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NN – Fuzzy EHORM: Energy Efficient Lifetime Maximization Clustering Technique using Neural Fuzzy Approach for Wireless Sensor Networks

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Abstract – Wireless Sensor Networks (WSNs) are made up of sensor nodes that operate on limited, non-rechargeable battery power with constrained processing capabilities. Managing energy consumption is a critical challenge for prolonging network lifetime. Efficient data transmission requires minimizing energy usage while maximizing the operational lifespan of the network. To address this, developing energy-efficient clustering protocols is essential. In this study, a hybrid neural–fuzzy approach is proposed for cluster formation and optimal cluster-head (CH) selection aimed at stabilizing energy utilization and extending network longevity. To further enhance energy efficiency, an Energy-Hole Removing Mechanism (EHORM) is integrated into the neural–fuzzy framework employing sleep–awake strategies for sensor nodes to reduce power consumption. In the proposed neural network – fuzzy integrated Energy-Hole Removing Mechanism (NN–fuzzy EHORM), a neural network predicts the energy levels of candidate cluster heads, leveraging learning from power-related data along with the measured signal strength of each node. Sensor nodes with higher residual energy, guided by the base station's central location are preferentially chosen as cluster heads to minimize overall energy consumption. Simulation results demonstrate that the proposed hybrid model outperforms traditional methods across multiple metrics including learning rate, energy consumption, packet delivery ratio, network lifetime, residual energy and throughput.

Index Terms – Wireless Sensor Networks, Neural Networks, Energy Consumption, Fuzzy Logic, Cluster Head, Lifetime Maximization.

1. INTRODUCTION

Wireless sensor systems are becoming a frontline research domain due to their large potential application area. By transmitting data from the local atmosphere to the network using sensor nodes, it bridges real and digital worlds [1]. It is a comprised and spatially disseminated self-directed system remotely transmitting and congregating information to perceive assured impactful functions in the physical and ecological conditions. Each device connected to this sensor network is competent to transmission, processing and simultaneous sensing [2]. Exploiting these potentials on a sensor device provides a massive volume of undeniable applications.

Environmental monitoring and animal herd tracking monitoring are the most important and ancient applications of wireless sensor networks. Furthermore, hostile territory and intruder /sniper detection tracking in military battlefields are one of the essential applications of WSNs [3]. In addition, WSNs are known for their noteworthy usage in retail and industrial control, medical applications and healthcare to monitor and maintain patient records, smart device collaboration in the name of a smart city or smart world, impactful advantages in security and emergency field, traffic monitoring such as air and rail transport etc. [4].

Wireless sensor networks are self-configured networks with self-oriented ability which are spread globally to promote exchanging of data through the air. It contains a count of sensory nodes with restricted battery-powered energy and process. The key functionalities of these network nodes are to timely process the data locally and send or receive it for data communication [5]. Wireless sensing systems are constructed with sensory units, a sensing field and a base station coupled

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with a terminal user. In WSNs, sensing data are transmitted directly or through the sensory nodes towards the base station (BS) depending upon the network's construction. WSNs contain a number of sensory units with minimal power and functions which are powered by batteries [6]. The transmission is associated with the battery connected with the nodes. Even though WSNs are known for sensor node routing, it has its own demerits as follows: network scalability, poor memory and low storage, higher energy consumption, increasing configuring cost. Among them, energy depletion is considered as a key issue which affects network durability. Significant power is obligatory for the large-scale deployment of WSNs, and it is not feasible to routinely recharge the battery modules of a vast quantity of compact network units [7].

Sensory units consume a substantial quantity of battery capacity for data dissemination and the time it takes to transmit a packet varies depending on how far apart the units sending and retrieving the message unit are from one another. There are still several algorithms being developed to reduce energy waste as follows: routing / clustering, data correlation, energy harvesting, mobile intermediary units and central units, message accumulation, beamforming, cross-layer design for resource allocation, etc. [8]. Among these approaches, clustering has been recognized as an effective solution to overcome power depletion and increase the lifespan of wireless networks. There are diverse routing approaches and cluster-based techniques that have been researched and implemented to meet the architectural requirements of WSNs and increase the network's lifespan. By arranging nodes and allocating responsibilities while maximizing resource use, clustering is well-known as a topology control technique that improves network interfaces [9].

In the clustering technique, data is gathered to form clusters by employing minimum distance, dataset intensity and graph-like geometric distributions. It comprises of sensory nodes and a cluster head (CH), which is shown in figure 1. To reduce energy consumption, sensor nodes are spread widely into clusters [10]. The sensor node that functions as a leader for the rest of the nodes is called a cluster head, which is allotted a role to the sensors based on their energy usage. Cluster heads are accountable for delivering sensor data aggregated at the sensory units and relayed to the base station. Each cluster accommodates one or more than one cluster head. When reaching the sink node, sensor nodes with sensory information have drained energy and are subjected to substantial network traffic forced on these sensory nodes, a phenomenon that is termed the energy-hole problem [11]. Researchers find that aggregating data effectively addresses the energy depletion issue. To resolve the problem and to lengthen the network lifetime, clustering the sensor nodes is essential. Key benefits of the clustering algorithm are:

- Reduction of routing table volume.
- Limiting the exchanged communication's repetitiveness.
- Controlling and reducing energy depletion.
- Prolonging the network's lifespan.

