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EFFICIENT AND OPTIMIZED DATA ROUTING IN WIRELESS SENSOR NETWORK USING NEURAL NETWORK

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Abstract: Wireless Sensor Networks (WSNs) are crucial in applications such as environmental monitoring and military surveillance, where energy efficiency is key. This study focuses on optimizing cluster head selection to enhance energy efficiency in WSNs using Backpropagation Feed-forward Neural Networks (BP-FNN) and artificial intelligence. Key parameters include node proximity, residual energy levels, and network topology. Dynamic adaptation based on transmitted sensor data ensures efficient resource utilization. Random weights and biases fine-tune the selection process, balancing energy consumption across the network. The BP-FNN model uses random weights and biases for activation, transferring the weighted sum to the hidden layer. The sigmoid activation function predicts cluster head selection probabilities, with a linear function processing the output. A Backpropagation-based training algorithm refines the model by propagating errors backward through the layers. Performance analysis considers packets sent to the cluster head, alive nodes, dead nodes, and total energy consumption. MATLAB simulations demonstrate the proposed protocol's superiority over LEACH, E-MODLEACH, and DEEC protocols in cluster head formation and energy efficiency, highlighting its potential for sustainable WSNs.

Keywords: Wireless Sensor Network, Cluster Head, Neural Network, LEACH, Routing

1. INTRODUCTION

A sensor network consists of multiple nodes designed to sense various environmental phenomena such as temperature, pressure, light, gas, and many more in a targeted region. These physical sources represent the real-world environment, and the sensor network facilitates the deployment and monitoring of these nodes in the environment. Essentially, sensors create a bridge between the physical world and the virtual world. There are numerous applications where sensor networks are extensively used,

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including military surveillance, environmental monitoring, industrial process monitoring, hazardous gas detection, and consumer applications. The Wireless Sensor Network (WSN) plays a crucial role in numerous real-life scenarios [1]. It is an emerging technology with capabilities for data collection, processing, and transmission. The advancement in microelectronics technology has led to the development of low-powered electronic circuits that consume minimal power for different hardware configurations. This advancement is pivotal because the conservation of energy in WSNs is essential for network durability. Sensor nodes are powered by batteries that have limited sensing and transmission ranges. Therefore, optimizing energy utilization in the network is critical to enhance the network's lifetime and performance. WSNs can be broadly classified into two major categories: homogeneous and heterogeneous networks. In a homogeneous network system, all nodes are similar, possessing equal battery capacity and similar hardware configurations such as memory and radio range. Conversely, in a heterogeneous network system, the nodes can vary in these aspects. Homogeneous WSNs typically have nodes with uniform capabilities, which simplifies network management and protocol design. However, this uniformity can also be a limitation, as all nodes deplete their energy reserves at similar rates, potentially leading to a rapid network collapse once a critical number of nodes run out of power[2][3].

In contrast, heterogeneous WSNs have nodes with diverse capabilities and energy reserves. This diversity can enhance the network's robustness and efficiency. For instance, nodes with higher energy reserves can take on more demanding tasks such as data aggregation or acting as cluster heads, thus distributing the energy consumption more evenly across the network. This approach can significantly extend the network's operational lifetime and improve its performance under varying conditions. WSNs are indispensable in applications that require continuous and reliable monitoring. In military surveillance, WSNs can be deployed to monitor borders or sensitive areas, providing real-time data on potential threats. Environmental monitoring applications use WSNs to track changes in weather patterns, pollution levels, or wildlife movements, offering valuable data for research and conservation efforts. In industrial settings, WSNs monitor processes to ensure they run smoothly and safely, detecting any anomalies that might indicate equipment failure or hazardous conditions [4].

