EE-FNN: An Intelligent Hybrid and Fuzzy Neural Network Framework for Energy-Efficient Cluster Head Selection to Enhance Learning Efficiency in Special Education

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HOW TO CITE:

Sushil Lekhi, Dr. Satvir Singh (2026). EE-FNN: An Intelligent Hybrid and Fuzzy Neural Network Framework for Energy-Efficient Cluster Head Selection to Enhance Learning Efficiency in Special Education. International Journal of Special Education, 41(3s), 803-820.

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ABSTRACT:

Wireless Sensor Networks (WSNs) are essential for many different applications, such as smart cities, healthcare, industrial automation, surveillance for the military, and environmental monitoring. Motivated by microelectronics progress, WSNs use low-power circuits to maximize energy consumption—an important consideration considering the short battery life of sensor nodes. In order to improve energy efficiency in WSNs, this research looks at several optimization techniques. It compares the EE-FNN protocol against OEERP, LEACH, BCDCP, and DRINA. The results show that, with an initial energy consumption of 7.8 J and a maximum energy consumption of 46.8 J, EE-FNN continuously exhibits the lowest energy consumption, demonstrating its better energy management skills. Furthermore, EE-FNN achieves a Packet Delivery Ratio (PDR) of 99.7% to 100% and maintains throughput rates between 77,605 bps and 76,335 bps, demonstrating exceptional data transmission efficiency. On the other hand, protocols such as DRINA and BCDCP show worse data transmission performance and increased energy usage. The research also emphasizes how well EE-FNN can maintain network lifetime, as demonstrated by the fact that it can operate from 11,086 rounds to 1,847 rounds, much surpassing the performance of other protocols. These findings demonstrate how important energy-efficient protocols like EE-FNN are to improving WSN performance, ensuring trustworthy data transfer, and extending the lifespan of networks.

Keywords: Sensor Node, Cluster Head, Packed Delivery Ratio, Fuzzy Logic, Backprpagation

1. Introduction

Wireless Sensor Networks (WSNs) have become indispensable in numerous real-world applications due to their capabilities in data collection, processing, and transmission. This technological evolution is driven by advancements in microelectronics, leading to the development of low-powered electronic circuits that optimize power consumption across a range of hardware configurations [1]. The efficient management of energy within WSNs is paramount as sensor nodes

operate on limited battery capacities for their sensing and transmission tasks within the network. Therefore, maximizing energy efficiency is critical to extending the lifespan and enhancing the overall performance of WSNs [2]. Considering the classification of WSNs, they are broadly categorized into two main types: homogeneous and heterogeneous networks. In homogeneous networks, all nodes share similar characteristics, such as comparable battery capacities and hardware configurations, including memory and radio range capabilities. This uniformity simplifies network management and resource allocation but may limit adaptability to diverse environments or specialized tasks. On the other hand, heterogeneous networks comprise nodes with varying attributes, including different battery capacities, hardware specifications, and functionalities. This diversity allows for greater flexibility in network design and operation, enabling tailored solutions for specific application requirements [3]. The significance of energy conservation in WSNs cannot be overstated, considering the inherent limitations of battery-powered sensor nodes. Efficient energy utilization not only prolongs the network's lifespan but also contributes to improved performance metrics such as data transmission reliability, coverage area, and overall network scalability. Techniques such as energy-efficient routing protocols, adaptive duty cycling, data aggregation strategies, and smart power management algorithms are instrumental in achieving optimal energy utilization within WSNs [4]. The deployment of WSNs in various domains such as environmental monitoring, industrial automation, healthcare systems, smart cities, and military surveillance underscores the critical role of energy efficiency. In environmental monitoring, for instance, WSNs facilitate real-time data collection on temperature, humidity, air quality, and other parameters crucial for environmental assessment and management. Energy-efficient WSNs ensure continuous data gathering without compromising on network reliability or sensor node longevity [5]. Similarly, in healthcare applications, WSNs enable remote patient monitoring, medication adherence tracking, and vital signs monitoring, necessitating reliable and energy-efficient network operations to support continuous healthcare services [6]. In Wireless Sensor Networks (WSNs), the role of a Cluster Head (CH) is crucial for optimizing energy utilization and prolonging the network's lifespan. The CH acts as a coordinator within a cluster of sensor nodes, facilitating data aggregation, processing, and communication with the Base Station (BS) or sink node. Efficient selection of CHs is paramount in achieving optimal energy utilization across the network.

One of the primary objectives of CH selection is to distribute energy-consuming tasks strategically, ensuring that nodes with higher energy reserves or better connectivity assume leadership roles. Several factors influence CH selection algorithms, including node energy levels, distance to the BS, data transmission requirements, and network topology. Energy-aware CH selection algorithms aim to balance energy consumption among nodes, preventing premature battery depletion in critical nodes. Techniques such as probabilistic algorithms, where nodes with higher residual energy probabilities are more likely to become CHs, help in this regard. Additionally, dynamic clustering protocols periodically reassign CH roles to different nodes, preventing energy imbalances and extending network longevity. Figure 1 shows the architecture a Wireless Sensor Network architecture.

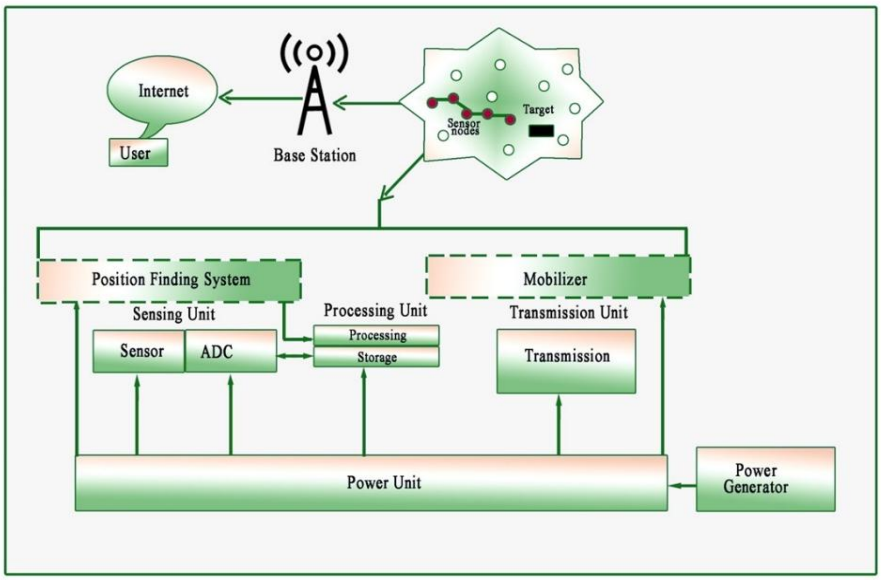


Figure 1: Architecture of WSN

2. Related Work

The ongoing advancements in Wireless Sensor Networks (WSNs) underscore the need for innovative strategies to tackle energy efficiency challenges effectively. Recent research efforts have made significant contributions towards this goal.