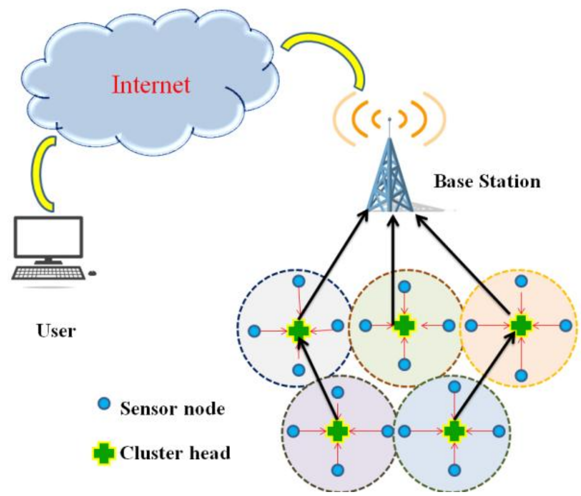

Figure 1 Clustering in WSNs

1.1. Problem Statement

WSNs are now widely adopted across diverse domains like environmental sensing, healthcare systems, military surveillance and industrial automation. Despite their significance, the scarce energy availability in sensor nodes remains a fundamental drawback. Continuous data transmission and uneven energy usage often cause some nodes to deplete their energy faster, which results in premature failures and the formation of energy holes within the network. Such energy holes, particularly around cluster heads and sink nodes, not only shorten the overall network lifetime but also disrupt reliable data delivery. Existing clustering and energy management methods provide partial solutions to lengthen the lifespan of the network by electing an efficient CH. This highlights the need for an energy-efficient, intelligent and adaptive clustering mechanism that can lengthen the operational lifetime of WSNs, alleviate energy hole issues and ensure balanced energy consumption across the network.

1.2. Objectives of this Research

- To develop an energy-efficient lifetime maximization clustering technique for WSNs using a neural-fuzzy approach.
- To incorporate an energy-hole removal strategy to distribute the workload evenly and reduce energy drain around sinks nodes.

- To optimize cluster head selection based on residual energy, count of alive nodes and distance factors using neural-fuzzy logic.
- To conserve energy utilization efficiency and extend the overall network lifetime by reducing premature node failures.
- To evaluate the studied NN–Fuzzy EHORM technique through simulation and performance comparison with existing clustering protocols in terms of energy consumption, network lifetime, packet delivery ratio, residual energy and throughput.

Incorporation of clustering with a neural network approach provided an effective solution to prolonging the network lifespan by minimizing energy consumption. Neural networks contain a number of layers with interconnected nodes or neurons that replicate the human brain architecture and functionalities [12]. It includes one input layer, one output layer and multiple latent layers. The input layer captures the input features; hidden layers can be one or many that processes the data originating at the input layer and subsequently send them towards the output layer. Finally, the output layer predicts and yields results.

1.3. Contributions

The distinctive contributions of this study are summarized below:

1. Neural-fuzzy approach is introduced to enhance power utilization and network lifetime maximization by selecting optimal cluster head selection.
2. The proposed architecture exploits the benefits of supervised learning to elect the optimal cluster head in a dynamic manner by utilizing historical data depending upon the various energy usage levels.
3. Further, the energy-hole reduction strategy i.e. EHORM is integrated with the neural – fuzzy approach to effectively alleviate the energy depletion issue by increasing the network's energy usage for impulsive breakdown of node reduction and enhancing network stability.
4. Extensive experimental simulation results demonstrated the outperformance of the studied NN-Fuzzy EHORM model with an improvement in prolonging network lifespan with an average of 30% dead nodes and 75% alive nodes at round 13,511 during transmission.
5. Energy efficiency of the studied model is acquired by consuming 35% during data transmission and aggregation and improving the average of residual energy by 68%.

We need a hybrid clustering approach to achieve these objectives. In this research, a novel hybridization of neural network and fuzzy logic is proposed, featuring an energy efficient hole-removing strategy. In a neural network - fuzzy EHORM (NN-Fuzzy EHORM) approach, a neural network is incorporated with a fuzzy system to lengthen the wireless network's lifetime by minimizing power utilization of sensory units in the network by implementing energy hole-removing techniques. The upcoming sections of this paper are presented below. Section 2 depicts the related works. The proposed methodology is elaborated in section 3. Simulated outcomes and discussion are illustrated in section 4. The conclusion of the research is presented in section 5.

2. RELATED WORK

Various researchers have studied several methods to diminish the energy dissipation of sensing units and maximize the life span of wireless sensory systems based on cluster formation and optimal cluster head selection. This section outlines a few pertinent contributions proposed for the problems.

In [13], integration of a quantum PSO and fuzzy inference system is studied to curtail the power utilization and prolong the lifespan of the network, where Lévy flight and Gaussian perturbation for amending the location are collaborated to avert entrapping in optima. Authors demonstrated the efficiency of the studied model by throughput, energy consumption, residual energy, deviation of energy and scalability. This method offers several advantages including balanced energy consumption across the nodes, reduced hotspots near the base station and an overall longer network lifetime. However, despite these benefits QPSO with Sobol sequences and Lévy flights suffers from higher computational overhead and may face scalability complexities involved in scaling to large networks. A fuzzy logic-based energy optimization clustering algorithm is proposed in [14], in which it is established that the power dissipation corresponding to the data transceiver in single-hop forwarding is comparatively lower than the energy consumed by the multi-hop forwarding scheme in a sensor communication network. The degree of proximity to the sink node and the shortest path, multiparameter and fuzzy routing are achieved parameters to evaluate the proposed fuzzy logic scheme. The experimental result demonstrates the effectiveness of the model studied concerning energy efficacy and energy stability. Compared to conventional approaches such as NN-iLEACH and basic LEACH, which often rely on random or fixed CH selection, the fuzzy-logic method distributes load more evenly and extends network lifetime. While it improves energy efficiency over traditional methods, it still lacks predictive mechanisms and adaptive scheduling which can limit overall network stability and throughput.

