increases the lifetime of the WSN.

The break of this paper is structured as tracks: We go through the fundamentals of WSNs and fuzzy reason in Unit 2. The proposed approach's practice road map is presented in Unit 3. The performance evaluation is presented in Section 4, which starts with the imitation locations, moves on to the presentation measures, and concludes with the findings and comments. The overall conclusions of the study are given in Section 5. This section also looks at possible directions for more research.

2. Literature review

Elavarasan et al. [11] developed an efficient fuzzy-based continuous node refining method that makes use of the multilayer routing design of WSNs. The primary goal of radio device networks is to provide a secure means of inter-level message. The goal is to keep track of the sensor node and see where it is and what it is doing. To determine how effective, the procedure is, the incessant bulge refinement method was devised. The method can identify any nodes that are not optimal for message and remove them from the network. The node that is accountable for sending information has complete authority over all the other nodes along the sending chain.

Poluru et al. [12] attempted Energy Adaptive Distributed Energy-Efficient Clustering (EADEEC) and recommended it for assuring the resilience of WSNs over the duration of their service generation and enhancing the value of their device nodes. The Improved Distributed Energy-Efficient Clustering (I-DEEC) procedure separates the system bulges into dual layers of standard and progressive hexagons. This is done so that the procedure can consider the detachment between the base position and the nodes in the same area. This technique allows device bulges to select a cluster head and then calculates the sum of the relation between the detachment to the node and the quantity of vigor that is still available.

Xie et al. [13] used the ensemble approach to develop a better hierarchy procedure for low-energy clustering. The primary focus of this research is on enhancing and perfecting the LEACH approach. They investigate the LEACH cluster's energy waste at each stage and possible solutions. The cutting-edge LEACH algorithm was developed to cut down on the amount of energy that is wasted by each node. The outcome of a comparison demonstrates that the new approach enhances the performance of the network and makes it more resilient by ensuring that energy is dispersed uniformly across all nodes.

Zhu et al. [14] The authors came up with a distributed protocol that makes a cluster structure and chooses a rendezvous node (RN) that has enough power for a long time and is close to the mobile sync (MS). The cluster scheme of this algorithm makes a structure with clusters of different sizes. The size of each cluster has the opposite effect on how far apart the cluster heads are from the MS path. The proposed protocol reduced the power used by the network and can be used in many places, such as industrial settings with a lot of different kinds of sensor data. Daniel et al. [15] showed an energy-efficient tree-based resilient cluster header-based framework for densely distributed WSN IoT devices based on three measurements: neighborhood repetition, bisection indexing, and algebraic connections.

The goal of Li et al. [16] is to deliver a less power-intensive clustering algorithm for networks. Clustering cycles assume that each node has an equal supply of energy. This protocol determines which node will act as CH by considering the remaining power, detachment to the BS, and immediacy to other cluster members. The BS distance between level-2 CH nodes is less than that between level-1 CH nodes. The level-1 level of CH transmits the cluster information to the level-2 level of BS. Level-1 CH reduces anxiety while level-2 CH saves energy. energy consumption that is meticulous. New settings must be set before the cluster can be restarted. The CH selection threshold probability is different from the expected value for LEACH on both levels, which causes energy excursion.

FLECH [17] conducts clustering in a WSN environment that is non-uniform. Each node determines the probability value using three fuzzy input parameters. The fuzzy system's input parameters consist of a bulge's centrality, remaining vigor, and detachment from the base station. The formation of clusters and the collection of data are dual working stages of FLECH. In the initial step of clustering, a chance value is applied to determine the best number of groups. The data is collected by BS during the additional stage of clustering. In gathering, nodes joint the CH that is closest to them.

HEEC [18] is a hybrid technique for energy-efficient clustering of objects of different sizes. It clusters across numerous layers and employs a multi-hop routing strategy. For clustering, a combination of centralized and distributed techniques is effective. The BS develops layers and uses neighboring node information to finalize the protocol strategy. For data transmission, inter-cluster and intra-cluster directing with multi-hopping version is used. A significant improvement in energy efficiency is the result of a reduction in control messages. A discretionary license helps preserve data quality.

Khan et al. [19] described a distance-aware PR-LEACH routing method for energy optimization in IoT networks. In this investigation, we shall employ energy-efficient routing strategies. The old protocol was clearly inferior to the current one, which has many advantages. The proposed protocol uses a local threshold computation as opposed to the parent protocol's global threshold computation. This enhancement is essential for the protocol to become dynamic and efficient. Low-power sensor nodes and the cloud could interact better with the help of a new Internet of Things protocol.

M. M. Shurman et al. [20] devised the fuzzy sense algorithms for CH election in cluster based HRPs. Rather than using a robust grouping of attributes, such as remaining energy, BS proximity, resident detachment, concentration, importance, etc., each of these fuzzy sense-founded organizations employs a partial blend of these characteristics when selecting CHs. Some examples of these features are: The academic literature discusses clustering strategies that use centralized, distributed, and hybrid kinds of fuzzy logic. Fuzzy logic-based CH voting, on the other hand, necessitates a large number of CPU series and memory, so most of them are centralized. Moreover, fuzzy logic-based gathering techniques require global data of sensor properties. Having sensors send this data back and forth would be a waste of resources (power and data transfer capacity). Therefore, fuzzy logic-based clustering in WSN is not advised in favour of centralized techniques.

Jain and colleagues [21] EEFRP forms k optimum clusters using the FCM clustering algorithm. The obligation of determining the ideal number of groups falls on the BS. One of the strengths of EEFRP is that the primary groups are fixed, and subsequent procedure implementation chooses CHs from those secure collections. This is an advantage over other approaches. Because the fuzzy implication approach is used, the path that goes from the device bulge to the sink is the definitive one. The EEFRP is a method for multi-hop clustering that can be used. The amount of residual energy as well as the costs associated with message are used as fuzzy inputs in the process of picking the cluster head for each group.

L. Zhao et al. [22] propose junction-based ELITE routing for IDT-SDVN. The proposed scheme has four phases: policy training, generation, deployment, and relay selection in physical networks. First, the policy learning phase uses parallel DT agents to derive single-target policies. Second, the generation phase combines learned policies and generates new ones based on communication needs. Third, deployment selects the best generated policy based on real-time network status and message types. The controller sends the requester vehicle a road path based on the selected policy. Sun et al. [23] present a method for SI optimization they call cuckoo search chicken swarm optimization (CSCSO) for picking the optimum simulated sensor nodes to employ in an antenna array. Using CSO, A improves LEACH by determining the most effective path for information transmission between CHs and BS. To combat the challenges of WSN localization, CSO was used.

Zhao et al. [24] proposed plan has two parts: figuring out the route and letting the vehicle decide where to go based on several factors. In this paper, we build a topology diagram for SDVNs so that we can find the best routing paths. An intelligent multi-attribute routing scheme is proposed that uses fuzzy logic and a technique of order preference by similarity to ideal solution (TOPSIS) algorithm to find the next-hop forwarder. Moharamkhani et al. [25] As an effective routing protocol for clustered WSNs, the moFIS-BFO fuzzy knowledge-based metaheuristic model based on the multiobjective fuzzy inference system (moFIS) and bacterial foraging optimization (BFO) is suggested. The moFIS is used in the moFIS-BFO model to determine each node's likelihood of becoming a CH based on a variety of factors, including degree difference, residual energy, overall distance to neighbors, and distance to the base station.