Rao et al. (2017) introduced a groundbreaking approach using Particle Swarm Optimization (PSO) for Cluster Head (CH) selection, targeting energy consumption optimization crucial for data aggregation and communication tasks within WSNs[7].

Parwekar (2018) innovatively explored the SGO method, focusing on energy-efficient clustering to streamline energy usage within WSN clusters, thus potentially extending network longevity[8].

In a related vein, Zhao et al. (2018) elevated optimization techniques by enhancing the Genetic Wolf Optimization (GWO) algorithm to minimize energy consumption in routing paths, showing notable improvements in data transmission efficiency[9].

Building upon these concepts, Vijayalakshmi and Anandan (2019) introduced a multi-objective Tabu Search Particle Swarm Optimization (TS-PSO) mechanism for CH selection, aimed at concurrently optimizing multiple network objectives for enhanced overall performance[10].

Additionally, Kousar et al. (2020) ventured into hierarchical clustering using type-2 fuzzy logic, showcasing its ability to boost the effectiveness and efficiency of mobile WSNs[11].

Verma et al. (2019) further expanded these optimization strategies by employing a genetic algorithm-based approach for CH selection in heterogeneous WSNs, highlighting significant enhancements in network performance metrics. Together, these studies provide a robust foundation for addressing energy efficiency challenges in WSNs, paving the way for future innovations and practical implementations in this dynamic field [12].

Rai and Daniel (2023) introduced a novel fuzzy logic approach, termed FEEC, designed to enhance energy efficiency within Wireless Sensor Networks (WSNs). Their study delved into optimizing the cluster formation process to reduce energy consumption effectively. Through a comprehensive evaluation of FEEC's performance, the research provides valuable empirical evidence and insights into its efficacy. This work significantly contributes to the WSN domain by presenting a promising solution for energy efficiency, which holds substantial implications for the design and operational aspects of sensor networks[13].

In a related study, Rai and Daniel (2022) developed an innovative model focusing on intruder detection using WSNs, with a strong emphasis on energy

efficiency as a critical factor. Their efforts aimed to optimize system performance while minimizing power consumption, offering an effective and energy-efficient solution in the realm of intruder detection systems. The insights gleaned from this research are invaluable for researchers and practitioners seeking to bolster security measures within WSN environments[14].

LEACH (Low-Energy Adaptive Clustering Hierarchy)

LEACH is a well-known clustering protocol in WSNs designed to prolong network lifetime and conserve energy. It operates by randomly selecting Cluster Heads (CHs) among sensor nodes based on their energy levels [1]. The CHs then perform data aggregation and compression before transmitting the aggregated data to the Base Station (BS) [2]. LEACH is characterized by its self-organizing capabilities, where CHs are re-elected in each round to distribute energy consumption evenly across nodes [3]. This protocol effectively reduces energy consumption during data transmission and extends the overall network lifetime.

$$T(n) = \begin{cases} p/\{1 - p(rmod(1/p)\} & \text{if } n \in G \\ 0 & \text{else} \end{cases} \quad (1)$$

Where,

n represents the total number of nodes, p indicates the desired percentage of nodes as Cluster Heads (CH), r signifies the previously selected CH in the last 1/p rounds, and G denotes a set of potential CHs [10].

BCDCP (Base-station Controlled Dynamic Clustering Protocol):

BCDCP is a centrally controlled routing protocol aimed at optimizing energy efficiency in WSNs. It divides the network into sub-clusters and employs energy-aware clustering strategies to select Cluster Heads (CHs) based on energy levels [4]. BCDCP utilizes multiple hop data transmission policies and Code Division Multiple Access (CDMA) mechanisms to minimize energy consumption during data forwarding [5]. By dynamically adjusting clustering and routing based on energy availability, BCDCP ensures efficient data transmission and extended network longevity.

DRINA (Data Routing for In-Network Aggregation):

DRINA focuses on constructing efficient routing trees and determining optimal paths for data transmission in WSNs. It introduces distinct roles such as Collaborator nodes, Coordinator nodes, and Relay nodes to facilitate data collection, aggregation, and transmission [6]. Collaborator nodes detect and collect data in response to events, which is then forwarded to the Coordinator node for aggregation and subsequent transmission to the Base Station (BS) [7]. Relay nodes play a crucial role in forwarding data between the Coordinator node and the BS, ensuring reliable and efficient communication across the network [8].

OEERP (Optimized Energy Efficient Routing Protocol):

OEERP is a routing protocol designed to optimize energy consumption in WSNs by dynamically adjusting routing paths based on energy levels and network conditions [9]. It employs intelligent routing algorithms that consider node energy levels, distance to the Base Station (BS), and traffic conditions to route data efficiently [10]. OEERP utilizes techniques such as data aggregation, adaptive routing, and sleep scheduling to minimize energy consumption and prolong network lifetime [11]. This protocol aims to achieve energy efficiency while maintaining reliable and timely data delivery in WSNs.

Table 1: Comparative analysis of different existing protocols

Protocol	Description	Limitations
LEACH (Low-Energy Adaptive	LEACH prolongs network lifetime by randomly selecting Cluster Heads (CHs) based on energy levels and	• Inefficient for large-scale networks due to random CH selection.

Clustering Hierarchy)	distributing energy consumption evenly.	
BCDCP (Base-station Controlled Dynamic Clustering Protocol)	BCDCP optimizes energy efficiency by dividing networks into sub-clusters and employing energy-aware clustering. Utilizes CDMA for data transmission, but requires computational capability at base stations.	• Centralized approach may lead to single point of failure. • Complexity increases with network size.
DRINA (Data Routing for In-Network Aggregation)	DRINA constructs efficient routing trees and roles for data collection and transmission. Relies on distinct node roles, which can add complexity and overhead.	• Potential overhead from role management. • Scalability challenges with large networks.
OEERP (Optimized Energy Efficient Routing Protocol)	OEERP dynamically adjusts routing paths based on energy and traffic conditions. Utilizes adaptive routing and sleep scheduling for efficiency.	• Overhead from dynamic routing adjustments. • Complexity increases with network dynamics. - Limited scalability for highly dynamic networks.

3. Proposed Model

The enhancement of traffic data transmission efficiency from the Cluster Head (CH) to the Base Station (BS), an innovative approach leverages a Fuzzy Technique for route optimization. As the focal point of data aggregation within its cluster, the CH collects traffic data from internal nodes. Utilizing an AI-driven search mechanism, the objective is to determine the most optimal route, ensuring swift and reliable data transfer to the BS for subsequent analysis and processing. This technique uses the intelligence of fuzzy logic enabling the network to adapt dynamically to changing traffic patterns and environmental conditions, thereby enhancing overall performance and resource utilization in Wireless Sensor Networks (WSNs). The EE-FNN approach, which stands for Energy Efficiency using Fuzzy Enabled Neural Network, presents a novel methodology that harnesses the power of fuzzy logic and neural networks to enhance energy efficiency in WSNs. This essay delves into the intricacies of EE-FNN, exploring its components, working principles, applications, benefits, and potential impact on the field of WSNs. EE-FNN integrates two powerful computational paradigms: fuzzy logic and neural networks. Fuzzy logic allows for the representation of imprecise and uncertain information, mimicking human decision-making processes. Neural networks, on the other hand, excel at learning complex patterns and making predictions based on data. By combining these approaches, EE-FNN creates a robust framework for energy optimization in WSNs.

