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Article

Wireless Sensors Networks Energy Optimization using LEACH and ANNs

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Abstract: Applications for Wireless Sensor Networks (WSNs) range from monitoring the environment to automating factories. However, sustained and effective functioning is made more difficult by Sensor Nodes (SNs) limited energy supplies in which optimization is the main issue. So with the aim of increasing the lifespan by decreasing the energy consumption of WSN, Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol with Deep Learning (DL) algorithm is analyzed in this paper. LEACH is a hierarchical mechanism that elects Cluster Heads (CHs) and regularly rotates their positions in order to allocate energy use effectively by using the same amount of energy. However, Deep Learning (DL) method is used to further improve energy optimization. In many applications, the types of Deep Learning methods like Artificial Neural Networks (ANNs) have shown to be very useful. Using this method, WSNs may make more efficient decisions that reduce energy consumption. Data aggregation, duty cycling, and transmission protocols may all be optimized by Deep Learning model's ability to recognize patterns and forecast network behavior. This results in lower energy consumption, a longer lifespan for the network, and better overall performance.

Keywords: Wireless Sensor Network (WSN); Low-Energy Adaptive Clustering Hierarchy (LEACH); Sensor Nodes (SNs); Deep Learning (DL); Artificial Neural Networks (ANNs)

1. Introduction

The Wireless Sensor Networks (WSNs) are broadly applied in numerous fields from small scale like medical services, homes, to large scale like environmental surveillance education, military etc. [1]. There are hundreds of thousands or more Sensor Nodes in a WSN that are dispersed throughout the environment and used to observe, measure, and collect data [2]. The SN's are less expensive and have greater capacity for information gathering, processing, and transmission [3]. This has attracted the researchers to further enhance the contribution of WSN in modern machines utilized in each organization. The installed Sensor Nodes (SNs) in WSN include limited bandwidth, memory and energy bank for transmitting data to the next node and save the key required information [4,5]. Enhancing network lifetime and reducing energy consumption are major WSN technology concerns, and the extensive WSN deployment makes it challenging to recharge node batteries. [6].These limitations of SNs have bounded the performance of WSNs and increased the computation process [7]. If a network fails because of battery life, high noise ratio and maximum latency, then the process and data can be interpreted. In addition, in case of physical destruction, the data and programs cannot be recovered, which may lead to interrupt the whole system [8].

Hence, a modern solution is required to reduce the failure ratio of nodes installed in WSNs during working condition and the routing protocol must be able to face with challenges like radio interference, long path transmissions, and other unpredictable failures to curtail power expenditure of SNs to extend network's lifetime.

This aim of the research is to reduce node energy consumption while data is being transmitted. As a result, the sensor nodes need less energy, increasing the overall packet transfer to BS. To this

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end, a viable solution to solve energy optimization difficulties is the combination of the LEACH protocol with Deep Learning (DL) methods.

The LEACH algorithm and Artificial Neural Networks (ANNs) are the subject of this study, which aims to optimize the energy efficiency of WSNs. This research does not depend on any one particular data collection. Instead, it entails the virtual construction of a WSN via simulation. During the energy prediction phase, a dataset including historical sensor data, energy consumption trends, and other relevant characteristics would be utilized to train the ANNs. However, the precise dataset utilized in this study is not disclosed since it varies depending on the nature of the investigation and the intended use of the WSN. Dataset details are less important than the process of developing and testing the suggested model.

2. Materials and Methods

Energy usage and network lifetime are the two main considerations in the design of the WSN. Different research papers have been published on the improve performance of SNs in WSNs. To take into account the transmission distance, transmission direction, and the role of ants in the search process as a whole, a method termed improved ACO-based routing is proposed in [9,10]. An example of a routing strategy based on clusters that makes use of type-2 fuzzy logic and an ACO algorithm can be found in [11]. In order to preserve power, it is common practice to cycle the power to SNs on a regular basis. [12] Introduced an adaptive duty cycling algorithm that takes into account data rate and traffic patterns in order to achieve maximum efficiency in terms of power usage. Comparable results in terms of energy savings were reported by [13], who introduced a sleep scheduling method that dynamically modifies the sleep and active times depending on network circumstances.