With the goal of lengthening the lifespan of a wireless network and provide even energy utilization in the sensor network, an energy-aware routing fuzzy approach is studied in [15] to select the potential cluster head selection among various cluster nodes with the whole non-probabilistic

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scheme. In this approach, three fuzzy variables are utilized to enhance the network lifetime, such as residual energy and span connecting the cluster head to the base station. Cluster members with peak energy remaining are selected as cluster heads using a fuzzy approach; hence, the model outperformed and compared with the traditional LEACH model. It handles multiple input parameters including energy, distance and node density simultaneously to make more informed CH selections than purely random or fixed methods. Yet, the method focuses primarily on energy and CH selection but it does not explicitly optimize routing paths or reduce packet loss, which can affect overall network performance. To develop optimum and energy-aware clusters in WSNs, a neuro-fuzzy integration scheme is proposed in [16]. It includes two subsystems, namely the neural network and fuzzy system, each of them employed to form clustering and cluster head selection and increase energy by optimizing tentative cluster heads, respectively. The authors described the studied model as achieving 37% of energy restored in WSNs, and the efficacy of the model is evaluated regarding rate of packet drop, energy consumption and network lifetime. Compared to conventional methods like LEACH, this approach ensures more balanced energy usage and delays node failures. However, while the neuro-fuzzy model improves energy efficiency, it still exhibits computational complexity due to the neural network training and fuzzy inference.

In [17], a novel network-based routing and clustering algorithm with LEACH is proposed to lengthen the operational lifespan of the network and abate the power depletion. EHORM is integrated with this neural network CH selection approach to rectify the energy draining in the node. The proposed architecture outperformed the existing and traditional LEACH by a 30% improvement in throughput, a 25% packet ratio and 40% energy consumption. The protocol reduces hotspots near the base station by balancing the communication load among nodes and intelligent CH rotations. Nevertheless, the model assumes relatively stable network conditions. Hence, sudden changes in topology or traffic may affect CH selection and energy balancing. An energy hole-removing mechanism for WSNs is studied in [18] to eradicate energy holes from the networks. It exploits Eth threshold energy to discover the highest distance between nodes to compute the highest energy usage for transmitting data. When a node's energy level is lower than E_{th}, then data transmission would not happen. For efficient energy utilization, nodes share communication responsibilities more evenly and minimizing redundant transmissions. However, this method reacts to existing energy patterns but does not predict future energy depletion which may lead to inefficiencies over time.

In [19], a novel dynamic clustering head selection approach is studied to expand the network lifetime. The author exploited the on-Demand optimal clustering algorithm (OPTIC) for wireless sensor networks where CH is selected dynamically instead of periodically. The model studied attained improved energy balance at 18% and an extended lifetime at 19%. It reduced communication cost, Clusters are formed only when necessary and minimizing redundant control message exchanges. Yet, the method does not explicitly address the uneven energy depletion near the base station which can still create energy holes. A Cluster-based energy optimization algorithm deploying a mobile sink is developed in [20] to optimize the energy depletion of WSNs. Comprehensive selection of CH and designing of a motion performance function are two approaches utilized to achieve the outcome. This model exploits a mobile sink alone, which causes data loss and delays while performing on a large area. Moreover, dynamic clustering and sink mobility reduce energy consumption especially for nodes by this method. In contrast, its performance relies on the effective movement pattern of the mobile sink and poor routing decisions can still lead to energy imbalance. A study on energy-efficient clustering and routing paradigms for lifetime improvement in WSNs is demonstrated in table 1.

Table 1 A Study on Energy-Efficient Clustering and Routing Approaches for Lifetime Improvement in WSNs

Paper	Method	Advantages	Limitations
[13]	Quantum Particle Swarm Optimization with Sobol sequences and Lévy Flights	• Balanced energy consumption • Reduced hotspots • Longer network lifetime	• Computational overhead • Potential scalability issues in large networks
[14]	Fuzzy-logic-based energy optimized routing	• Balances energy consumption • Prolongs network lifetime Adapts to various traffic patterns	• Accurate parameter tuning and fuzzy rule design is needed • Higher computational complexity

[15]	Fuzzy logic based CH selection using residual energy, node distance and intra cluster distance	• Reduces early node deaths compared to LEACH • Balances energy usage • Prolongs network lifetime	• Less effective in highly dynamic or large-scale WSNs • Dependency on well-defined fuzzy rules
[16]	Neuro-Fuzzy Energy Aware Clustering Scheme	• Lowers packet loss • Maintains higher node availability even in mobile conditions • Extends network lifetime	• Requires accurate signal strength estimation • Computational overhead due to hybridization of neural-fuzzy processing
[17]	Hybridization of neural network and iLEACH with energy hole removing strategy	• Reduces energy utilization • Improves throughput and packet delivery compared to LEACH/ILEACH.	• Computational overhead of neural network not fully addressed • Limited validation under dynamic or mobile conditions
[18]	Energy hole removing scheme with sleep/awake scheduling mechanism	• Reduces sink-node energy depletion • Balances energy use • Prolongs network lifetime	• Causes coverage gaps and latency • Threshold selection depends on accurate energy estimation.
[19]	Distributed on-demand clustering algorithm (OPTIC) using Alternating Direction Method of Multipliers (ADMM)	• Improves energy balance • Reduces unnecessary overhead • Extends network lifetime compared to periodic clustering methods	• Issues like mobility and link failures not fully addressed • ADMM adds computational cost
[20]	Cluster-Based Energy Optimization with Mobile Sink (CEOMS)	• Improves load balancing Reduces transmission delay • Extends network lifetime	• Assumes predictable sink movement and position awareness • computational overhead may affect low-power nodes

From this survey, it is obvious that the hybrid approach for CH determination is utilized in WSNs. Hence, this study formulates a hybrid approach of neural network–fuzzy logic with the EHORM technique to effectually outline the clusters and elect the optimal cluster head to alleviate energy overhead and boost the durability of WSNs.

3. PROPOSED MODELLING

3.1. Fuzzy Sub-System

In traditional cluster head selection techniques, CHs are elected by arbitrary selection. It has a huge shortcoming, specifically for datasets with massive volumes. Poor selection of CH causes several problems in sensor network processing. To overcome such an issue, a novel and effective neural network-based fuzzy approach is proposed to find an efficient CH among cluster members. Fuzzy logic is a non-probabilistic technique that enriches the CH selection process along with symmetric cluster creation to maximize the network's sustainability by lowering the power incurred by the sensory units integrated with a supervised learning neural network.

The proposed fuzzy approach comprises four phases as shown in figure 2.