3.1 Components of EE-FNN

1. **Fuzzy Logic Module:** The fuzzy logic module in EE-FNN is responsible for handling imprecise data related to energy consumption, node behavior, and environmental factors. It employs fuzzy sets, membership functions, and fuzzy rules to model the energy optimization problem.

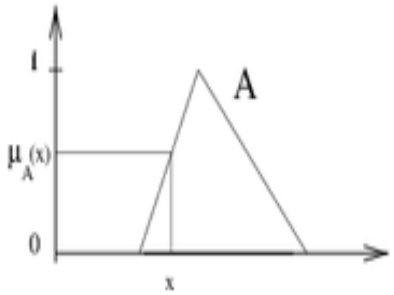


Figure 2. A triangle membership function

2.

$$\mu_x(Input\ Parameter) = \begin{cases} 1 & \text{if Input parameter} \leq \mathrm{TH}_1 \\ \mathrm{TH}_1 - \mathrm{Input} / \mathrm{TH}_1 - \mathrm{TH}_2 & \text{if } \mathrm{TH}_1 < Input\ parameter < \mathrm{TH}_2 \\ 0 & \text{if Input parameter} \geq \mathrm{TH}_2 \end{cases}$$

The fuzzy module of the proposed model is shown in figure 2.

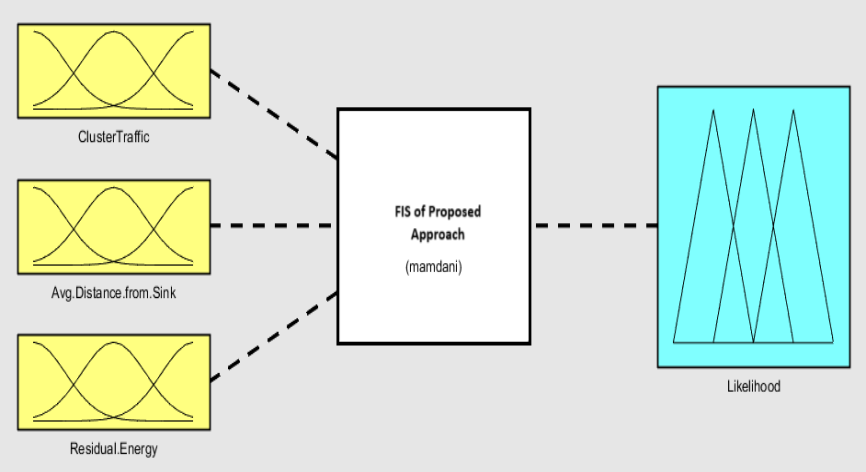


Figure 3: Fuzzy module of the proposed model

3. **Neural Network Module:** TFeedforward neural networks (FNNs) play a crucial role in Wireless Sensor Networks (WSNs) by optimizing energy consumption through adaptive algorithms, processing and analyzing sensor data for anomaly detection and decision-making, detecting and classifying events, contributing to localization and fault diagnosis tasks, optimizing routing paths and communication strategies, supporting adaptive control and security enhancement algorithms, thus making WSNs more energy-efficient, intelligent, and reliable across various applicationsIn the realm of Wireless Sensor Networks (WSNs), optimizing energy consumption is a paramount concern due to the inherent resource constraints of sensor nodes. The neural network module acts as the learning and prediction engine in EE-FNN. It processes input data from the fuzzy logic module, learns energy consumption patterns, and generates optimized control decisions for WSN nodes. Figure 4 shows backpropagation used in the proposed model.

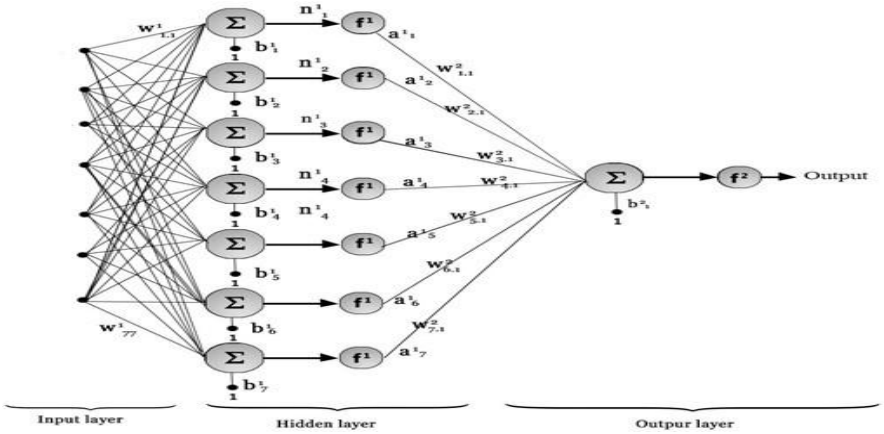


Figure 4: Backpropagation used in the proposed model

4. **Energy Optimization Algorithms:** EE-FNN incorporates advanced energy optimization algorithms within its framework. These algorithms dynamically adjust node parameters such as transmission power, sleep schedules, and data aggregation strategies to minimize energy consumption while maintaining network performance.

3.2 Working Principles of EE-FNN

A feedforward neural network (FNN) represents a fundamental architecture in artificial neural networks (ANNs), characterized by its sequential flow of information from input to output layers without feedback loops. In FNNs, neurons are organized into layers, including input, hidden, and output layers, where each neuron in a layer is connected to every neuron in the subsequent layer. This network structure allows FNNs to process data in a forward direction, transforming input signals through weighted connections and activation functions to produce output predictions. FNNs are widely used in various machine learning tasks, such as classification, regression, and pattern recognition, due to their ability to learn complex nonlinear relationships within data and generalize well to unseen examples when properly trained.

The operation of EE-FNN can be summarized into several key steps:

1. **Data Acquisition:** Sensor nodes collect data related to energy usage, network conditions, and environmental variables.
2. **Fuzzy Logic Processing:** The acquired data is fed into the fuzzy logic module, which processes it using fuzzy inference systems to derive fuzzy control actions.

In our examination of the Fuzzy-based technique, we've pinpointed three critical parameters, each accompanied by its respective Fuzzy membership function, crucial in determining the optimal next hop selection

a) **Cluster Traffic (α1)**: It plays a vital role in energy-efficient communication within Wireless Sensor Networks (WSNs). Efficient traffic data management is crucial for reducing energy usage and ensuring reliable network connectivity. This parameter focuses on monitoring and optimizing traffic conditions, which is essential for conserving energy in WSNs, especially considering the energy-intensive nature of data transmission by sensor nodes. The fuzzy membership for cluster traffic is shown in figure 5.