In [26] suggest the LEACH-SF cluster-based routing protocol, which forms balanced clusters and extends the network lifetime in WSNs. In LEACH-SF, balanced clusters are created using a fuzzy c-means clustering algorithm, and the correct cluster heads are then chosen using a Sugeno fuzzy system that has been optimized. The residual energy, distance from the sink, and distance from the cluster centroid are local characteristics of the sensor nodes that are used as the fuzzy input. In [27] a combined heuristic-metaheuristic algorithm called FH-ACO for joint VNF placement and routing in the NFV architecture has been introduced. It is based on a two-stage fuzzy inference system and ant colony optimization. Our goal was to simultaneously benefit from the benefits of heuristics—namely, high responsiveness—and metaheuristics (i.e., high solution quality). This paper to created two fuzzy heuristics with multiple criteria for evaluating servers and links.

Mahnaz Sohrabi et al. [28] proposed model has elective and non-elective demands. Medical urgency, substitution allowance, and product freshness classify these demands. Real-world uncertainties are captured using hybrid fuzzy stochastic programming. Blood platelets are modelled. The solution is found using a metaheuristic technique based on genetic algorithms and simulated annealing. Sensitivity analysis gives decision-makers context. Hojjatollah et al. [29] presented an application-specific clustering algorithm (named FFA-RF) for wireless sensor networks as an adaptable online protocol. The FFA-RF algorithm is a combination of fuzzy heuristics (i.e., the Mamdani fuzzy inference system), metaheuristics (i.e., the firefly algorithm), and homogeneous ensemble machine learning (i.e., random forest). Specifically, a fuzzy heuristic-metaheuristic technique based on the Mamdani fuzzy inference system, and the firefly algorithm is described.

K. Shaukat et al. [30] propose a protocol evolved from the LEACH protocol by taking energy and distance of nodes in WSN into account when selecting CHs. However, this protocol is only used when there is BS in the sensor area. However, we are unable to implement this protocol with BS located far from the sensor area. In [31] propose DEAR-2, a routing protocol for a heterogeneous wireless ad-hoc network. The energy and device type awareness features of the Device and Energy Aware Routing (DEAR) routing algorithm have been embedded in the face routing algorithm, which only focuses on guaranteed delivery.

Hardas [32] examines the social and mechanical factors that influence cybercrime and cyber security, and thus verbalizes the relevant circumstances and threats of cybercrime in Pakistan. The study drew closer to the issue of cybercrime from both hypothetical and investigative perspectives.

In [33] proposed and computed the localization error for a mobile anchor-based localization algorithm that follows C-shaped trajectories in a 3D-based network The mobile anchor node continues to send beacons and obtains RSSI values for each node. In [34,35] presented a taxonomy to characterize the various aspects of time-series anomaly detection. One of the major challenges in current anomaly detection techniques is to detect anomalies based on the type of activities or context to which a system is exposed.

Hatamian et al. [36] propose congestion-aware routing and a fuzzy-based rate controller for wireless sensor networks (WSN). Utilizing a priority-based mechanism that provides a novel queueing model, the proposed method attempts to differentiate between locally generated data and transit data. In [37] investigates the genetic algorithm (GA) as a dynamic technique for determining optimal CHs. Furthermore, an innovative fitness function based on the specified parameters is presented. Each chromosome with the lowest fitness function is chosen by the base station (BS), and its nodes are introduced to the entire network as proper CHs. Hasheminejad et al. [38] describes a trustworthy tree-based data aggregation method. Sensor nodes in the proposed method are organized in the form of a binary tree. Then, aggregation requests are authenticated using a shared key, and the aggregation process begins if the request is acknowledged.

In [39] determine the minimum number of sensor nodes required to perform active sensing to monitor a specific area; and to determine the quality of service that a given sensor network can provide. In [40] Every node is clustered and scored. Next, the nodes with the highest scores are selected as CHs. Then the network is partitioned. Here, mobile sinks have been applied to save the energy of nodes. Hamid Barati et al. [41] propose a fuzzy logic-based two-level clustering and content-based routing method. Several parameters are used in first level clustering: energy, node capacity, and number of neighbors. The summary of recent proposed is in Table 1.

Table 1. Summary of recent proposed routing protocols.

References	Method	Data transmission	Evolutionary model	Energy efficiency	Year
Elavarasan et al. [11]	Efficient fuzzy Logic	Single Hop	No	Poor	2020
Poluru et al. [12]	Energy Adaptive Distributed Energy-Efficient Clustering (EADEEC)	Multi hop	No	Good	2020
Xie et al. [13]	LEACH	Single Hop	No	Good	2019
Bokhari [18]	HEEC	Single Hop	No	Good	2016
Moharamkhani et al. [25]	multiobjective fuzzy inference system (moFIS)	Single Hop	No	Good	2021
Shokouhifar et al. [26]	LEACH-SF	Single Hop	No	Good	2017
Hassan, M. U. et al. [31]	DEAR-2	Single Hop	No	Good	2019

3. Proposed systems

Energy-efficient routing is discussed, as well as a DEEC method based on fuzzy logic. A novel opportunistic routing approach has been developed to reduce overall power consumption and provide more equitable power distribution across nodes in a radio device system. One of the new features of Fuzzy Logic-DEEC is an updated parameter for choosing the CHs. In the sections that follow, this paper introduces the terminology and fitness functions that will be integral to the proposed methodology. Figure 1 is an example of our suggested procedure.

Figure 1 depicts the construction of the planned FL-DEEC technique. A WSN comprises of spatially dispersed devices and one or additional sink bulges. Users transmit information to the WSN component (also called base positions). Wireless Sensor Networks (WSNs) are self-configured, infrastructure-free wireless networks that screen physical or environmental factors, such as temperature, complete, trembling, compression, flexibility, or pollution, and transmission their information to a dominant site. The WSN data is processed using a random factor and fuzzy logic, and the cluster head is chosen using a fuzzy method and checked for fitness function, i.e., the average intra-cluster distance and average sink distance are estimated.

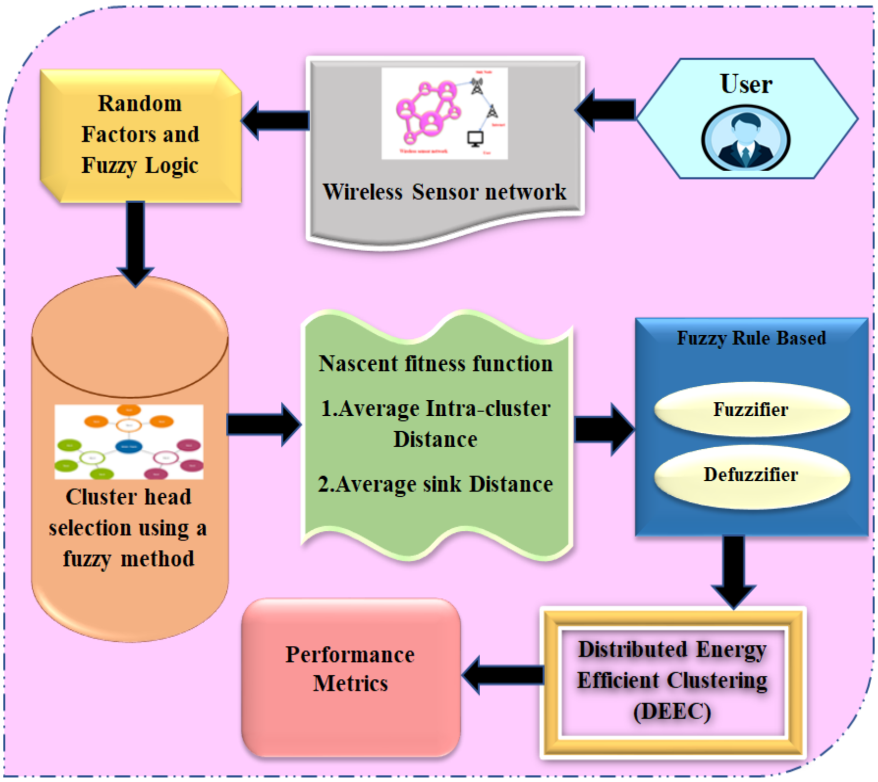

Figure 1. Proposed model of FL-DEEC method.