- A fuzzifier is used to accept the input that is normalized and comprised. Then the inputs are rehabilitated into linguistic components.
- Fuzzy rules are used to accumulate the IF-THEN rules for fuzzy evaluation purposes.

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- Fuzzy inference engines are exploited to unite the input value and IF-THEN fuzzy rule for reproduction of reasoning, which results in inference engines.
- Defuzzification is the mechanism of switching the fuzzy outcome into a crisp value using a defuzzifier.

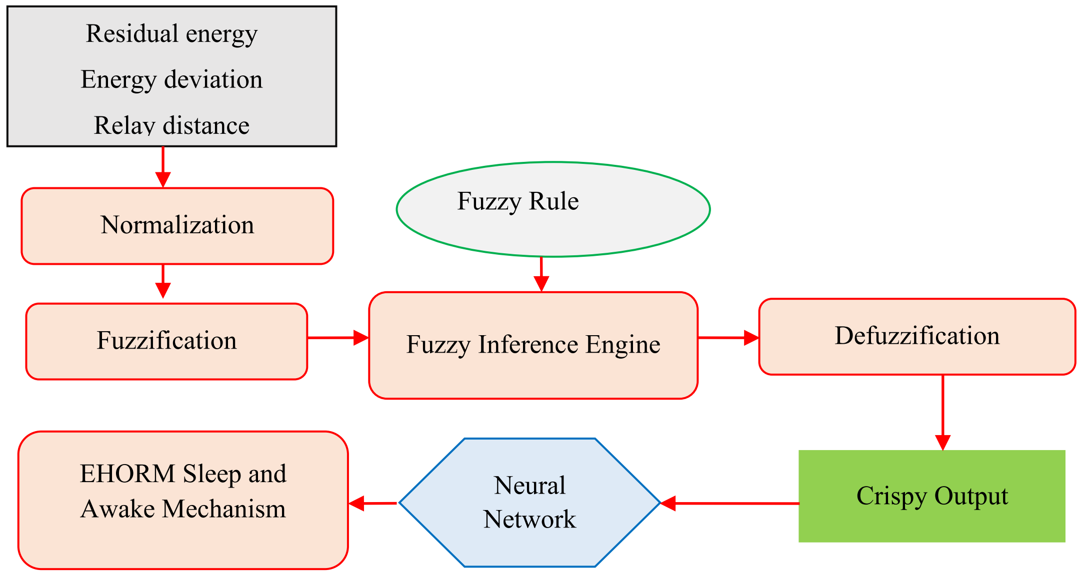

Figure 2 Fuzzy Model Architecture for NN – Fuzzy EHORM

3.2. Neural Network System

The network is trained using supervised learning techniques. Consider W is the weight factor of the network with n count of input cells where μ and L are the convergence rate and input given to the cell respectively. Then the equation for the training process of the sensor network using a single layer perceptron is given in the equation (1).

$$W_n(t-1) = W_n(t) + \mu \times (O_D - O_N) \times L \qquad (1)$$

Where $O_D - O_N$ indicates the deviation between the network's output (O_N) and the desired output (O_D). Weight adjustment for this network is written in an equation (2).

$$W_N = W_O + N \times \mu \times I_{Pre} \times (O_D - O_N) \qquad (2)$$

W_N and W_O are the updated or new weights and existing or old weights; I_{Pre} represents the previous layer's input and N indicate an active neuron of the network. Then the output of every network for various weight adjustments is given in equation (3).

$$\begin{cases} f_1(I_1 \times W_1) \\ f_2(I_2 \times W_2) \\ f_n(I_n \times W_n) \end{cases} \qquad (3)$$

Where, I_1, I_2 and I_n are the inputs given to the network with the activation functions f_1, f_2 and f_n and the associated weights W_1, W_2 and W_n respectively. There are n inputs in the system. These inputs include the sensor node's obtained signal strength and residual energy that is trained by the supervised learning neural network. Energy consumed by the network is indicated by the system input as a constant variable. The neural network architecture for the NN-Fuzzy approach is visualized in figure 5 that constituted of input layer, latent layers and output layers with rules of perceptron learning and weight adjustment. Training neurons of network trained the highest energy and effective link quality for the selection of tentative CHs, where the link quality is the ratio of strength of the signal and highest strength available. The upper neurons contain predetermined weights with function linearity and the lower neurons encompass weights needed to be trained. The collections of inputs can be mapped to a desired output O_D through neurons. The desired output O_D is achieved by employing the single-layer perceptron. The proposed hybridized neural network approach provides dependable and energy competent CH for the wireless sensor networks.

3.3. Workflow of the Proposed Model

1. Data Collection from Sensor Nodes

- Each sensor node reports its current energy level, activity status and other relevant parameters to the network.

2. Neural Network Evaluation

- A neural network processes the collected data to learn patterns in energy consumption and node behavior.
- It predicts which nodes are most suitable for tasks like CH selection derived their residual energy mobility factor and data transmission range.

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3. Fuzzy Logic

- Fuzzy logic evaluates the nodes using factors such as energy level, mobility factor and data transmission range simultaneously.
- Each criterion is represented as a fuzzy variable and the fuzzy rules determine the threshold for each node.

4. Cluster Head Selection

- Nodes with the highest threshold from the fuzzy evaluation are selected as cluster heads.
- This ensures that nodes with sufficient energy and proper activity levels handle the extra workload.

5. Sleep–Awake Scheduling

- Based on the NN–Fuzzy evaluation, nodes with low energy are put into sleep mode.
- Active nodes handle sensing and data transmission and ensuring energy is efficiently distributed across the network.

6. Dynamic Adjustment and Iteration

- After each round, energy levels are updated and the node performance is re-evaluated by the neural network.
- Fuzzy logic recalculates suitability scores, potentially rotating cluster heads and adjusting sleep–awake schedules.

7. Maximizing Network Lifetime

- By continuously combining predictive evaluation by the neural network and fuzzy logic, the network balances energy usage.
- This prevents early depletion of nodes and prolongs the overall network lifetime while maintaining reliable data transmission.