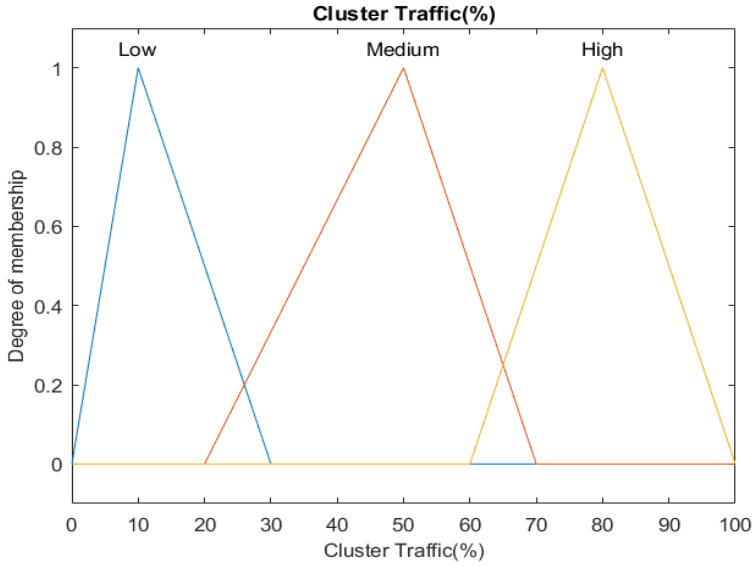


Figure 5: Fuzzy membership used for cluster traffic

b) **Average Distance from the Sink (α2)** : It is a critical factor in ensuring energy efficiency within Wireless Sensor Networks (WSNs). Minimizing the average distance between

Cluster Heads (CH) and the sink is essential for reducing energy consumption during data transmission and improving the network's overall performance. Efficient management of this parameter contributes significantly to optimizing energy usage and enhancing the reliability of data communication in WSNs. The fuzzy membership for average distance is shown in figure 6.

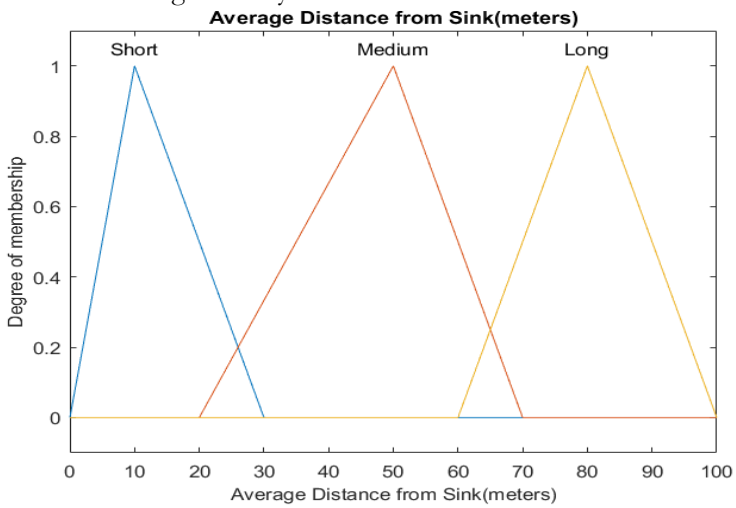


Figure 6: Fuzzy membership used for average distance

a) **Residual Energy of Node (α3)** : It is a vital metric in Wireless Sensor Networks (WSNs) for ensuring energy efficiency. It represents the remaining energy level of each node in the network. By considering the residual energy of nodes when selecting the next hop or routing path, energy consumption can be optimized, leading to improved network performance and prolonged network lifespan. Efficient utilization of node energy plays a key role in maintaining reliable communication and minimizing energy wastage in WSNs. The fuzzy membership for residual energy is shown in figure 7.

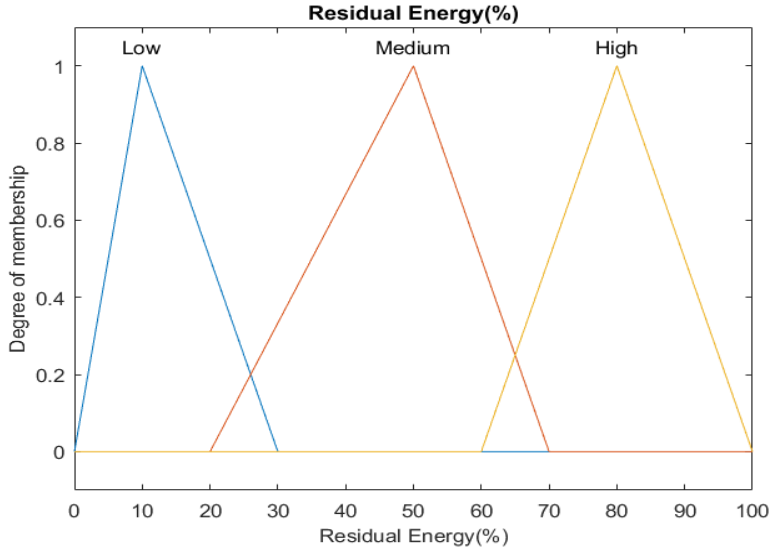


Figure 7: Fuzzy membership used for residual energy

3. **Neural Network Learning:** The fuzzy control actions serve as training data for the neural network module. The neural network learns optimal energy-saving strategies based on historical data and current network states.
4. **Decision Making:** The trained neural network makes real-time decisions regarding energy

optimization for individual sensor nodes. These decisions are implemented to adjust node behavior and energy consumption patterns.

5. **Feedback Loop:** EE-FNN operates in a feedback loop, continuously monitoring network performance and updating its models to adapt to changing conditions and optimize energy efficiency.

The computation steps for the proposed Feed-forward Neural Neywork algorithm are as follows:

$$z_i^1 = f^1\left(U_{i,j}^1 x_j + c_i^1\right) = f^1\left(m_i^1\right) = \log\ \sin\left(U_{i,j}^1 x_j + c_i^1\right)$$

Where,

$$logsin(n) = \frac{1}{1+e^{-n}}\,(\text{sigmoid function}) \quad (1)$$

We opt for the sigmoid function because of its range between 0 and 1, making it well-suited for probabilistic predictions within our model's framework.

- The index ii represents the neuron's sequence number.
- jj signifies the number of inputs (ranging from $p1=1 p1=1$ to 5). The output $aiai$ is then linked to the subsequent layer, referred to as the output layer, which employs a linear function $f2f2$ to advance the data. The equation corresponding to this statement can be articulated as:

$$z^2 = f^2\left(V_{i,1}^2 z_i^1 + d_1^2\right) = f^2(m_1^2) = \text{purelin}\left(V_{i,1}^2 z_i^1 + d_1^2\right) \quad (2)$$

$$z_1^2 = \left(f^2\left(V_{i,1}^2 f^1\left(U_{i,j}^1 x_j + c_i^1\right) + d_1^2\right)\right) = \text{purelin}\left(V_{i,1}^2 \log\ \sin\left(U_{i,j}^1 x_j + c_i^1\right) + d_1^2\right) \quad (3)$$

In the first iteration of the training procedure of the ANN, all the input metric p_i contains the values of C, T,…..are randomly assigned weights for each equation according to the initial conditions of the input parameters, the weight matrix is represented as $W_{i,j}^1, W_{i,1}^2$ by adding the initial values in the associated bias vectors as b_i^1, b_1^2.