After the fitness function estimation, the data is processed based on the fuzzy rules where fuzzifier and de-fuzzifier are used. The process of transforming a clear quantity into a fuzzy one is referred to as “fuzzification”. The fuzzy consequences are mapped to create crisp results by a process called defuzzification, which is the inverse process of the fuzzification procedure. The DE fuzzifier’s job is to take the values that are ambiguous and turn them into clearer ones using information provided by the fuzzy implication machine. The data is optimized using DEEC (Distributed Energy Efficient Clustering) and, finally, the data is validated to prove its performance over the other existing techniques.

3.1. System model

Whenever the edge detachment (d_0) is greater than the broadcast detachment (d), the node’s vigor ingesting is comparative to d^2 [42,43]. The total quantity of vigor used by each node to send an L-bit packet of data is shown in the following equation:

$$E_{t,x}(L,d) = \begin{cases} L \times E_{ele} + L \times \varepsilon_{fs} \times d^2, if d < d_0, \\ L \times E_{ele} + L \times \varepsilon_{mp} \times d^4, if d \geq d_0, \end{cases} \tag{1}$$

vigor lost in the process of the circuit, i.e., spreaders or receivers; ε_{fs} signifies the intensifying energy of the free interplanetary prototypical; ε_{mp} represents the amplifying vigor of the multipath prototypical; and d_0 represents the threshold broadcast range.

In a similar manner, the subsequent calculation describes the amount of energy that is consumed by the receiver route to receive L bits of data.

$$E_{rx}(L) = L \times E_{ele}, \tag{2}$$

where E_{rx} is the vigor compulsory to accept info and E_{ele} is the vigor indulgence per bit compulsory to purpose the route, i.e., spreaders or receivers, and is influenced by a number of issues, including inflection, numerical encrypting, signal dispersion, and filtering. E_{rx} and E_{ele} are both referred to as the energy required to receive information.

In overall, the broadcast of the wireless wave is extremely mutable and extremely difficult to prototypical. The entire energy loss can be strongminded by using the equation below:

$$E_{total} = E_{tx} + E_{rx}. \tag{3}$$

3.2. Selection of cluster heads using fuzzy approach

A survey of the relevant publications reveals that several of them set out to investigate the factors that contribute to clustering. The remaining SN energy was considered while putting the CHs into the WSNs. In contrast, the method proposed here considers remaining vigour, node centrality (NC), and neighborhood overlap (NOVER) when selecting a bulge as a CH. The suggested technique for WSN routing also includes an assessment of link quality [44,45].

The necessity to select the optimal group head complicates the WSN's cluster-building procedure. Data from the SNs is gathered by the CH node and relayed to the BS. Professionals in the field of wireless sensor networks (WSNs) have demonstrated that fuzzy logic is superior to strict logic when it comes to choosing the best CH. This paper used fuzzy logic to restrict the pool of candidates for CH down to three. NC, NOVER, and leftover energy from sensor networks can be used together to decrease overall energy ingesting and upsurge sensor longevity. Each of the variables is defined below:

Residual Energy: All nodes with the maximum residual energy will be designated for the CH's assortment. Assume that E_i represents the node's initial energy. After "t", the node E's (energy) expenditure is shown as follows

$$E(t) = (n_{tpkts} \times a) + (n_{rpkts} \times b), \tag{4}$$

$$E_{RES} = E_i - E_t,$$

where n_{tpkts} and n_{rpkts} signify the amount of information packages conveyed and conventional, correspondingly. "a" and "b" are coefficients with standards among and (0, 1).

NC: it designates the step to which the designated CH is dominant to the complete system of its neighbors:

$$NC = \frac{\sqrt{\sum d^{2(c_i, c_j)}/IT}}{M}, \tag{5}$$

where d (c_i, c_j) is the distance among the collection head bulge and any of its child bulges.

NOVER: When determining the degree of mutual neighborhood between the end bulges of a link, the NOVER approach is utilized as the measuring technique. A connection between dual bulges in the same system is required for a link with a high NOVER, whereas an assembly between dual bulges in separate systems is sufficient for a link with a low NOVER. The neighbors of bulges u and v are strongminded autonomously by u and v, respectively [46].

$$NOVER(u-v) = \frac{2*|N(u) \cap N(v)|}{|N(u)|+|N(v)|-2}. \tag{6}$$

In this case, each u and will have the same set of neighbors, and NOVER will equal “1”.

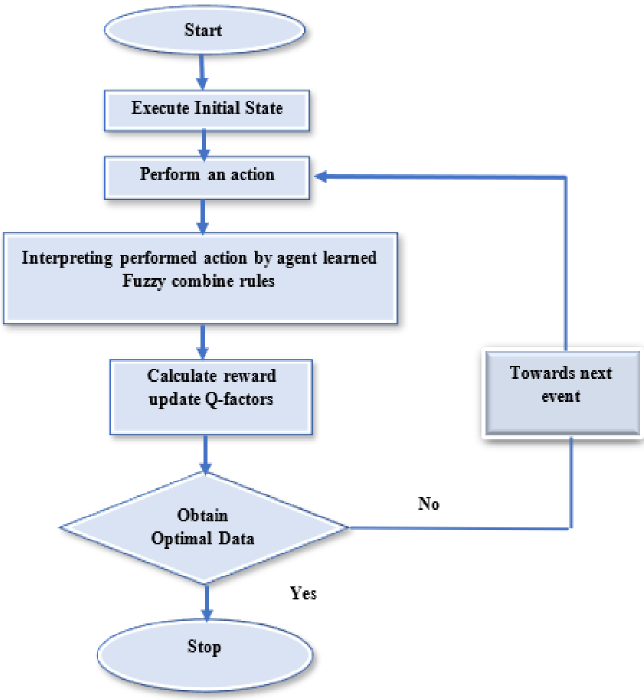

Figure 2. Flowchart of a fuzzy reinforcement learning method.

Table 2. Fuzzy rule set used for the research.

Rule	Residual energy	NC	NOVER	Rank
1	High	close	Medium	High
2	Medium	Adequate	poor	Medium
3	Low	Adequate	poor	Low
4	High	close	Good	Very high
5	Medium	close	Medium	Very low
6	Low	Far	High	Medium

The process flow for fuzzy reinforcement learning is depicted in Figure 2. Fuzzy set transformation occurs at the input stage, where remaining vigor, NOVER, and NC scheme inputs are processed. Features with short, average, and high remaining energy are accessible. The three criteria for NC membership are proximity (i.e., near), relevance (i.e., appropriateness), and distance. Table 2 classifies NOVER's features into three categories: good, medium, and poor.

3.2.1. Nascent of the fitness functions.

The following is a list of the parameters that are accountable for the expansion of the suitability purpose. To selecting the CHs, a fitness purpose is computed. Because of this fitness purpose, the node that has the extreme energy and the node that is positioned closest to the BS both have a greater likelihood of being chosen as the CH.