3.4. Proposed Fuzzy Integrated Neural Network with EHORM Mechanism

In the studied approach, CH is determined to rely on the mean of residual energy, mobility factor and data transmission range. These intermediates perform a vital role in CH selection among cluster members, which range from (0, 1) to general normalization. Residual energy indicates the power retained by the sensing units after finishing the task assigned to them. After the completion of fuzzification of input values, the resultant fuzzy system is obtained using 150 fuzzy rules based on expert practice applied to them. When the candidate has achieved the highest values for residual energy, transmission range and mobility speed, then it will be selected as a CH up to the data attained at the BS destination.

The proposed neural-fuzzy integrated EHORM architecture is illustrated in figure 3. The neural network for the studied approach encompasses an input layer, an output layer and two intermediate layers with associated weights. Before the training of the nodes for learning, all nodes are labeled as 0 and 1 in accordance with their responsibility as cluster member or cluster head, which will enhance the process of finding the efficient CH among all members. The network structured with multiple sensor nodes, each initialized with energy E_i and threshold energy E_{th} is defined to decide which nodes are eligible for data transmission. All sensor nodes are deployed across the network and their energy levels are monitored periodically. Nodes that fall below the threshold enter a sleep mode to conserve energy, while active nodes transmit data to the base station (BS). This sleep–awake strategy ensures that energy is used efficiently and that nodes possessing higher energy are prioritized for tasks such as transmission and CH selection.

Within each cluster, the NN–Fuzzy system evaluates the energy levels of nodes and the number of sleeping nodes to select the cluster head (CH). A node takes on the responsibility of a cluster head when it satisfies the required energy level, while other nodes continue to function as regular cluster members. The CH coordinates the cluster, gathers data from member nodes and forwards it to the BS. This process is repeated in rounds, with packet delivery monitored for both CHs and the BS, until the network reaches the end of its lifetime. Algorithm 1 presents EHORM integrated NN-Fuzzy Based Cluster Head Selection for Network Lifetime Maximization. By combining clustering, NN–Fuzzy-based CH selection, threshold energy control and sleep–awake cycles, the proposed model ensures balanced energy consumption, avoids early depletion of nodes and provides reliable data delivery throughout the network. EHORM integration with the NN-fuzzy mechanism for accomplishing energy depletion involves the following functions.

1. Forming of clusters – Wireless sensor networks comprise several cluster members along with a cluster head which is elected by the neural–fuzzy scheme to steer and organize them to complete the task assigned to them within the cluster.
2. Sleep and awake function – Energy conservation is done by employing the sleep and awake functionality of EHORM to accumulate the power of batteries. This can be done alternatively. When the sleep mode is enabled, the sensor node blacks out its process and retains the energy. If the awake node is enabled, then the data is transmitted to BS.
3. Node with higher energy determination – To set the threshold energy (E_{th}) for the remaining nodes, the higher energy node is ascertained depending upon the energy it holds.

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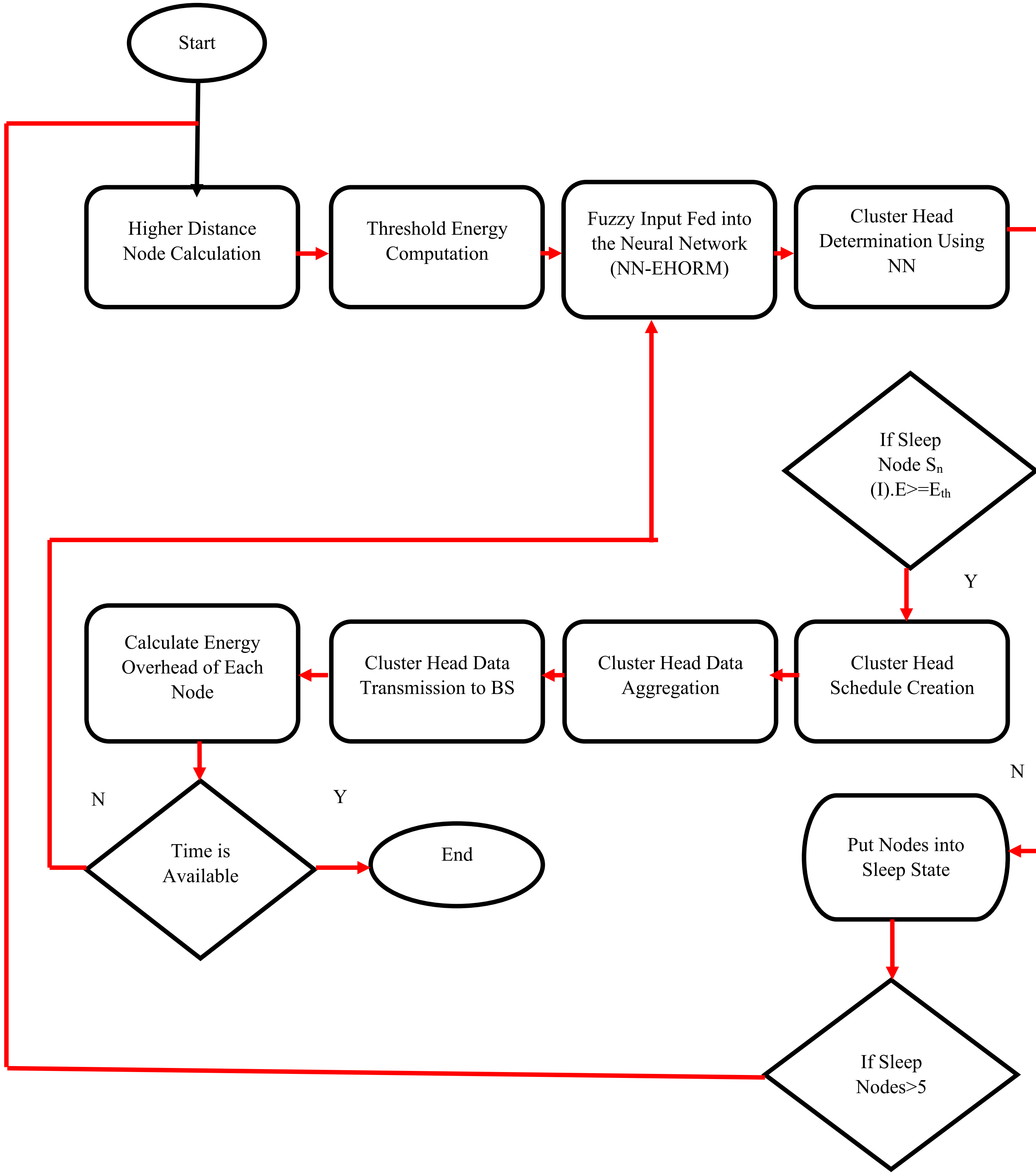