Furthermore, WSNs are crucial in hazardous gas detection, where they can provide early warnings of leaks or dangerous concentrations of gases, thereby preventing accidents and ensuring safety. Consumer applications of WSNs include smart homes, where sensors monitor various parameters to enhance comfort, security, and energy efficiency. The architecture of a WSN typically includes sensor nodes, sink nodes, and a communication network. Sensor nodes collect data from their environment and transmit it to sink nodes, which aggregate and forward the data to a central system for processing and analysis. The communication network, which can be based on various wireless technologies, facilitates the data exchange between nodes and the central system [5].

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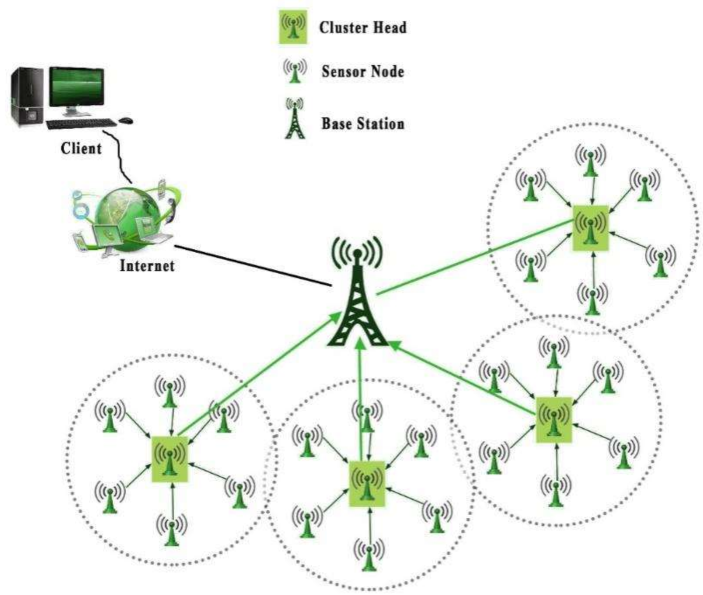

Figure 1: Architecture of Wireless sensor network

1.1. Major areas where WSN is widely used

The different areas are as follows:

(i) Forest Fire Detection

In order to monitor forest fire detection, a number of sensors are placed at different places and positions in the forest. In the case of fire detection, the sensor node generates an alert signal to the respective base station. The information for fire detection is stored in the Cloud for processing to predict any fire-catching activity that may occur similar to past scenarios [4]. The respective persons may also get the alert message to take preventive actions immediately.

(ii) Traffic Monitoring and Control

It is very important to control the traffic of the city for a smooth ride experience for the users/drivers. The Cloud-enabled sensors assist in the management of traffic control in various ways such as real-time traffic information to vehicle drivers, remote traffic control, information for nearest parking for vehicles, detection of various safety guidelines such as whether the seat belt is followed by the driver or not [5]. It results in a reduction in fuel cost and travel time that will improve productivity per man-hour.

(iii)Healthcare Monitoring

In healthcare monitoring, sensors are mounted on the body of the patients. The body-mounted sensors are used to monitor different activities of the body such as temperature, heartbeat, pulse rate, blood oxygen level, etc. The doctors, nurses, and medical researchers can easily and quickly get these collected data from any hospital stored in a sensor-based Cloud [6].

The rest of the paper is divided into following sections: section-2 contains literature review, section-3 contains proposed methodology, section-4 contains results and discussion, and finally section 5 contains

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conclusion and future work.

2. LITERATURE REVIEW

The Low Energy Adaptive Clustering Hierarchy (LEACH) protocol stands as the standard in Wireless Sensor Networks (WSN), relying on hierarchical routing [7]. This protocol operates through two distinct phases: the setup phase and the steady-state phase. Employing a multi-hop transmission approach for data exchange, LEACH organizes sensor nodes into clusters, determining the sensor network's lifetime in terms of transmission rounds. However, as the distance from Cluster Heads (CH) to Base Stations (BS) increases due to network expansion, more energy is consumed for data transmission, leading to suboptimal performance, particularly in larger networks.