Average Intracultural Distance (f1): When determining the size of the intra-cluster space, the dimension used is the sum of the detachments among the device bulges and each CH is that the detachment between individual clusters wants to be shortened in instruction to bring down the amount of vigor that is used by the system. It is provided since device bulges consume some amount of power whenever they connect with their own CH, as demonstrated below:

$$f1 = \sum_{j=1}^{m}\left(\frac{1}{lj}\sum_{k=1}^{lj} dis(s_k, CHj)\right). \tag{7}$$

Average Sink Distance (f2): The entire amount of device nodes that are present in a particular CH is proportional to the average sink detachment that must be travelled among the base position and the CH in question. Because space has such a big bearing on energy usage, this facet is presently being taken into thought. Because of this, there is an imperative to shorten this distance to conserve energy.

$$f2 = \sum_{j=1}^{m}\left(\frac{1}{lj} dis(CHj, BS)\right). \tag{8}$$

Residual Energy (f3): Because of all these factors, the life cycle of a network is dependent on the usage of vigor; therefore, there is an urgent essential to cut back on energy use. As a direct importance of this, this criterion is given deliberation. It is computed as the sum of the current drives of all the positions that have been provided. Since the entire amount of energy needs to be exploited, each impartial purpose must be stable by its conflicting [47,48].

$$f3 = \frac{1}{\sum_{j=1}^{m}(E_{CHj})}. \tag{9}$$

CH Balancing Factor (f4): The group must uphold its equilibrium; because of the accidental federation of device bulges, there is a possibility that some big groups and some tiny collections will emerge. As a direct importance of this, this quality is considered when decisive appropriate levels of energy use.

$$f4 = \sum_{j=1}^{m}\frac{n}{m} - l_j. \tag{10}$$

All the aspects of fitness that were just discussed are completely synchronized with one additional. The fitness purpose is described in the following way:

Fitness function = (p × f1) +(q × f2) +(f3 × r) +(f4 × (1 − p + q + r)),
where p, q, and r signify continuous rate and p + q + r = 1.

3.3 Distributed energy efficient clustered (DEEC)

For a heterogeneous WSN, the DEEC protocol provides a decentralized, energy-efficient clustering solution. Individually bulge's residual vigor is compared to the network regular to determine the probability used to choose the cluster leaders. Each node's starting and final energies determine its unique epoch round number. In a heterogeneous WSN, every node has its unique energy profile, and the DEEC procedure is responsible for adjusting the rotating epoch of the distributed energy-efficient gathering procedure built on the fuzzy logic method in accordance with these profiles. Nodes that have high starting energy and high energy that has been retained have a greater chance of becoming cluster chiefs than nodes that have low total energy [49]. The DEEC procedure can increase the generation of a system, and in particular the stability period, through the utilization of this technology.

$$pi = p\frac{E(r)}{E(r)i}. \tag{11}$$

The DEEC protocol calculates probabilities using a metric built on the difference among the node's remaining vigor and the system's mean energy (Eq 11). However, it is challenging to have a global understanding of how much energy is typically produced by each node in the system. Using Eq 2, the DEEC protocol figures out how much situation energy each node should send out through individually round, assuming that this is the best value for the life of the network.

Multi-level assortment is designed to increase K as much as possible (number of CH). Becoming a CH is a higher priority at nodes with high leftover energy. For this reason, a node's and the network's total residual energies play a role in the development of a CH. As a node's remaining energy goes up, so does the chance that it will become a CH.

Where E(r) stands for the round's average energy, calculated as follows:

$$E(r) = Etotal(1 - R)/N. \tag{12}$$

The value of the total Energy is given as:

$$Etotal = N * (1 - m) * Eo + N * m * Eo * (1 + a). \tag{13}$$

Where R is the entire number of rounds that occur during the system's lifespan. Let's call this quantity E_{round} and say it represents the amount of vigor that the network uses in one round. R is roughly equivalent to:

$$R = \frac{E_{total}}{E_{round}}. \tag{14}$$

4. Results and discussion

4.1. Experimental setup

The planned procedure is carried out with the aid of the MATLAB 2021b programme. The network begins with the nodes spread out randomly. The improved EM technique has been used to categorize all SNs into groups. The cluster leaders are chosen for each group built on their remaining vigor, NOVER, and NC. To determine which CHs are most important, proposed work look at their strength, NOVER, and distance from the nearest NC. After a sink is fixed and SN data is acquired, the CH node immediately relays the information to the BS. Aside from that, the FL-CSO algorithm uses a good routing strategy to move the movable sink everywhere the system and get information from all CHs [50–53].

The proposed method is compared to the LEACH, HEED, MBC, and FRLDG clustering and routing protocols to see how well it works. In comparison to other methods, 500 nodes are used to calculate the performance parameters of system lifetime, throughput, energy consumption, bit error rate, buffer occupancy, end-to-end delay (E2ED), and packet delivery ratio (PDR). In these simulations, a space of 1000 m^2 by 1000 m^2 was filled with 100 sensor nodes that were all the same and 9 cluster head nodes that had unlimited battery power.

In these simulations, a 1000 m^2 region is monitored by 100 sensor nodes and nine cluster head nodes. The suggested data collection system was used to mimic the network's performance in terms of packet delivery ratio (PDR), throughput, packet loss ratio (PLR), total vigor, and accuracy. The effects of cumulative the number of deployed nodes on the overall system performance are depicted in Figures 3–8 [54–56].

As a result, for different transmit power levels, the transmitter will increase the number of nodes in the sequence. From a list of reachable nodes ranked by energy cost, the sender selects the node with the lowest energy consumption. When compared to the existing protocol, EEOR takes less time to send and receive data and has a smaller routing list. In terms of total energy consumption, EEOR outperforms the existing method. EEOR outperforms other existing protocols in terms of packet loss rates and end-to-end latency.

4.2. Alive node

Table 3 and Figure 3 show an alive node analysis of the FL-DEEC method with existing systems. An instantaneous dimension of the entire number of bulges that have not yet used up all their available vigor is the number of bulges that are still active, or "alive". The statistical evidence demonstrates beyond a reasonable doubt that the planned FL-DEEC technique is superior to all additional approaches that are currently in use in each. For example, with 100 nodes, the FL-DEEC technique has 44.21% of alive nodes whereas the other techniques like SEP, HEED, LEACH, and DEBUC have alive nodes of 27.37%, 31.28%, 35.27%, and 40.45% respectively. Similarly, with 500 nodes, the FL-DEEC method has 34.21% of alive nodes, whereas the other techniques like SEP, HEED, LEACH, and DEBUC have alive nodes of 19.45%, 21.21%, 25.36%, and 31.47%, respectively.

Table 3. Alive node analysis for FL-DEEC method with existing system.

No. of Nodes	SEP	HEED	LEACH	DEBUC	FL-DEEC
100	27.37	31.28	35.27	40.45	44.21
200	25.44	28.45	32.54	38.27	42.11
300	22.65	25.38	30.56	35.13	40.11
400	20.12	23.13	28.13	32.87	36.23
500	19.45	21.21	25.36	31.47	34.21

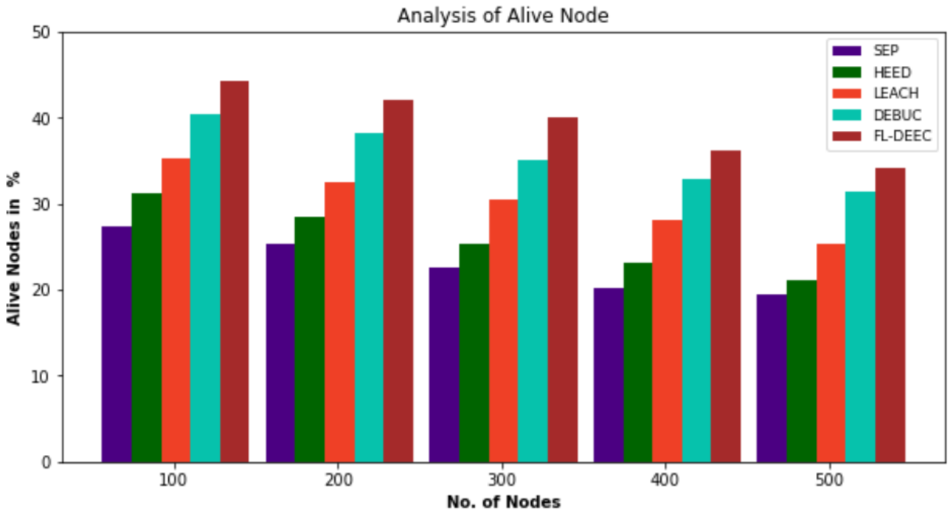

Figure 3. Alive node analysis of FL-DEEC method with existing system.