Figure 3 Flow Diagram of the Proposed NN-Fuzzy EHORM Scheme

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4. Threshold energy fixing – After recognizing the higher energy, the recognized energy level is utilized to transmit the data. Energy less than the threshold level is prohibited from the transmission process to retain energy for prolonging lifetime.
5. Periodical checking of energy – Within a specific duration, nodes in a network undergo energy level checking to prevent the battery from draining and conserve the energy by making them idle.
6. Transmitting the data - Node with E_{th} level energy is only permitted for data transmission to BS.

By setting the threshold energy level, energy hole issues occurring in the network are alleviated using hole-removing mechanism. It occurs when the number of nodes loses its energy next to the BS which causes the unstable network in WSNs. By importing EHORM, energy of the sensing nodes is evenly distributed to boost the network's lifespan.

Input:

N: Number of sensor nodes

E_i: Initial energy of each sensor node

E_{th}: Threshold energy

Output:

CH: Cluster head

Energy efficient lifetime maximization

1. Initialize node energy level

2. Deploy all sensor nodes across the network

3. For each sensor node i in N:

Set preliminary energy E_i

4. Define threshold energy parameter E_{th}

5. For round = 1 to MaxRounds do

For each node i in N:

if E_i<= 0 then

NodeStatus[i] ← Dead

else if E_i<= E_{th} then

NodeStatus[i] ← Sleeping

increment sleeping node count $S_n = S_n + 1$ // S_n- Sleeping node

else

NodeStatus[i] ← Alive

6. Cluster Head (CH) Selection:

Use NN-Fuzzy subsystem to evaluate current energy of nodes within each cluster

Compare nodes based on threshold energy and sleeping node count

If E_i>= E_{th} and $S_n < 0$, then mark node as CH and add to CH_list

7. For nodes not selected as CH, mark as Normal nodes

8. Compute packets delivered to BS and CHs

9. Check termination:

If network lifetime or maximum rounds reached, end process

Else, return to Step 5 for next round

Algorithm 1 EHORM Integrated NN-Fuzzy Based Cluster Head Selection for Network Lifetime Maximization

4. SIMULATION RESULTS AND DISCUSSIONS

4.1. Experimental Analysis

The MATLAB (R2022a) simulator is utilized to simulate the proposed model, which includes area dimensions of 200 m x 200 m with 100 numbers of nodes to evaluate the communication efficacy. Required specifications for simulated results are indicated in table 2.

Table 2 Simulation Configuration

S.No	Specifications	Values
1	Network deployment area	200m x 200m
2	Count of units	100
3	Initial energy of units	0.5 Joules
4	Sink	x = 100, y = 100
5	Packet size of data	4000 bits
6	Energy aggregation	5 nj/bit
7	Amplifications of power (ε_{f_s})	10 (Pj/bit/m2)
8	Amplifications of power (ε_{mp})	0.0013 (Pj/bit/m4)
9	Energy transmitted and received	50 (nj/bit
10	Count of rounds	14000

4.2. Performance Comparison

The effectuality of the studied research is equated with the existing clustering approaches for evaluation purposes. NN-iLEACH [17], QPSOFL [13] and Neural-Fuzzy (NNFL) [16] are taken for the comparison to evaluate the proposed model, which also provided their impactful contribution to the field

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of wireless sensor networks. NN-iLEACH and QPSOFL are outperformed by NNFL. Even though, the proposed NN-Fuzzy EHORM surpassed all other methods by integrating a neural network with fuzzy logic and an energy-hole mechanism. The outperformance of the studied model is assessed with significant parameters such as learning rate, energy consumption, residual energy, network lifetime, packet delivery ratio and throughput.

4.2.1. Learning Rate

Convergence rate in a neural network is a key parameter that regulates the extent of weight modification during training. It essentially controls the scale of each adjustment step as the model tries to minimize the error or loss function. When the convergence rate is excessively high, the model might overshoot the optimal solution, while a rate that's too low can make training very slow or get stuck in local minima. Figure 4 illustrates the learning rate for the training and validation sets. The proposed neural network model benefits from an improved learning rate schedule, leading to enhanced training performance and convergence speed. The graph shows that the model's error gradually decreases as training progresses over multiple epochs. At the beginning, both training and validation losses are high because the weights are initialized randomly. With continued training, the training loss reduces consistently, demonstrating that the model is learning effective parameters. The validation loss also follows a similar downward trend, which confirms that the model can generalize well beyond the training data.