In [8], researchers proposed the MOD-LEACH protocol, leveraging historical data to balance energy consumption across the network and prolong its lifespan. By dynamically adjusting the number of cluster heads based on previous rounds' cluster head states, remaining energy, and the number of neighboring nodes, MOD-LEACH aims to optimize cluster size for improved energy efficiency.

The TEEN protocol, introduced in [9], offers a reactive solution tailored for time-centric applications within homogeneous WSN environments. Similar to LEACH, TEEN employs specific criteria for selecting Cluster Heads. However, TEEN introduces soft and hard thresholds to minimize transmissions, thereby conserving node energy. This approach enhances both network lifespan and stability period.

In [10], the Stable Election Protocol (SEP) was proposed, featuring a two-level heterogeneous routing structure comprising normal nodes (NN) and advanced nodes (AN). ANs possess higher energy reserves compared to NNs. SEP employs weighted probability to elect CHs, favoring ANs over NNs. However, SEP's efficiency in node deployment is not guaranteed.

In [11], authors present the Distributed Energy-Efficient Clustering Protocol (DEEC), an improved variant of SEP that enhances heterogeneity to multiple levels. DEEC's CH selection process relies on dynamic probability, favoring nodes with higher remaining energy to become CHs. By considering both node energy reserves and the average energy level of the network, DEEC optimizes CH formation, thus improving overall network efficiency.
Network scalability is a significant issue in Wireless Sensor Networks (WSNs). A network that functions well with low-dimensional data should also perform effectively with high-dimensional data. Additionally, if the system can manage a small number of nodes, it must also scale efficiently to accommodate a larger network. While various existing schemes offer valuable features, they often fall short in terms of scalability. Therefore, the system should be designed to handle scalability along with other critical aspects such as low energy consumption. Sensor-collected data is essential for various forecasting tasks, making energy-efficient deployment crucial, especially in remote monitoring areas where battery replacement is not feasible.

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The problem statement focuses on integrating Wireless Sensor Networks (WSNs) into data analysis systems while prioritizing energy efficiency and durability. The objective is to develop energy-efficient protocols for data analysis within WSNs. This involves addressing challenges related to energy consumption management, data integrity, and real-time processing.

3. METHODOLOGY OF PROPOSED APPROACH

In the proposed work, Wireless Sensor Networks (WSNs), optimizing cluster head selection for energy efficiency is paramount. Leveraging Backpropagation Feed-forward Neural Networks (BP-FNN) and artificial intelligence, WSNs learn from past data to select cluster heads strategically. Parameters such as node proximity, residual energy levels, and network topology influence cluster head selection. The transmitted sensor data informs dynamic adaptation, ensuring efficient resource utilization [12]. Random weights and biases fine-tune the selection process, balancing energy consumption across the network. Mathematical models guide algorithms tailored for energy-efficient cluster head selection. WSNs strive to maximize energy efficiency while maintaining network performance. Through sophisticated modeling and optimization, WSNs pave the way for sustainable wireless sensor networks [13] [14] [15]. Random weights are applied to the inputs ($p_i * W_{i,j}^{h}$) and bias (b_1, b_2…b_n=1) is applied for the activation of the model, and this weighted input sum is transferred to the hidden layer.

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

$$a_i^1 = f^1(W_{i,j}^1 p_j + b_i^1) = f^1(n_i^1)$$

$$= logsin\left(W_{i,j}^1 p_j + b_i^1\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Where,

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

The sigmoid function is used here because it exists between 0 to 1, and hence it is suitable for predicting the value based on probability in our model.