4.3. Accuracy analysis

Table 4 and Figure 4 deliver a comparison of the FL-DEEC method's accuracy to that of popular methods already in use. The findings prove that the proposed strategy outperforms the current best practices. For instance, given 100 data points, the FL-DEEC technique obtains an accuracy of 94.21%, whereas the SEP method achieves 87.84%, the HEED method achieves 89.78%, the Faster LEACH method achieves 90.43%, and the DEBUC method reaches 92.17%. Using 500 data points, the proposed method obtains a 97.54% accuracy when compared to the 92.33%, 93.66%, 94.21% and 96.33% achieved by SEP, HEED, LEACH and DEBUC, respectively. It is reasonable to conclude that the FL-DEEC method is superior.

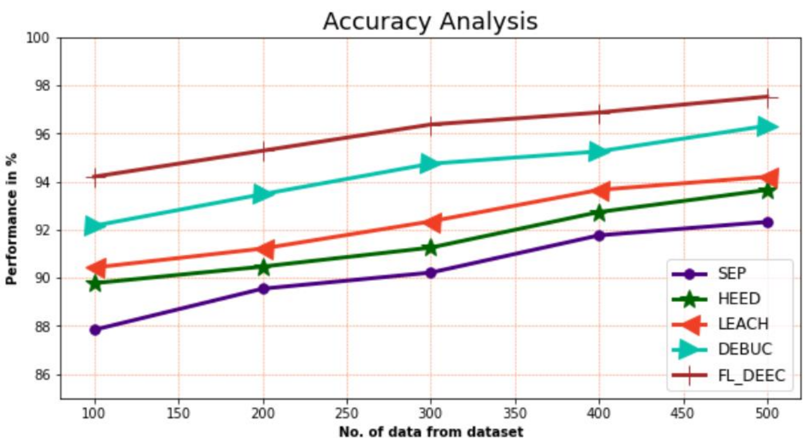

Figure 4. Accuracy analysis of FL-DEEC method with existing system.

Table 4. Accuracy analysis for FL-DEEC method with existing system.

No. of data from dataset	SEP	HEED	LEACH	DEBUC	FL-DEEC
100	87.84	89.78	90.43	92.17	94.21
200	89.55	90.47	91.22	93.48	95.29
300	90.22	91.26	92.35	94.75	96.38
400	91.77	92.74	93.66	95.26	96.88
500	92.33	93.66	94.21	96.33	97.54

4.4. Energy consumption

Table 5 and Figure 5 display the energy consumption study of the FL-DEEC method with present methods. The proposed method consumes very little energy when compared to the other techniques for any number of nodes. For example, with 100 nodes, the FL-DEEC method consumes only 35.67J while the other methods like SEP, HEED, LEACH, and DEBUC consume 48.76J, 46.11J, 43.27J, and 40.16J respectively. Similarly, with 500 nodes, the proposed FL-DEEC method consumes only 43.47J whereas the other methods like SEP, HEED, LEACH, and DEBUC consume 56.33J, 54.22J, 52.22J, and 48.26J respectively. The proposed method shows higher performance with less energy consumption.

Table 5. Energy Consumption Analysis for FL-DEEC method with existing system.

No of Nodes	SEP	HEED	LEACH	DEBUC	FL- DEEC
100	48.76	46.11	43.27	40.16	35.67
200	50.12	48.27	46.45	42.36	37.57
300	52.23	50.22	48.38	44.38	39.26
400	54.76	52.22	50.27	46.44	41.46
500	56.33	54.22	52.22	48.26	43.47

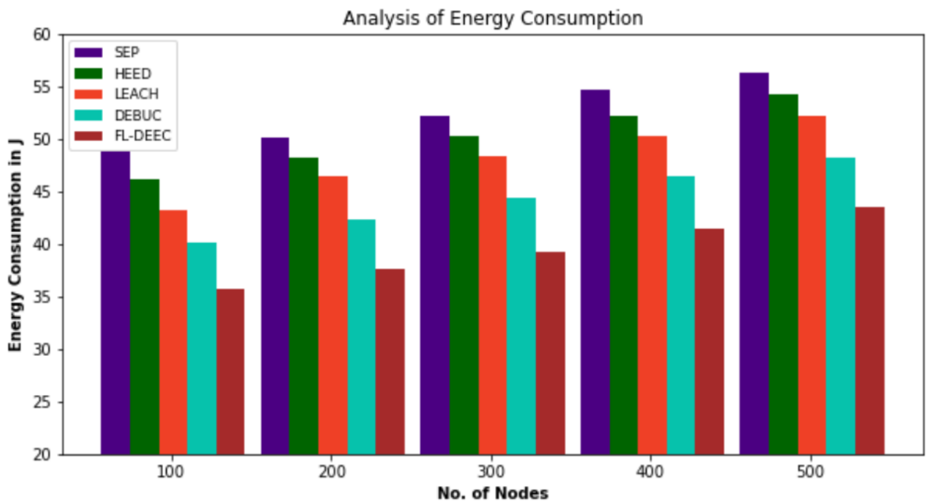

Figure 5. Energy consumption analysis for FL-DEEC method with existing system.

4.5. *Throughput*

Table 6 and Figure 6 describe the throughput study of the FL-DEEC technique with the existing approaches. The data clearly shows that the planned technique outstrips the other techniques in all aspects. For example, with 100 data points, the FL-DEEC method has a throughput of 963.67 kbps while the other existing methods like SEP, HEED, LEACH, and DEBUC have a throughput of 759.25 kbps, 804.16 kbps, 848.65 kbps, and 901.64 kbps, respectively. Similarly, with 500 data points, the proposed method has 1057.74 kbps of throughput while the other existing methods, SEP, HEED, LEACH, and DEBUC have a throughput of 793.36 kbps, 841.45 kbps, 873.79 kbps, and 938.72 kbps, respectively. This proves that the FL-DEEC technique has higher performance with greater throughput.

Table 6. Through analysis for FL-DEEC method with existing system.

No of Nodes	SEP	HEED	LEACH	DEBUC	FL- DEEC
100	759.25	804.16	848.65	901.64	963.67
200	772.85	818.28	857.18	918.17	973.86
300	781.87	828.27	862.56	921.66	982.46
400	789.25	831.82	868.28	931.54	1026.46
500	793.36	841.45	873.79	938.72	1057.74

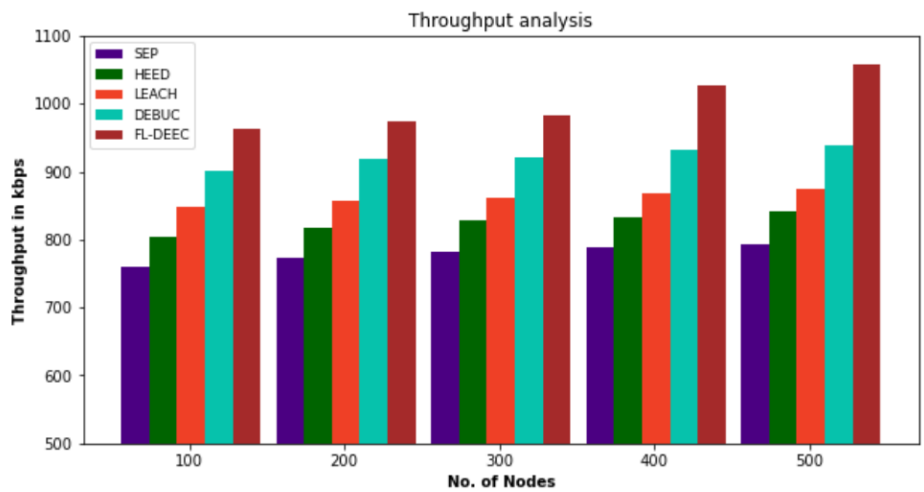

Figure 6. Throughput Analysis for FL-DEEC method with existing system.