Similarly, we can calculate the overall output of the proposed model.

- The total hidden layer output is computed as:

$$x_j^h = f\left(\sum_{i=1}^{n_i}\left(x_i U_{i,j}^h\right) + \left(c_j^h U_{(n_i+1,j)}^h\right)\right) \quad (4)$$

Where p_j^h: output of the hidden layer node j, p_i : ith input, $w_{i,j}^h$: weight of interconnection links from input node i with the hidden node j ,b_j^h: applied bias signal to the hidden node j (b_j^h=1 in ideal case),$w_{n_{i+1,j}}^h$: weight linking the bias b_j^h to the hidden layer node j , n_i : no. of nodes in the input layer.

- The total output of the output layer nodes is computed as:

$$x_k^o = f\left(\sum_{j=1}^{n_k}\left(x_j^h V_{j,k}^o\right) + \left(d_k^o V_{(n_h+1,k)}^o\right)\right) \quad (5)$$

Where p_k^o : output received from the output node k ,$W_{j,k}^o$: weight of interconnection links from the hidden node j to output node k, b_k^o : applied input bias signal to the output node k ($b_k^o = 1$ in ideal case),$W_{h_{i+1,k}}^o$: weight linking the biasb_k^o to output node k ,n_h : no. of nodes in hidden layer.

- Calculate δ_k^o for each output nodes as:

$$\delta_k^o = x_k^o(1 - x_k^o)\left(x_k^T - x_k^o\right) \quad (6)$$

Whereδ_k^o: error at the output end of the neuron (target-output) multiplied with the derivative of $f(x)$, x_k^T is the desired output(target output)of node k.

- Calculate δ_j^h for each of the hidden nodes is computed as:

$$\delta_j^h = x_j^h\left(1 - x_j^h\right)\sum_{k=1}^{n_0}\left(\delta_k^o V_{j,k}^o\right) \quad (7)$$

Where$\delta_j^h$is called the derivative of$f(x)$ which is determined by computing the sum of the weights multiplied with the output (delta).

- The associated weights of the output layer are adapted as:

$$W_{j,k}^{o}(t+1) = W_{j,k}^{o} + (t) + \mu\delta_{k}^{o}p_{j}^{h} + \alpha\Delta W_{j,k}^{o}(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Where the learning constant lies 0<μ<1, and 0 < α < 1 is the applied momentum constant

$$\Delta W_{j,k}^{o}(t) = W_{j,k}^{o}(t) - W_{j,k}^{o}(t-1) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(9)}$$

•The weights associated with the hidden layer are adjusted as:

$$= \Delta W_{i,j}^{h}(t+1) = W_{i,j}^{h}(t) + \mu\delta_{j}^{h}p_{i} + \alpha\Delta W_{i.j}^{h}(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(10)}$$

Where the learning constant lies 0<μ<1, and 0 < α < 1 is the applied momentum constant

$$\Delta W_{i,j}^{h}(t) = W_{i,j}^{h}(t) - \Delta W_{i.j}^{h}(t-1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(11)}$$

• The above steps are continued until the square of error is smaller than a prescribed value (initial), specified as:

$$e = \sum_{k=1}^{n_o}(p_{k}^{T} - p_{k}^{o})^{2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(12)}$$

Input: X[][] = Matrix of Input Layer parameters
Output: O[][] = Predicted Output
Initialization: P[] = Each row of Matrix X[][], S[][] = Sum of each row of Matrix X[][], num_rows = rows of X[][], num_cols = columns of X[][], num_sum_rows = rows of S[][], num_sum_cols = columns of S[][], W[][] = Weight Matrix, Th[][] = Threshold Value, E[][] = Error Matrix

```
for each row i from 1 to num_rows
    sum_val = 0
    for each column j from 1 to num_cols
        P[j] = X[i][j]
        sum_val = sum_val + P[j]
    end for
    S[i][1] = sum_val
end for
for each row k from 1 to num_rows
    do
        NO_CHANGE = 0
        BIAS = 1
        Th[][] = {0}
        Initialize W[][] with random values between -1 and 1
        for each row m from 1 to num_sum_rows do
            for each column n from 1 to num_cols do
                O[m][n] = 0
                for each row y from 1 to num_rows do
                    O[m][n] = O[m][n] + (S[m][y] * W[y][n])   \\ Calculation of Weighted Input
                end for
            end for
        end for
        Perform a forward pass to find the predicted output
        for each row p from 1 to num_sum_rows do
            for each column q from 1 to num_sum_cols do
                E[p][q] = Th[p][q] - O[p][q]    \\ Calculation of Error in the network
                If (E[p][q] > Th[p][q])
                    NO_CHANGE = 1
                    Backpropagation to determine weight change
                    Update weights
                end if
            end for
        end for
    while (NO_CHANGE == 1)
end for
return matrix O[][]
```

4. Simulation and Result Analysis

The EE-FNN protocol, incorporating Neural Network with Fuzzy logic, is implemented and simulated using the MATLAB simulator. MATLAB proves to be an ideal software choice for analyzing and assessing the results derived from work conducted on Wireless Sensor Networks (WSNs). Its capabilities allow for comprehensive evaluation of the EE-FNN protocol's performance, including aspects like energy efficiency, data reliability, and network scalability.

4.1 Network Deployment

The comparison between the proposed EE-FNN technique and existing methods involves estimating the number of RE (Reliable Energy) nodes at each step of cluster formation. EE-FNN introduces a groundbreaking approach to cluster formation known as Fuzzy-Neural Net, where clusters are formed based on the likelihood values of the nodes. Table 2 outlines the fundamental parameters considered during network configuration, providing insights into the factors influencing cluster formation and network performance.

Table 2. Initial Network Parameters

Criteria	Values
No of Nodes	150
Sensing Region	200*200m
Radius of cluster (r)	25m
Initial Energy of node	200J
Transmission Rate	400Kbps
Transmission Power	0.02Watts
Packet size	512 bytes
Packet Generation Interval	0.1 sec

The efficiency of EE-FNN is compared to the existing approaches through simulations based on several performance parameters such as load balancing ratio, number of residual nodes, packet delivery ratio ,network lifetime , residual energy, throughput, and energy consumption.

The efficiency of the EE-FNN protocol is evaluated against existing approaches through extensive simulations, focusing on various performance metrics. These metrics include the number of residual nodes, load balancing ratio, network lifetime, packet delivery ratio, throughput, residual energy, and energy consumption. By comparing these parameters across different scenarios and under varying network conditions, researchers can assess the effectiveness and superiority of EE-FNN in terms of load balancing ratio, number of residual nodes, packet delivery ratio ,network lifetime , residual energy, throughput, and energy consumption.

During the deployment phase of the proposed protocol, a total of 150 nodes are strategically placed within a region measuring 200 x 200 square meters, as illustrated in Figure 8. This deployment setup forms the basis for conducting simulations and evaluating the performance of the protocol under realistic network conditions, taking into account factors such as node density, coverage area, and communication range.