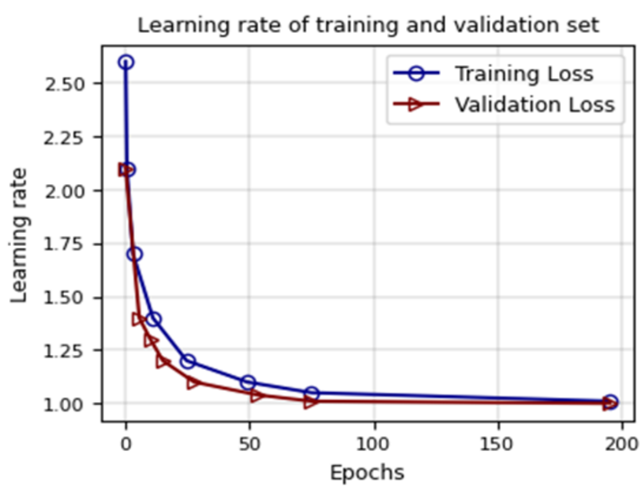

Figure 4 Learning Rate for the Training and Validation Sets

4.2.2. Energy Consumption

The total amount of energy taken for sensing the data and for data transmission and received over the WSN is termed as energy consumption. It is considered an inevitable parameter for measuring the network lifetime. Existing techniques such as NN-iLEACH, QPSOFL and NNFL are facing an insufficient routing schedule from the BS to the destination node, which causes them to drop their data packets while transmitting them. By selecting the optimal cluster head, the proposed NN-Fuzzy EHORM minimizes energy consumption by 35% during transmission. This is demonstrated in figure 5. The neural network predicts potential CHs based on residual energy and node behavior, while fuzzy logic refines the decision by handling uncertainty in parameter like sleep–awake status. This ensures that only the most energy-efficient nodes are chosen as CHs, preventing weak nodes from being overburdened. Nodes with energy below the threshold are switched to sleep mode, avoiding unnecessary transmissions and conserving their energy. This balances energy usage across the network and delays early node deaths. By aggregating data at the CH and minimizing redundant transmissions, the model reduces the total number of network communication which is the major source of energy drain in WSNs.

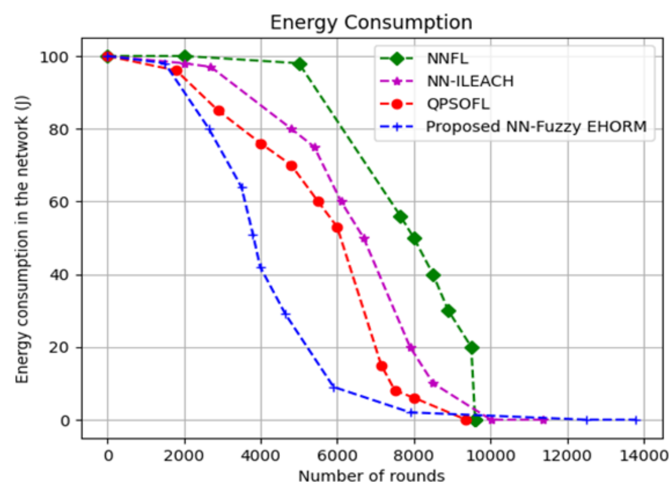

Figure 5 Energy Consumption

4.2.3. Throughput

It measures the entire count of packets communicated from the CH to the hub unit. It also includes the number of packet transmissions from cluster members to cluster heads in clusters.

Throughput =Number of packets received (bits)/Total time (s)

From figure 6, it is evident that the NN-Fuzzy EHORM approach utilized lower energy to transmit the sensory nodes over the routing path to stabilize the network performance, which enriches the throughput more than the existing competitive approaches. Throughput is calculated by the measurement of the nodes and their rotations. By intelligently selecting cluster heads through neural prediction and fuzzy decision-making, nodes with sufficient residual energy handle routing tasks. This prevents early node deaths that typically

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reduce throughput in conventional schemes. Furthermore, the sleep–awake scheduling mechanism ensures that low-energy nodes conserve power instead of dropping out, which sustains a higher number of active nodes participating in communication over multiple rounds. Based on these, the presented model is achieved superior throughput with 480 packets, whereas existing methods such as NN-iLEACH, QPSOFL and NNFL attained 390 packets, 270 packets and 210 packets, respectively.

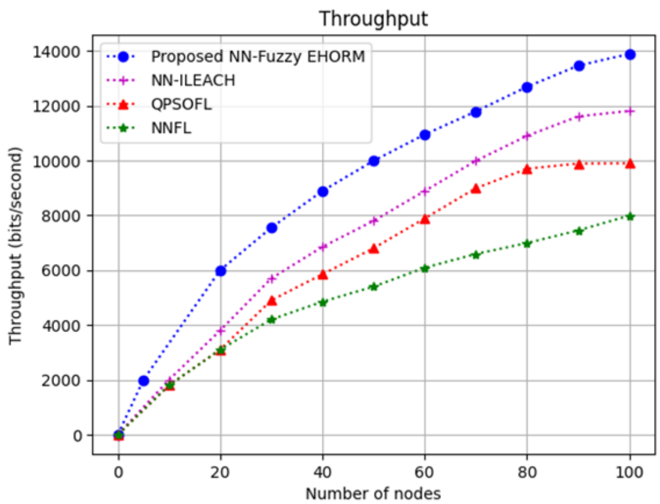

Figure 6 Throughput

4.2.4. Packet Delivery Ratio

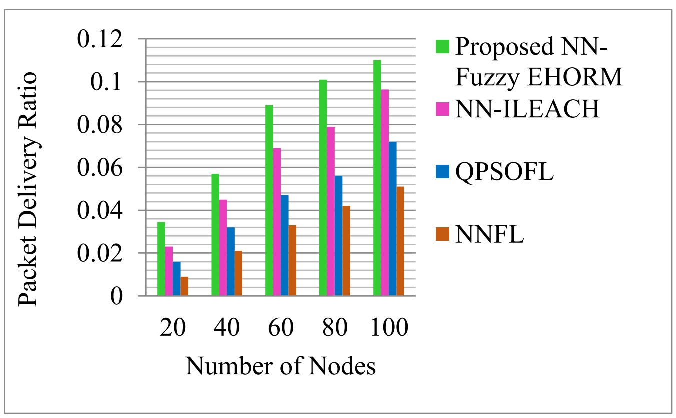

Figure 7 Packet Delivery Ratio

Successful transmission of message unit percentage from the initiating unit to the terminating node is termed as the packet delivery ratio (PDR). Figure 7 illustrates the PDR of the proposed model is improved by 40%, which is a significant enrichment compared with three existing clustering algorithms (NN-iLEACH – 25%, QPSOFL – 17% and NNFL – 9%). It is accomplished by the collaborative implementation of the effective optimal CH selection technique and energy-hole removing mechanism. Cluster heads selected by the studied model are not only high-energy nodes but also optimally positioned to reduce communication failures. In addition, the energy-hole removal mechanism prevents early depletion of nodes near the base station which is a common cause of packet drops in traditional schemes. By maintaining more active nodes with balanced energy and reducing routing failures, the proposed model achieves higher reliability in packet delivery over existing techniques.