4.6. *Packet delivery ratio (PDR)*

When individuals talk about the “package distribution ratio”, they are referring to the ratio of the total quantity of packages that were directed from the source bulge to the entire quantity of packages that were conventional at the destination. Figure 7 presents a contrast of the levels of functionality offered by the nodes across a variety of operational modes. SEP, HEED, LEACH, DEBUC, and FL-DEEC procedures are examples of these protocols. For 20 nodes, it is 87.12% of PDR for the FL-DEEC method, while the previous procedures such as SEP, HEED, LEACH, and DEBUC processes have achieved a PDR of 78.13%, 80.15%, 82.42%, and 83.86%, respectively. The presentation of the FL-DEEC process, on the additional pointer, provides greater results when associated to the presentations of the additional procedures. Correspondingly, with 100 nodes, the planned method has a PDR of 89.68% while it is between 79.73% and 85.59 % for the other existing methods.

Table 7. PDR Analysis for FL-DEEC method with existing system.

No of Nodes	SEP	HEED	LEACH	DEBUC	FL-DEEC
20	78.13	80.15	82.42	83.86	87.12
40	78.51	81.26	82.85	85.11	87.47
60	79.41	81.68	83.53	86.36	88.17
80	78.92	80.82	84.52	86.83	89.36
100	79.73	81.94	84.76	85.59	89.68

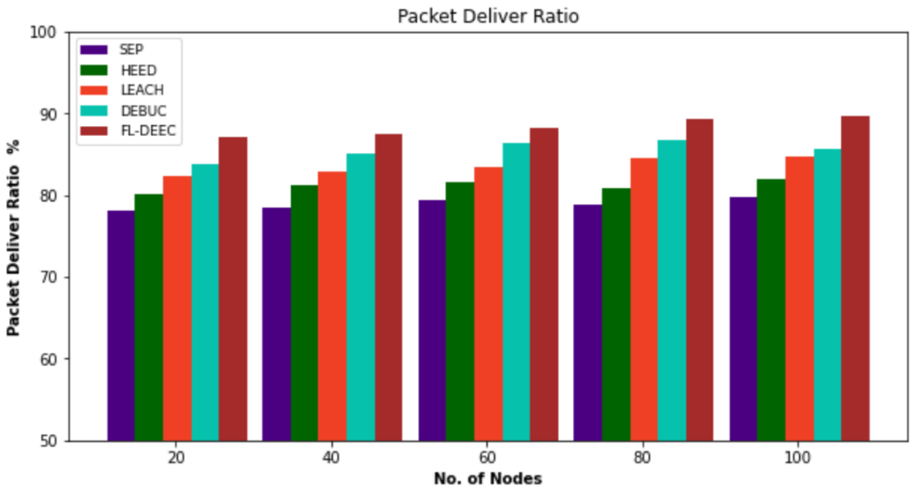

Figure 7. PDR Analysis for FL-DEEC method with existing system.

4.7. Packet loss ratio (PLR)

Table 8 and Figure 8 explain the package loss ratio examination of the FL-EEC technique with other present techniques. The data clearly explains that the proposed technique has the minimum PLR associated to the extra approaches in all aspects. For example, with 20 nodes, the proposed method has a PLR of 21.27%, while it is 27.43%, 26.05%, 24.33%, and 22.58% for SEP, HEED, LEACH, and DEBUC, respectively. The FL-DEEC method has greater performance with less PLR. Similarly, with 100 nodes, the proposed method has 22.47% of PLR whereas the methods for SEP, HEED, LEACH, and DEBUC have PLR of 29.32%, 26.94%, 25.73%, and 23.95%, respectively.

Table 8. PLR Analysis for FL-DEEC method with existing system.

No of Nodes	SEP	HEED	LEACH	DEBUC	FL-DEEC
20	27.43	26.05	24.33	22.58	21.27
40	27.84	26.25	24.56	22.74	21.53.
60	28.43	26.58	24.87	23.43	21.83
80	28.87	27.14	25.41	23.73	22.11
100	29.32	26.94	25.73	23.95	22.47

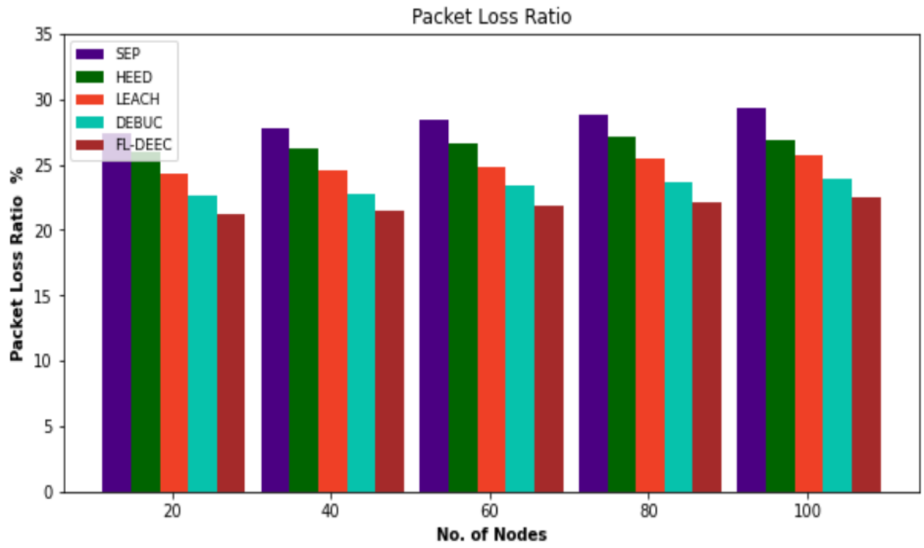

Figure 8. PLR Analysis for FL-DEEC method with existing system.

5. Conclusions

Utilizing every parameter that has an impact on the energy efficiency of the WSN directing procedure is advised to get the greatest results from energy-efficient routing procedures. Additionally, it is advised to incorporate them in a way that demonstrates how much each impacts the WSN's energy efficiency. In this paper, the FL-DEEC clustering method for energy-efficient routing protocols was introduced. In addition, this paper suggested an effective fuzzy logic that this clustering method uses to carry out CH voting. This fuzzy reason uses five metrics to assess each sensor's likelihood of being a CH. These factors include the sensor node's remaining energy, its distance from the BS, the thickness of nearby device bulges everywhere the potential CH, the compactness of nodes nearby, and the average amount of locally spent energy. This is directly responsible for raising an issue with WSN's overall energy footprint because of its widespread adoption. Our studies have centered on developing more effective strategies for reducing the network's energy consumption. It will extend the network's useful life span. The FL-DEEC approach suggests using fuzzy logic to increase the efficiency of a network's communication while reducing its energy consumption. In this paper determine how effective our method is by comparing it to others, such as LEACH, DEBUC, and UCNPD. In addition, the proposed method has a 4347%, 41.46%, 39.26%, 37.57% and 35.67% reduction in average energy consumption when compared with the conventional algorithms. In conclusion, the proposed solutions performed well in terms of throughput, packet loss rate, percentage of living nodes, and percentage of properly delivered packets. However, there may be occasional delays in the transmission because protocol was designed for massive scalability. Furthermore, we introduced the idea of adopting the Gini index measurement mean for measuring the extent to which the WSN clustering algorithm can balance energy consumption through all WSN sensor nodes. We evaluated the energy efficiency of routing protocols in WSN for the metric of energy distribution balancing using the Gini index as a valid measurement tool.

Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of interest

The authors declare no conflicts of interest.