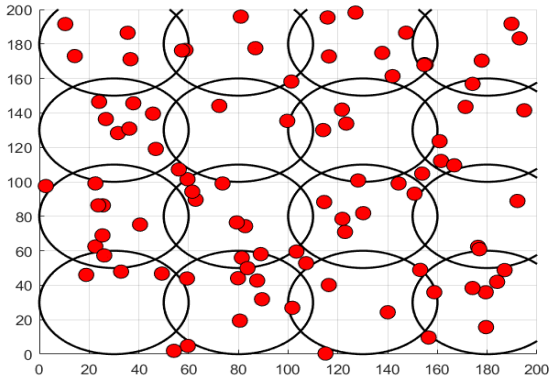


Figure.8. Node deployment phase

In the cluster formation phase of the proposed protocol, clusters are formed using the PSO technique and the proposed E-FEERP is used to send the data from CH to BS as shown in Figure 9.

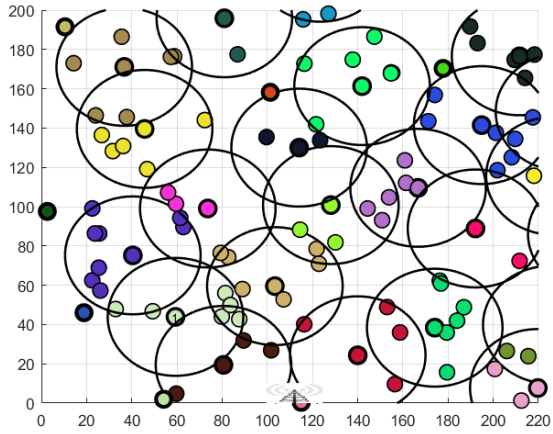


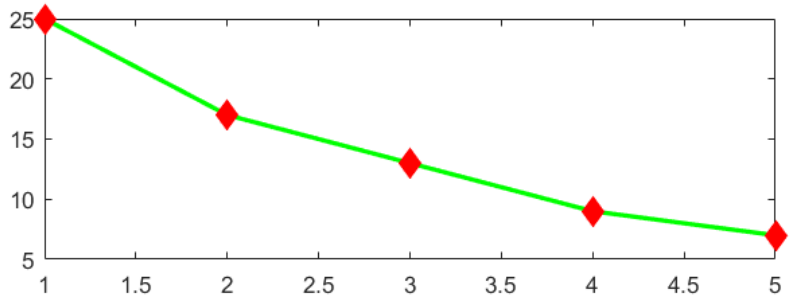
Figure.9. Cluster formation and data transmission phase

4.2. Performance Comparison

The efficiency comparison between EE-FNN and existing approaches is conducted across several key performance parameters:

a. Number of Residual Nodes

In the proposed methodology, clusters are organized based on their Fuzzy Value (FV). During each iteration, a priority index is assigned to every node, designating each node as a potential Cluster Head (CH). This iterative process continues until either there are zero or very few residual nodes left in the Wireless Sensor Network (WSN), known as a global_iteration, prompting the cluster formation process to halt. Figure 10 illustrates the residual nodes remaining at the end of this iteration. Utilizing the proposed EE-FNN(Energy Efficient-Fuzzy Neural Network) based protocol results in a significantly lower number of residual nodes compared to existing protocols. Specifically, E-FEERP yields only 6 residual nodes, while OEERP, LEACH, BCDCP, and DRINA produce 35, 42, 17, and 19 residual nodes, respectively. This reduction in residual nodes not only showcases the efficiency of EE-FNN but also leads to an improved average network lifetime, demonstrating the protocol's effectiveness in optimizing energy utilization and network longevity.



	EE-FNN	OEERP	LEACH	BCDCP	DRINA
Series1	25	17	13	9	7

Figure. 10. Residual energy of the protocol

b. Energy Consumption

The energy consumption of an individual node in a Wireless Sensor Network (WSN) primarily comprises three main components: sensing, computation, and communication. Sensing involves the node's ability to gather data from its surroundings, computation refers to the processing and analysis of collected data, and communication involves transmitting data to other nodes or base stations. Each of these activities consumes energy, and it is feasible to calculate the overall energy consumption of a node by considering the energy expended in each of these components. This calculation can be crucial in assessing the overall energy efficiency of a node and optimizing its performance within the network.

$$E_c = E_i - E_r \quad \text{.....(17)}$$

The total energy dissipation of nodes across different time slots is computed and compared between the existing approach and the proposed EE-FNN method, as illustrated in Figure 17. The findings indicate that EE-FNN exhibits the lowest energy consumption among the compared approaches, with energy usage increasing gradually as simulation time progresses. This observation highlights the energy efficiency of EE-FNN, highlighting its potential to minimize energy dissipation and prolong the operational lifespan of nodes within the Wireless Sensor Network (WSN) environment.

Table 3: Energy consumption statistics of proposed and existing protocols

EE-FNN	OEERP	LEACH	BCDCP	DRINA
7.8	5	10	12	20
15.6	10	17	19	25
23.	27	28	30	37
31.2	30	37	47	52
39	45	60	75	90
46.8	70	88	10	124

The total energy consumption in the network (measured in joules, J) across five different protocols (EE-FNN, OEERP, LEACH, BCDCP, and DRINA) at varying intervals, it is evident that EE-FNN consistently exhibits the lowest energy consumption, highlighting its efficiency in managing energy within the network. Starting at 7.8 J, EE-FNN shows a gradual increase to 46.8 J at the highest interval, maintaining a significantly lower consumption compared to the other protocols. OEERP follows, with initial consumption at 5 J but increases to 70 J, indicating higher energy usage as the network operates longer. LEACH and BCDCP show similar initial trends but diverge significantly, with LEACH reaching up to 88 J, while BCDCP spikes dramatically to 124 J. DRINA, however, starts at a high initial consumption of 20 J and continues to escalate, peaking at 124 J, indicating the least energy efficiency. This analysis underscores EE-FNN's superior performance in energy conservation, making it a more suitable option for energy-efficient network management compared to the other protocols shown in figure 11.

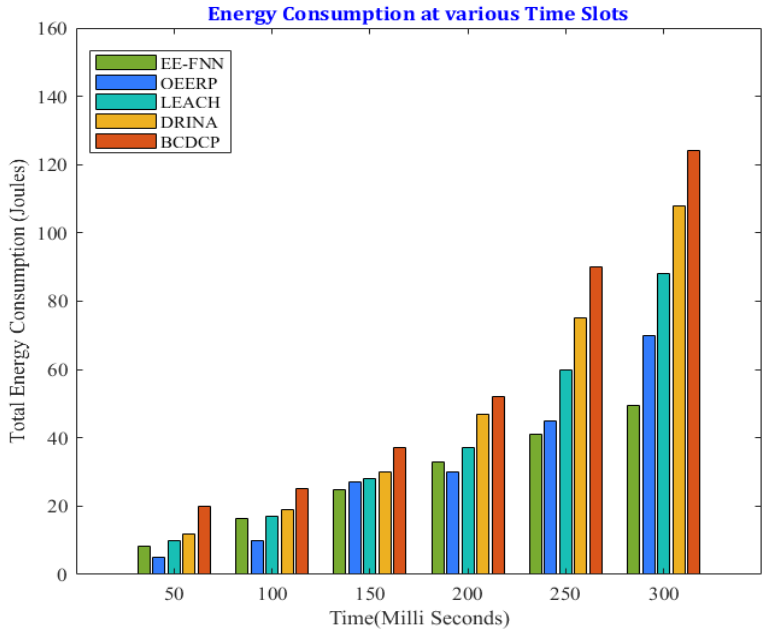


Figure. 11. Overall energy consumption during various time periods.