The outcome of a_i is connected to the next layer called the output layer, which contains a linear function f^2 to transfer the data further. The equation of the statement can be expressed as:

$$a^2 = f^2\left(W_{i,1}^2 a_i^1 + b_1^2\right) = f^2(n_1^2)$$
$$= purelin(W_{i,1}^2 a_i^1 + b_1^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

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In the represented BP-ANN model, the expression of the output layer having only a single hidden layer is represented as:

$$a_1^2 = (f^2\left(W_{i,1}^2 f^1\left(W_{i,j}^1 p_j + b_i^1\right)\right) + b_1^2\ )$$
$$= purelin(W_{i,1}^2 logsin\left(W_{i,j}^1 p_j + b_i^1\right) + b_1^2) * (i = 1\ to\ 6, j = 1\ to\ 6) \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In ANN, a Backpropagation-based training algorithm is used in a feed-forward approach that is interlinked by multiple layers[16][17]. Suppose a set of input is delivered through the input nodes (input layer). The given input set is propagated through all of the hidden layers and into the output layer until the output is received at the output end of the ANN. The actual output is compared to the predicted output, and an error signal is calculated for each output node. The error signals are then transmitted from the output layer back to the hidden layers. The process continued until the error signal reached the predicted requirement for link weight modification [18].

The different layers of ANN are explained as follows:

Input Layer: This layer is responsible for taking the input from the users.
Hidden Layer: The hidden layer resides between input and output layers and performs all the computation work that needs to get the hidden features and patterns used to predict the outcome.
Output Layer: The various inputs that pass through a series of transformations with the assistance of the hidden layer, which further results in determining the output is conveyed with the help of this layer.

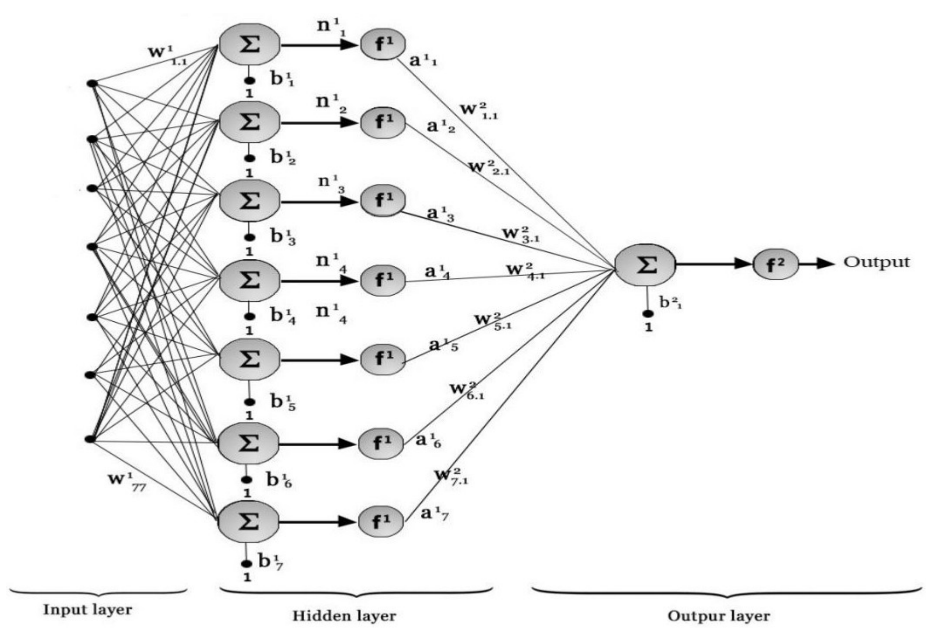

Figure 2 : Architecture of Neural Network

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The backpropagation will be used to get the optimal Cluster Head prediction in the network for data transmission to Base Station (BS) operation.
Performance analysis will be conducted using parameters such as packets sent to cluster head, alive nodes, dead nodes, Total Energy consumption in the network.