References

1. A. Giorgetti, M. Lucchi, E. Tavelli, M. Barla, G. Gigli, N. Casagli, et al., A robust wireless sensor network for landslide risk analysis: System design, deployment, and field testing, *IEEE Sens. J.*, **16** (2016), 6374–6386. https://doi.org/10.1109/JSEN.2016.2579263
2. B. Rashid, M. H. Rehmani, Applications of wireless sensor networks for urban areas: A survey, *J. Netw. Comput. Appl.*, **60** (2016), 192–219. https://doi.org/10.1016/j.jnca.2015.09.008
3. S. Lindsey, C. S. Raghavendra, PEGASIS: Power-efficient gathering in sensor information systems, *Proceedings, IEEE Aerospace Conference Proceedings*, 2002, 3. https://doi.org/10.1109/AERO.2002.1035242
4. M. M. Shurman, M. Al-Mistarihi, K. Drabkh, A. Naji, Hierarchal clustering using genetic algorithm in wireless sensor networks, *2013 36th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO2013)*, 2013, 479–483.
5. J. Suhonen, M. Kohvakka, V. Kaseva, T. D. Hämäläinen, M. Hännikäinen, *Low-power wireless sensor networks: Protocols, services and applications*, Springer: Berlin, 2012.
6. M. M. Shurman, Z. Alomari, K. Mhaidat, An efficient billing scheme for trusted nodes using fuzzy logic in wireless sensor networks, *Wireless Eng. Technol.*, **5** (2014), 62–73. http://doi.org/10.4236/wet.2014.53008
7. P. Subbulakshmi, P. Mohan, Mitigating eavesdropping by using fuzzy based mdpop-q learning approach and multilevel stackelberg game theoretic approach in wireless CRN, *Cogn. Syst. Res.*, **52** (2018), 853–861. http://doi.org/10.1016/j.cogsys.2018.09.021
8. M. R. Senouci, A. Mellouk, M. A. Senouci, L. Oukhellou, Belief functions in telecommunications and network technologies: An overview, *Ann. Telecommun.*, **69** (2014), 135–145. https://doi.org/10.1007/s12243-014-0428-5
9. N. Subramani, P. Mohan, Y. Alotaibi, S. Alghamdi, O. I. Khalaf, An efficient metaheuristic-based clustering with routing protocol for underwater wireless sensor networks, *Sensors*, **22** (2022), 415. http://doi.org/10.3390/s22020415
10. Z. S. Fei, B. Li, S. S. Yang, C. W. Xing, H. B. Chen, L. Hanzo, A survey of multi-objective optimization in wireless sensor networks: Metrics, algorithms, and open problems, *IEEE Commun. Surv. Tut.*, **19** (2017), 550–586. https://doi.org/10.1109/COMST.2016.2610578
11. R. Elavarasan K. Chitra, An efficient fuzziness based contiguous node refining scheme with cross-layer routing path in WSN, *Peer Peer Netw. Appl.*, **13** (2020), 2099–2111. https://doi.org/10.1007/s12083-019-00825-0
12. R. K. Poluru, M. P. K. Reddy, S. M. Basha, R. Patan, S. Kallam, Enhanced adaptive distributed energy-efficient clustering (EADEEC) for wireless sensor networks, *Recent Adv. Comput. Sci. Commun.*, **13** (2020), 168–172. https://doi.org/10.2174/2213275912666190404162447

13. P. H. Xie, M. Lv, J. J. Zhao, An improved energy-low clustering hierarchy protocol based on ensemble algorithm, *Concurr. Comp.: Pract. E.*, **32** (2019), e5575. https://doi.org/10.1002/cpe.5575
14. C. Zhu, S. Wu, G. J. Han, L. Shu, H. Y. Wu, A tree-cluster-based data-gathering algorithm for industrial WSNs with a mobile sink, *IEEE Access*, **3** (2015), 381–396. https://doi.org/10.1109/ACCESS.2015.2424452
15. A. Daniel, K. M. Balamurugan, R. Vijay, K. Arjun, Energy aware clustering with multihop routing algorithm for wireless sensor networks, *Intell. Autom. Soft Comput.*, **29** (2021), 233–246.
16. H. Li, J. Liu, Double cluster-based energy efficient routing protocol for wireless sensor network, *Int. J. Wireless Inf. Netw.*, **23** (2016), 40–48. https://doi.org/10.1007/s10776-016-0300-9
17. B. Balakrishnan, S. Balachandran, FLECH: Fuzzy logic-based energy efficient clustering hierarchy for non-uniform wireless sensor networks, *Wirel. Commun. Mob. Comput.*, **2017** (2017), 1214720. http://doi.org/10.1155/2017/1214720
18. T. Y. Kord, M. U. Bokhari, SEPFL routing protocol based on fuzzy logic control to extend the lifetime and throughput of the wireless sensor network, *Wireless Netw.*, **22** (2016), 647–653. https://doi.org/10.1007/s11276-015-0997-x
19. F. A. Khan, A. Ahmad, M. Imran, Energy optimization of PR-LEACH routing scheme using distance awareness in internet of things networks, *Int. J. Parallel Prog.*, **48** (2018), 244–263. https://doi.org/10.1007/s10766-018-0586-6
20. M. M. Shurman, Z. Alomari, K. Mhaidat, K. An efficient billing scheme for trusted nodes using fuzzy logic in wireless sensor networks, *J. Wirel. Eng. Technol.*, **5** (2014), 62–73. https://doi.org/10.4236/wet.2014.53008
21. A. Jain, A. K. Goel, Energy efficient fuzzy routing protocol for wireless sensor networks, *Wireless Pers. Commun.*, **110** (2020), 1459–1474. https://doi.org/10.1007/s11277-019-06795-z
22. L. Zhao, Z. G. Bi, A. Hawbani, K. P. Yu, Y. Zhang, Y. Guizani, ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks, *IEEE T. Mobile Comput.*, 2022. https://doi.org/10.1109/TMC.2022.3179254
23. G. Sun, Y. H. Liu, S. Liang, Z. Y. Chen, A. M. Wang, Q.A. Ju, et al., A sidelobe and energy optimization array node selection algorithm collaborative beamforming in wireless sensor networks, *IEEE Access*, **6** (2018), 2515–2530. https://doi.org/10.1109/ACCESS.2017.2783969
24. L. Zhao, Z. H. Yin, K. P. Yu, X. Y. Tang, L. X. Xu, Z. Z. Guo, et al., A fuzzy logic based intelligent multi-attribute routing scheme for two-layered SDVNs, *IEEE T. Netw. Serv. Man.*, 2022. https://doi.org/10.1109/TNSM.2022.3202741
25. E. Moharamkhani, B. Zadmehr, M. Mohammad, J. Saber, M. Shokouhifar, Multiobjective fuzzy knowledge-based bacterial foraging optimization for congestion control in clustered wireless sensor networks, *Int. J. Commun. Syst.,* **34** (2021), e4949. https://doi.org/10.1002/dac.4949
26. M. Shokouhifar, A. Jalali, Optimized sugeno fuzzy clustering algorithm for wireless sensor networks, *Eng. Appl. Artif. Intel.*, **60** (2017), 16–25. https://doi.org/10.1016/j.engappai.2017.01.007
27. M. Shokouhifar, FH-ACO: Fuzzy heuristic-based ant colony optimization for joint virtual network function placement and routing, *Appl. Soft Comput.*, **107** (2021), 107401. https://doi.org/10.1016/j.asoc.2021.107401
28. M. Sohrabi, M. Zandieh, M. Shokouhifar, Sustainable inventory management in blood banks considering health equity using a combined metaheuristic-based robust fuzzy stochastic programming, *Socio-Econ. Plan. Sci.*, 2022, In press. https://doi.org/10.1016/j.seps.2022.101462
29. H. Esmaeili, V. Hakami, B. Minaei Bidgoli, M. Shokouhifar, Application-specific clustering in wireless sensor networks using combined fuzzy firefly algorithm and random forest, *Expert Syst. Appl.*, **210** (2022), 118365. https://doi.org/10.1016/j.eswa.2022.118365