There is a direct correlation between the total number of Sensor Nodes (SN) in a Wireless Sensor Network (WSN) and their energy usage. The total energy usage rises with the number of SN. Though at varying rates, all protocols show a gradual rise in energy usage over time. The suggested EE-FNN protocol uses less energy than other current protocols, as seen in Figure 17. Because it conserves energy resources and maximizes network efficiency, this decrease in energy consumption results in a longer network lifespan.

c. Throughput

The proposed EE-FNN protocol's throughput is contrasted with that of existing techniques in Figure 18. The effectiveness of data transmission to the intended recipient or Base Station (BS) is indicated by throughput, which is expressed in bits per second (bps). An efficient system is indicated

by a greater throughput value. The bar graph makes it very evident that the suggested EE-FNN technique outperforms current methods in terms of throughput. This suggests that EE-FNN performs better overall performance and increases the dependability of data delivery by more effectively transporting data throughout the network.

Table 4: Throughput statistics of proposed and existing protocols

EE-FNN	OEERP	LEACH	BCDCP	DRINA
77605	75000	57000	47000	42000
77605	74500	50000	48000	37000
77177	76000	53000	52000	32000
77092	70000	48000	40000	28000
76670	62000	45000	40000	25000
76335	55000	42000	37000	20000

The throughput (measured in bits per second) across five different protocols (EE-FNN, OEERP, LEACH, BCDCP, and DRINA) at varying intervals, it is clear that EE-FNN consistently achieves the highest throughput, indicating its superior performance in data transmission efficiency. EE-FNN maintains throughput values around 77,605 bps initially, showing minimal decline to 76,335 bps at the last interval. OEERP also demonstrates strong performance, starting at 75,000 bps but gradually. The throughput (measured in bits per second) across five different protocols (EE-FNN, OEERP, LEACH, BCDCP, and DRINA) at varying intervals, it is clear that EE-FNN consistently achieves the highest throughput, indicating its superior performance in data transmission efficiency. EE-FNN maintains throughput values around 77,605 bps initially, showing minimal decline to 76,335 bps at the last interval. OEERP also demonstrates strong performance, starting at 75,000 bps but gradually declining to 55,000 bps. LEACH shows a significant drop from 57,000 bps to 42,000 bps over time, reflecting moderate performance. BCDCP and DRINA, however, start at much lower initial throughput values of 47,000 bps and 42,000 bps respectively, with BCDCP declining to 37,000 bps and DRINA to 20,000 bps, indicating the lowest performance among the protocols. This analysis highlights EE-FNN's ability to maintain high throughput consistently, making it the most effective protocol for ensuring efficient data transmission in the network compared to the other protocols is shown in figure 12.

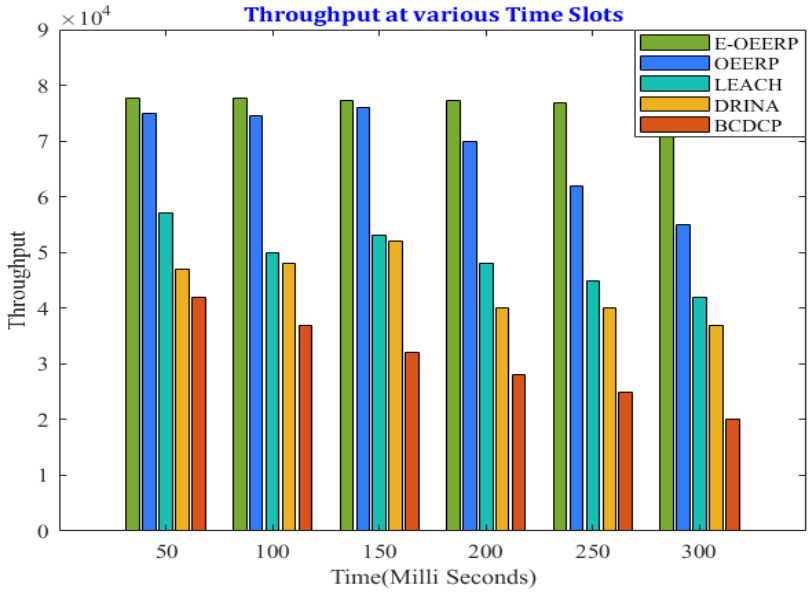


Figure. 12. Throughput at different time slots.

d. Packet Delivery Ratio

The Packet Delivery Ratio (PDR) is a crucial metric in Wireless Sensor Networks (WSNs) that measures

the ratio of successfully delivered packets to the total packets sent within the network. A higher PDR indicates a more reliable and efficient data transmission system, showcasing the network's ability to deliver data accurately and consistently. PDR is influenced by various factors such as network topology, routing protocols, node density, and communication range. Evaluating PDR provides insights into the network's performance, reliability, and overall data delivery capabilities, making it a key metric in assessing the effectiveness of WSN protocols and optimizations. The enhancement in Packet Delivery Ratio (PDR) reflects the efficacy of the EE-FNN protocol when contrasted with various existing routing protocols, as depicted in Figure 13.

Table 5: PDR statistics of proposed and existing protocols

EE-FNN	OEERP	LEACH	BCDCP	DRINA
100	94	90	75	70
100	97	85	78	74
99.8	95	87	78	76
99.8	94	89	82	78
99.8	95	90	84	80
99.7	96	90	86	82