4. RESULTS AND ANALYSIS

The simulation tests for the proposed method are conducted using MATLAB, a versatile environment ideal for numerical computation and programming. MATLAB excels in data analysis, method development, and model building. It offers a wide array of well-designed toolboxes tailored to various fields, including control systems, robotics, deep learning, artificial intelligence, wireless communications, and computational finance. One of MATLAB's key strengths is its Live Editor, which enables the creation of executable notebooks. These notebooks seamlessly combine code, output, and structured text, thereby enhancing the clarity and reproducibility of simulation results. Additionally, MATLAB includes prebuilt applications that support interactive and iterative task execution, making the simulation processes more streamlined and efficient.
The Parameters used are node proximity, residual energy levels, and network topology used for cluster head selection using the proposed backpropagation based approach. The proposed protocol in the model uses different parameters to determine energy efficiency, including the number of packets transmitted to the Base Station, the number of dead nodes in the network, and the number of alive nodes in the network. The different parameters used in the simulation is shown in Table 1.

Table 1: Parameters for sensor nodes deployment

Parameter	Value
Number of Sensor Nodes (SN)	100
Network Area	(100, 100) m^2
Free Space Model (Efs)	10 pJ/bit/m^2
Multi-path Model (Eamp)	0.0013 pJ/bit/m^4
Initial Battery Energy (E0)	0.5 J
Electronic Circuitry (ERX)	50 nJ/bit
Data Aggregation (EDA)	10 nJ/bit

The random deployment of the homogeneous sensor nodes is shown in Figure 3.

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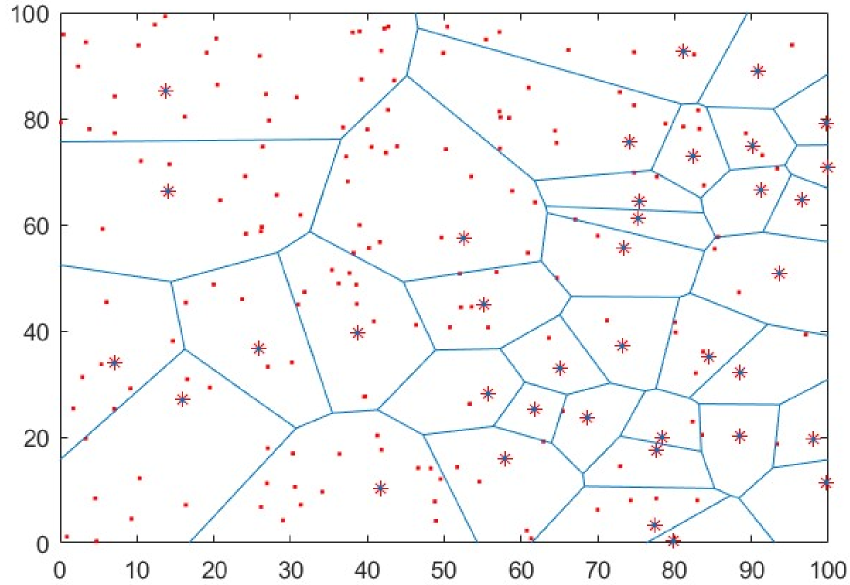

Figure 3: Sensor network deployment

The backpropagation based neural network uses the selected parameters to train the cluster head selection process. The neural network architecture is shown in Figure 4.