4.2.5. Residual Energy

It is termed as the power left in the active units after the operation has concluded. Residual energy is the computation of energy utilization by the nodes for each round during the data transmission and aggregation. The percentage of residual energy acquired by the NN-Fuzzy EHORM approach is 68%, whereas the existing methods, including NN-iLEACH obtained 49% and for QPSOFL and NNFL, it is 35% and 27% respectively. Nodes near the base station typically handle more traffic and are prone to early energy depletion, creating energy holes. The studied algorithm distributes communication tasks evenly, rotates CH roles, schedules low-energy nodes into sleep mode and balancing energy usage across the network. Cluster heads aggregate data from member nodes before forwarding them to the base station and minimizing redundant transmissions which reduces energy utilization per round. Hence, this higher residual energy represents the superiority of the introduced approach with three prior techniques for energy-aware network lifetime extension, as demonstrated in figure 8.

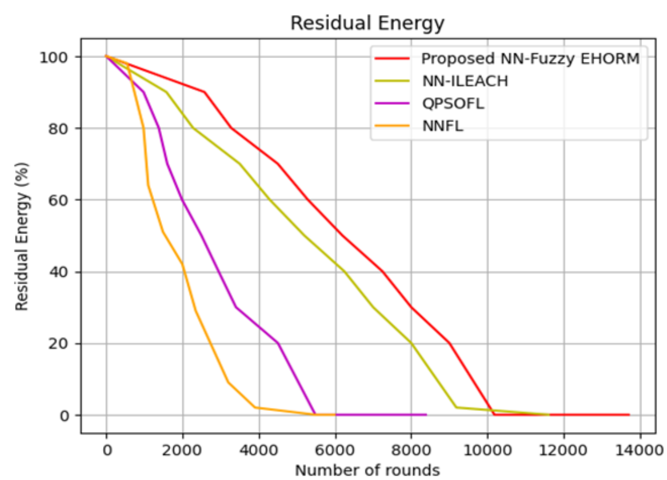

Figure 8 Residual Energy

4.2.6. Network Lifetime

The period during which the network remains functional is defined as its lifetime. Outcomes observed during the experiments illustrated the studied model surpasses the capabilities of existing approaches by achieving significance in extended network lifetime, as indicated in figure 9. The

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extended network life is based on the percentages of dead nodes during transmission. Compared with traditional methods, the presented methods lose only a few dead nodes at the end, which is a significant factor for prolonging the network. For the failure of the10th node, NNFL faced this at round 2680, QPSOFL at round 4542 and NN-iLEACH at round 6524 and the proposed NN-Fuzzy EHORM at round 13,511 which is relatively higher. Low-energy or idle nodes are put into sleep mode to conserve energy, while active nodes perform sensing and transmission to reduce unnecessary energy consumption. By maintaining more active nodes over time, the model ensures stable communication and a significantly longer network lifetime than conventional approaches.

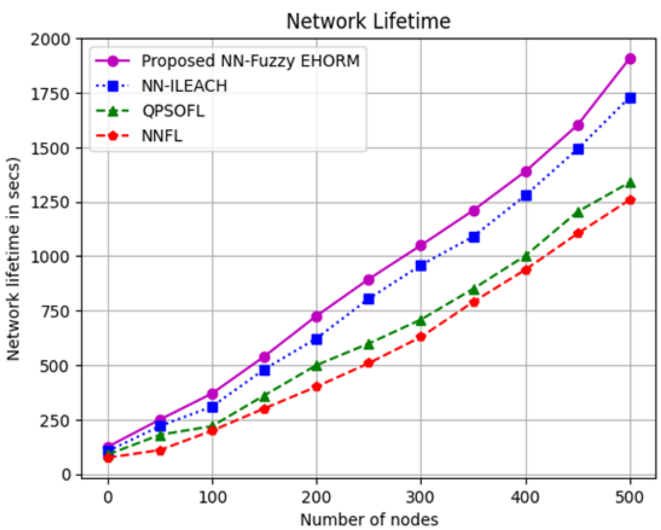

Figure 9 Network Lifetime

5. CONCLUSION

This research paper proposes Neural Network – Fuzzy Logic with EHORM (NN-Fuzzy EHORM), a revolutionary clustering and routing approach for energy-awareness and prolonging network lifetime in WSNs. A significant process of clustering techniques is selecting the optimal cluster head (CH) among the clusters, achieved using the NN-fuzzy approach. EHORM is exploited to reduce and limit the power dissipation of the network through removing the energy hole issues. By collaborating with them, a novel energy-conscious clustering approach is introduced to optimize the functional durability of the WSNs network. Seven parameters are considered to evaluate the efficacy of NN-Fuzzy EHORM with three competitive existing techniques such as NN-iLEACH, QPSOFL and NNFL. Extensive experimental results demonstrate the efficacy of the studied model and performance comparisons illustrate the outperformance of the proposed hybrid routing algorithm with existing algorithms. The simulation studies illustrate the presented model's superiority considering the network's operational duration, with considerable improvement of 30% dead nodes and 75% alive nodes at the end of the experiment. Furthermore, the proposed model achieves an increase in residual energy of an average of 68%, comparatively superior to the traditional methods. Based on these research findings, it is obvious that NN-Fuzzy EHORM is an advancing clustering method for developing energy-efficient WSNs. Even though NN-Fuzzy EHORM presented an outperformance in the energy depletion process, there is still room for future enhancement. In the future, intelligent learning and computational neural model strategies can be employed to elevate performance to the next level.

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