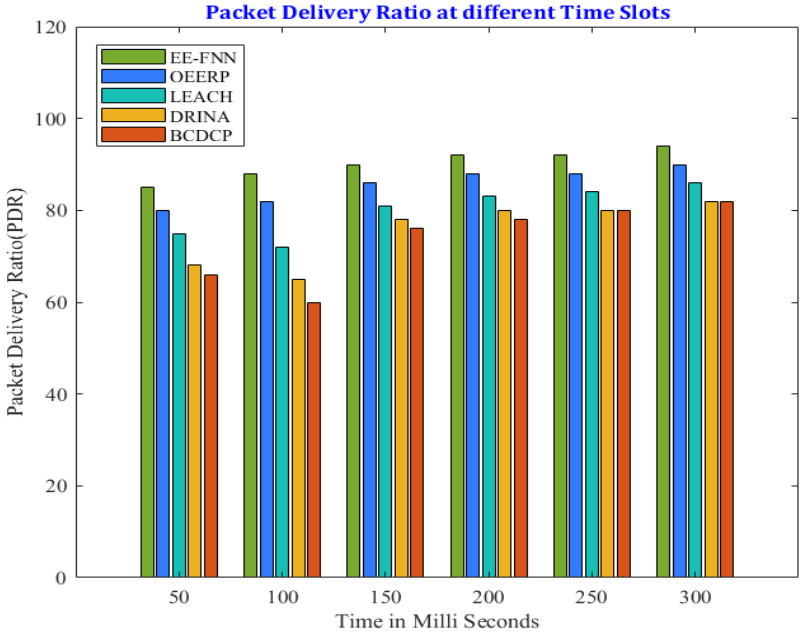


Figure.13. Packet Delivery ratio at multiple time slots

In terms of Performance Delivery Ratio (PDR), EE-FNN consistently achieved high values, ranging from 99.7% to 100%, indicating robust data delivery capabilities. OEERP also demonstrated stable performance with PDR values ranging from 94% to 97%, showcasing reliable data transmission. LEACH, although slightly lower in PDR compared to EE-FNN and OEERP, maintained a steady range between 87% and 90%, suggesting effective energy utilization for data transfer. BCDCP exhibited moderate PDR values ranging from 75% to 86%, highlighting its suitability for balancing energy efficiency and data delivery. DRINA showed the lowest PDR among the protocols, ranging from 70% to 82%, indicating potential improvements in data transmission reliability. Overall, the comparative analysis provides insights into the strengths and weaknesses of each protocol, aiding in informed decision-making for WSN deployment based on specific performance requirements.

e. Network Lifetime

In Wireless Sensor Networks (WSNs), designing routing protocols that are energy-efficient is essential to increasing the network's lifetime. This lifetime is largely dependent on how well the network's sensor nodes perform. The sensing, calculation, and transmission functions that sensor nodes carry out on their sensing areas have an immediate effect on the network's endurance. Enhancing the network lifespan can be achieved in part by preventing the transmission of duplicate

data. This can be accomplished by limiting the usage of long-distance communication, eliminating control overhead messages from the network, and consolidating sensed data to prevent duplication. By minimizing energy usage and decreasing network congestion, these solutions help WSNs operate for longer periods of time.

Table 3: Network lifetime statistics of proposed and existing protocols

EE-FNN	OEERP	LEACH	BCDCP	DRINA
11086	9000	6000	4200	3200
5543	4800	3700	3200	2400
3695	3400	3000	2400	2000
2771	2700	2400	2100	1800
2217	2100	1900	1700	1600
1847	2000	1800	1600	1400

The number of rounds or cycles until the first node failure was used to estimate the network lifespan, which indicated the durability and sustainability of the system. The network lifespan of EE-FNN was the longest, varying from 11086 rounds at the beginning to 1847 rounds throughout the course of following iterations. This demonstrates that EE-FNN can efficiently manage energy resources, extending the network's usable life is shown in figure 14. In addition, OEERP demonstrated a significant network lifespan, beginning at 9000 rounds and progressively dropping to 2000 rounds, demonstrating its effectiveness in maintaining network operation. In contrast to EE-FNN and OEERP, LEACH demonstrated a shorter operational lifespan while maintaining a balanced energy consumption, with a network lifetime that ranged from 6000 cycles at launch to 1800 rounds. Despite having shorter starting network lifetimes—4200 and 3200 rounds, respectively—BCDCP and DRINA showed steady declines across iterations, suggesting difficulties with energy optimization and network durability. Overall, the work highlights how important it is to select the right protocol to optimize the lifespan of WSNs, with EE-FNN and OEERP showing promise for extended network operational lives.

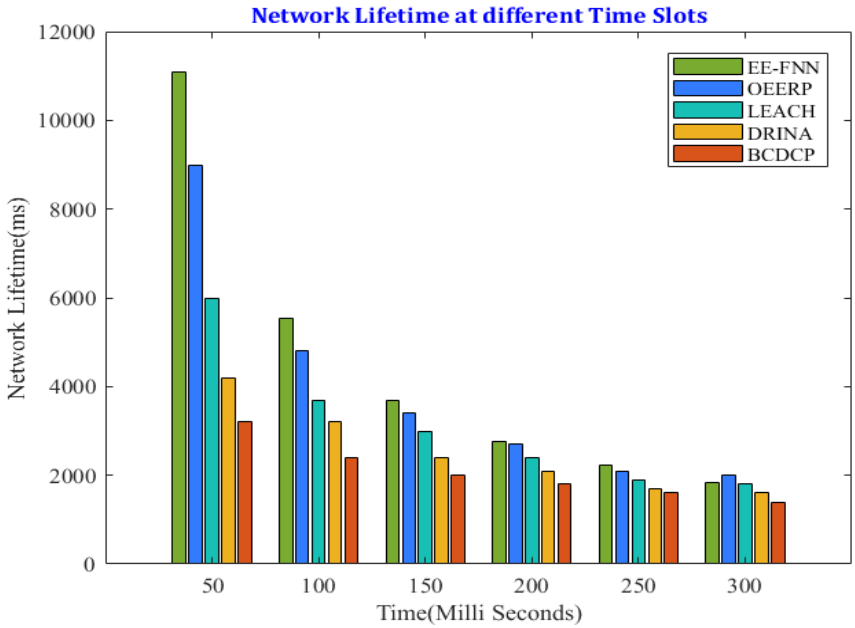


Figure. 14. Network lifetime comparison

When designing a network, keeping the aforementioned factors in mind can greatly extend the network's lifespan. The proposed strategy incorporates these factors, which substantially extend the network's lifespan. As seen in Figure 20, the EE-FNN protocol achieves a total lifespan that is greater than that of other protocols. This result highlights how well energy-efficient routing techniques and data transmission mechanism optimization may prolong the operating lifetime of Wireless Sensor Networks (WSNs). The proposed EE-FNN protocol optimally utilize energy

consumption inside the network and significantly extend the lifetime of WSN when compared to previous protocols, the proposed work has a longer lifetime.

5. Conclusion

In order to improve Wireless Sensor Networks' (WSNs') energy efficiency, a number of optimization strategies have been thoroughly examined in this research. The research highlights the improved performance of the EE-FNN protocol in numerous measures through an examination of protocols including OEERP, LEACH, BCDCP, and DRINA. With an energy consumption that is consistently lower than the other protocols—starting at 7.8 J and increasing to 46.8 J. EE-FNN consistently shows the lowest energy usage. This effectiveness demonstrates EE-FNN's capacity to regulate energy in the network, increasing its longevity. The improved data transmission efficiency of EE-FNN is further demonstrated by throughput analysis, which shows that it can sustain throughput values much higher than the other protocols, ranging from 77,605 bps to 76,335 bps. EE-FNN has strong data delivery capabilities with a Packet Delivery Ratio (PDR) ranging from 99.7% to 100%. Conversely, BCDCP and DRINA perform the worst in terms of energy consumption and data transmission efficiency, while other protocols, such as OEERP and LEACH, perform in a reasonable manner. The network lifespan study confirms the efficacy of EE-FNN even more, as the protocol maintains the longest operating period of time, going from 11,086 rounds in the beginning to 1,847 rounds in the end. This indicates that EE-FNN can effectively manage energy resources, which allows it to survive longer than existing approaches by a substantial value.

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