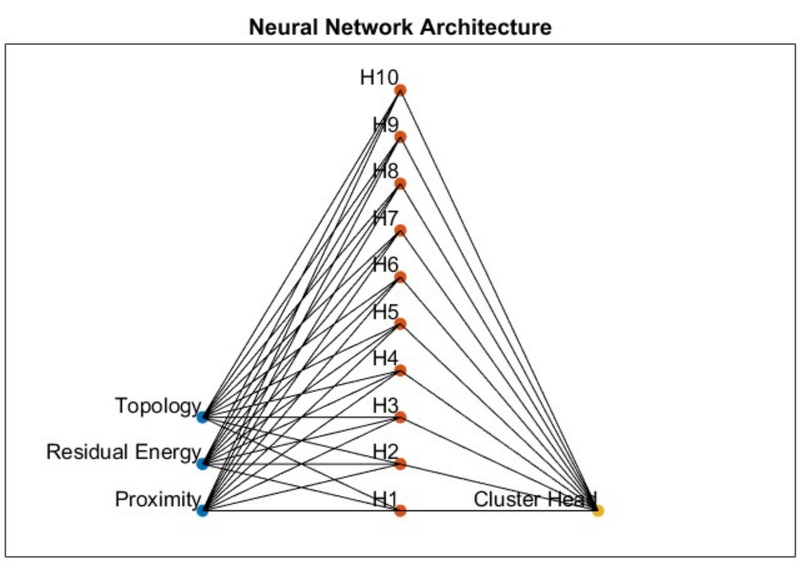

Figure 4: Selected parameters for neural network training

The proposed protocol transmitted 121818 packets to the BS, while the LEACH protocol transmitted 40887 packets; similarly, the E-MODLEACH protocol only 35789 packets to BS, and the DEEC protocol transmitted 33688 packets to the BS, shown in Figure 5

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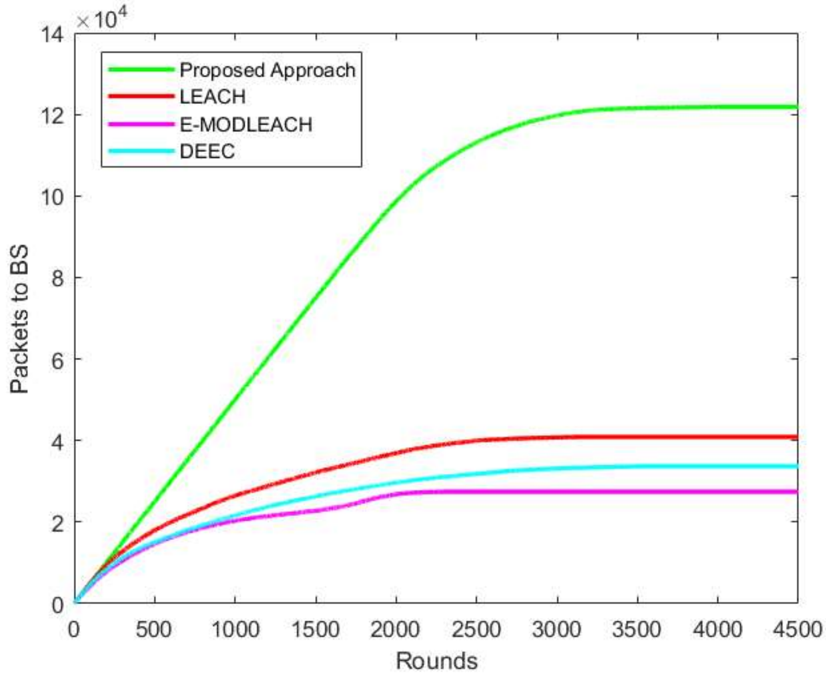

Figure 5: Packets transmitted to Base station

In the simulation, the number of rounds for exhausting the energy of all the nodes in the network is 3692, while in the LEACH protocol, it is 3120; in E-MODLEACH, it is 3506, and in DEEC, it is 3502 shown in Figure 6.