30. K. Shaukat, F. Iqbal, I. A. Hameed, M. U. Hassan, S. H. Luo, R. Hassan, et al., MAC Protocols 802.11: A comparative study of throughput analysis and improved LEACH, *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications, and Information Technology (ECTI-CON)*, 2020, 421–426. https://doi.org/10.1109/ECTI-CON49241.2020.9158097
31. M. U. Hassan, M. Shahzaib, K. Shaukat, S. N. Hussain, M. Mubashir, S. Karim, et al., DEAR-2: An energy-aware routing protocol with guaranteed delivery in wireless ad-hoc networks, In: *Recent trends and advances in wireless and IoT-enabled networks*, Springer: Cham, 2019. https://doi.org/10.1007/978-3-319-99966-1_20
32. B. M. Hardas, S. B. Pokle, Optimization of peak to average power reduction in OFDM, *J. Commun. Technol. Electron.*, **62** (2017), 1388–1395. https://doi.org/10.1134/S1064226917140017
33. I. Javed, X. L. Tang, K. Shaukat, M. U. Sarwar, T. M. Alam, I. A. Hameed, et al., V2X-based mobile localization in 3D wireless sensor network, *Secur. Commun. Netw.*, **2021** (2021), 6677896. https://doi.org/10.1155/2021/6677896
34. B. Pokle, Analysis of OFDM system using DCT-PTS-SLM based approach for multimedia applications, *Cluster Comput.*, **22** (2019), 4561–4569. https://doi.org/10.1007/s10586-018-2140-0
35. K. Shaukat, F. Iqbal, T. Mahboob A. Shaukat, The impact of artificial intelligence and robotics on the future employment opportunities, *Trends Comput. Sci. Inf. Technol.*, (2020), 50–54. https://doi.org/10.17352/tcsit/000022
36. M. Hatamian, M. Almasi Bardmily, M. Asadboland, M. Hatamian, H. Barati, Congestion-aware routing and fuzzy-based rate controller for wireless sensor networks, *Radio Eng.*, **25** (2016), 114–123. https://doi.org/10.13164/re.2016.0114
37. M. Hatamian, H. Barati, A. Movaghar, CGC: Centralized genetic-based clustering protocol for wireless sensor networks using onion approach, *Telecommun. Syst.*, **62** (2016), 657–674. https://doi.org/10.1007/s11235-015-0102-x
38. E. Hasheminejad, H. Barati, A reliable tree-based data aggregation method in wireless sensor networks, *Peer Peer Netw. Appl.*, **14** (2021), 873–887. https://doi.org/10.1007/s12083-020-01025-x
39. H. Barati, A. Movaghar, A. Barati, A. Z. Arash, A review of coverage and routing for wireless sensor networks, *Int. J. Electron. Commun. Eng.*, **2** (2008), 67–73.
40. E. Ghorbani Dehkordi, H. Barati, Cluster based routing method using mobile sinks in wireless sensor network, *Int. J. Electron.*, **110** (2023), 360–372. https://doi.org/10.1080/00207217.2021.2025451
41. E. Kiamansouri, H. Barati, A. Barati, A two-level clustering based on fuzzy logic and content-based routing method in the internet of things, *Peer Peer Netw. Appl.*, **15** (2022), 2142–2159. https://doi.org/10.1007/s12083-022-01342-3
42. M. Revanesh, V. Sridhar, M. A. John, CB-ALCA: A cluster-based adaptive lightweight cryptographic algorithm for secure routing in wireless sensor networks, *Int. J. Inf. Comput. Secur.*, **11** (2019), 637–662. https://doi.org/10.1504/IJICS.2019.103108
43. C. Omar, A. Koubaa, A. Zarrad, A cloud based disaster management system, *J. Sens. Actuator Netw.*, **9** (2020), 6. https://doi.org/10.3390/jsan9010006
44. P. Subbulakshmi, V. Ramalakshmi, Honest auction based spectrum assignment and exploiting spectrum sensing data falsification attack using stochastic game theory in wireless cognitive radio network, *Wireless Pers. Commun.*, **102** (2018), 799–816. http://doi.org/10.1007/s11277-017-5105-3

45. L. Qing, Q. X. Zhu, M. W. Wang, Design of a distributed energy efficient clustering algorithm for heterogeneous wireless sensor networks, *Comput. Commun.*, **29** (2006), 2230–2237. https://doi.org/10.1016/j.comcom.2006.02.017
46. A. R. Suhas, M. M. Priyatham, Lifetime and energy efficiency improvement techniques for hierarchical networks, *IJEAT*, **9** (2019), 62–72, 2019. https://doi.org/10.35940/ijeat.A1013.1291S619
47. S. Neelakandan, M. Prakash, B. T. Geetha, A. K. Nanda, A. M. Metwally, M. Santhamoorthy, et al., Metaheuristics with deep transfer learning enabled detection and classification model for industrial waste management, *Chemosphere*, **308** (2022), 136046. https://doi.org/10.1016/j.chemosphere.2022.136046
48. K. Lakshmanna, N. Subramani, Y. Alotaibi, S. Alghamdi, O. I. Khalafand, A. K. Nanda, Improved metaheuristic-driven energy-aware cluster-based routing scheme for iot-assisted wireless sensor networks, *Sustainability*, **14** (2022), 7712. http://doi.org/10.3390/su14137712
49. A. M. Bongale, C. R. Nirmala, A. M. Bongale, Hybrid cluster head election for WSN based on firefly and harmony search algorithms, *Wireless Pers. Commun.*, **106** (2019), 275–306. https://doi.org/10.1007/s11277-018-5780-8
50. N. Moussa, Z. Hamidi-Alaoui, A. E. B. El Alaoui, ECRP: An energy-aware cluster-based routing protocol for wireless sensor networks, *Wireless Netw.*, **26** (2020), 2915–2928. https://doi.org/10.1007/s11276-019-02247-5
51. D. K. Jain, X. Liu, N. Subramani, P. Mohan, Modeling of human action recognition using hyperparameter tuned deep learning model, *J. Electron. Imaging*, **32** (2022), 011211. http://doi.org/10.1117/1.JEI.32.1.011211
52. M. Singh, P. M. Khilar, A range free geometric technique for localization of wireless sensor network (WSN) based on controlled communication range, *Wireless Pers. Commun.*, **94** (2017), 1359–1385. https://doi.org/10.1007/s11277-016-3686-x
53. K. Shaukat, S. H. Luo, V. Varadharajan, A novel method for improving the robustness of deep learning-based malware detectors against adversarial attacks, *Eng. Appl. Artif. Intell.*, **116** (2022), 105461. https://doi.org/10.1016/j.engappai.2022.105461
54. K. Shaukat, S. H. Luo, S. Chen, D. X. Liu, Cyber threat detection using machine learning techniques: A performance evaluation perspective, *2020 International Conference on Cyber Warfare and Security (ICCWS)*, 2020. http://doi.org/10.1109/ICCWS48432.2020.9292388
55. S. Messous, H. Liouane, Online sequential DV-hop localization algorithm for wireless sensor networks, *Mob. Inf. Syst.*, **2020** (2020), 8195309. https://doi.org/10.1155/2020/8195309
56. Y. Alotaibi, S. Alghamdi, O. I. Khalaf, U. Sakthi, Improved metaheuristics-based clustering with multihop routing protocol for underwater wireless sensor networks, *Sensors*, **22** (2022), 1618. http://doi.org/10.3390/s22041618