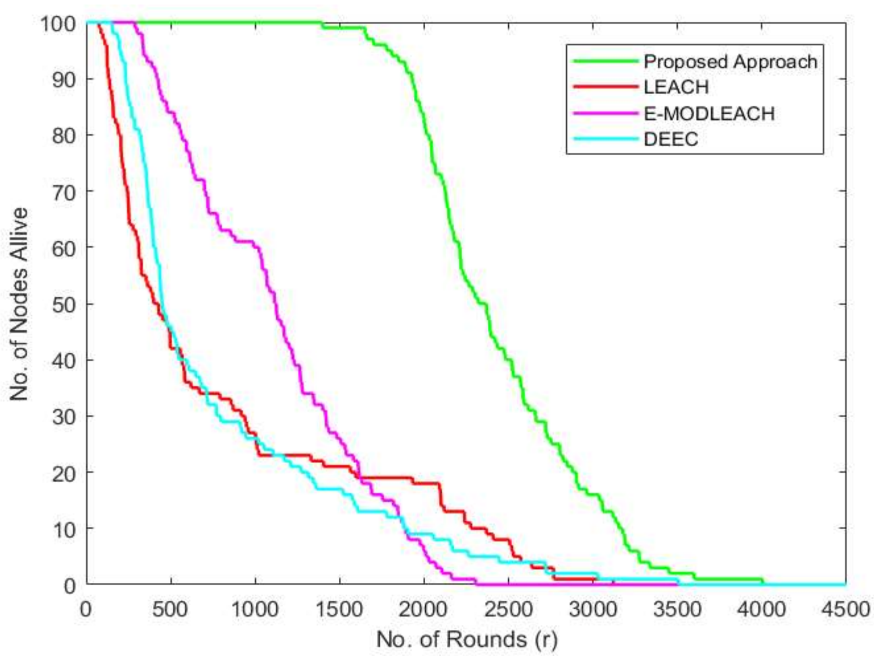

Figure 6: No. of alive nodes

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In the simulation, the number of rounds for dead nodes in the network of the proposed protocol is increased as is showed less dead nodes and it achieved better performance compared to LEACH, E-MODLEACH, and DEEC protocol as shown in Figure 7.

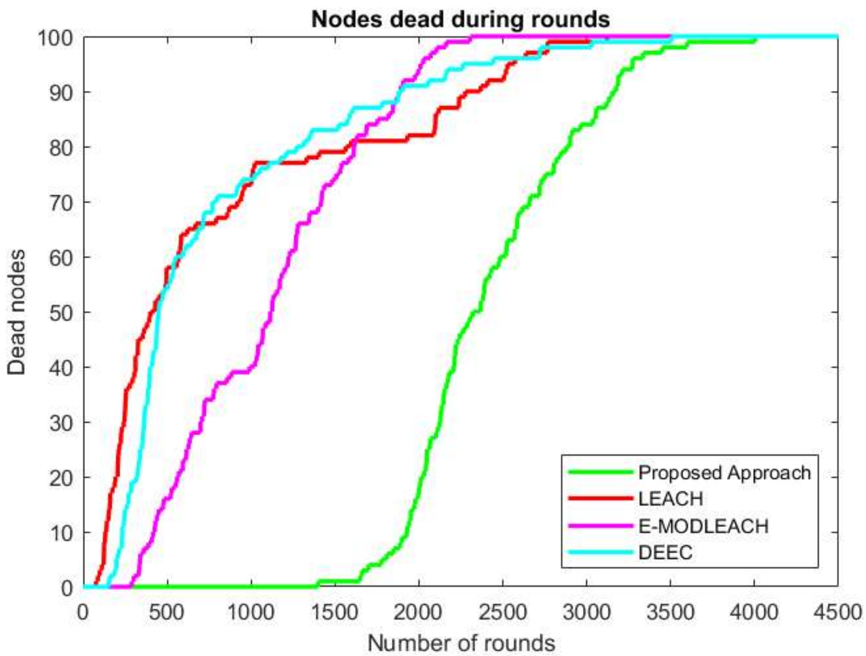

Figure 7: Number of rounds Vs. Dead nodes

The simulation result shows that the proposed protocol performs better than LEACH, MODLEACH, and DEEC protocol in terms of the number of cluster head formations and efficient energy consumption for more rounds in the data collection and transmission phase.

5. CONCLUSION

The proposed Backpropagation Feed-forward Neural Network (BP-FNN) model for cluster head selection in Wireless Sensor Networks (WSNs) significantly enhances energy efficiency. By integrating node proximity, residual energy levels, and network topology, the model ensures balanced energy consumption across the network. Simulation results in MATLAB demonstrate superior performance compared to LEACH, E-MODLEACH, and DEEC protocols, evidenced by increased packet transmissions to the base station and extended network lifespan. The findings underscore the potential of BP-FNN in optimizing cluster head selection, ultimately contributing to the sustainability and performance of WSNs.

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