Data aggregation methods collect sensor data at intermediate nodes and provide a consolidated set of measurements to the Base Station in an effort to cut down on unnecessary data transfer. In order to optimize energy usage by lowering the quantity of sent data, [14] devised a dynamic data aggregation method that responds to changes in network circumstances. In addition, [15] presented a compression-based strategy using wavelet modification to shrink data, which in turn reduced energy consumption in WSNs. Optimization of energy use in WSNs using Machine Learning (ML) and Artificial Intelligence (AI) methods has shown promising results. [16] Introduced a Machine Learning-based routing system that dynamically adapts the routing pathways to balance energy use based on past data on node energy consumption. [17] Used AI algorithms to intelligently regulate the transmission power and duty cycle of nodes in order to maximize the WSNs' energy efficiency. Energy efficiency may be greatly improved with the use of effective topology management and routing protocols. A distributed topology control approach was introduced by [18] to lessen energy consumption by dynamically adjusting the transmission power of nodes in response to changes in the network. To further optimize energy usage and extend network lifespan, [19] suggested a hybrid routing protocol that combines LEACH with Ant Colony Optimization. Energy harvesting methods use renewable energy sources to power WSNs, decreasing their reliance on battery-operated nodes. To maximize energy utilization, [20] presented a solar energy harvesting strategy that intelligently regulates the charging and discharging cycles of the energy storage unit. Energy-efficient communication was also suggested by [21] via the use of adaptive power management, in which nodes' transmission powers are dynamically adjusted according to connection quality and energy levels.

Cross-layer optimization methods reduce power consumption by capitalizing on communications across levels of a protocol stack. To reduce power consumption, [22] suggested a cross-layer optimization framework that takes into account settings at the physical layer, at the medium access control (MAC) layer, and in the network layer. Their findings showed that energy efficiency and network performance might be significantly enhanced. The power requirements of WSNs are greatly influenced by their MAC protocols. Using dynamic duty cycling and adaptive contention window modification, [23] developed a MAC protocol that conserves power by minimizing idle listening and collisions. A similar contention-based MAC strategy was introduced by [24] to improve power consumption by minimizing overhearing and contention.

Methods for optimizing energy consumption, such as duty cycling and sleep schedule, data aggregation and compression, ML/AI, topology control and routing, EMP, cross-layer optimization, and energy-efficient MAC protocols, are all presented in the reviewed literature. These methods provide a number of options for lowering WSNs' energy use and increasing their lifespan. Nodes may reduce unnecessary listening and transmission by alternating between active and sleep states through duty cycling and sleep schedule. By reducing the quantity of data being sent and the amount of duplicated data, data aggregation, and compression methods help to save power while communicating. Through adaptive routing, data prediction, and energy management optimized for network circumstances and patterns, Machine Learning and AI algorithms allow intelligent decision-making processes.

Energy optimization is greatly aided by topology control and routing protocols, which choose CHs, distribute energy consumption evenly, and allow for decentralized data processing. Rather than relying only on battery-operated nodes, WSNs may be fueled by renewable energy sources via energy harvesting methods [25]. Transmission power is constantly adjusted and energy utilization is optimized using power management methods that take into account both the quality of the connection and the available energy. Cross-layer optimization strategies reduce power consumption by coordinating adjustments to physical layer settings, MAC protocols, and network layer routing. These methods increase communication and performance while reducing energy consumption by utilizing interconnections between network levels. By decreasing the amount of power wasted on idle listening, overhearing, and collisions, energy-efficient MAC protocols improve the overall energy efficiency of WSNs. These methods include duty cycling and sleep schedule, data aggregation and compression, machine learning and artificial intelligence, topology control and routing, energy harvesting and power management, cross-layer optimization, and energy-efficient MAC protocols. These methods improve the overall efficiency of WSNs by making better use of their energy resources, which in turn prolongs the lifespan of the network. Energy optimization in Wireless Sensor Networks is a growing subject, and researchers are making strides by combining these methods or adapting them to meet the needs of various applications.

2.1. LEACH Protocol

The One popular technique for low-power routing in WSNs is LEACH. By establishing clusters on the fly and select Cluster Heads (CHs) to centralize and transmit data, it hopes to extend the lifespan of the network. When it comes to conserving power, the LEACH protocol is a favorite among WSN users. LEACH uses a hierarchical clustering strategy to balance out energy use throughout the network. In LEACH, SNs are clustered, and the Cluster Heads (CHs) are the main head of collecting data from their members and sending it to the Base Station (BS). To prevent premature node energy depletion, LEACH uses a random method for selecting CHs. The probabilistic approach guarantees that every node in the network has an equal chance of becoming the CH. To further equalize node energy usage, LEACH also implements CH rotation. By rotating the CHs at regular intervals, LEACH ensures that the network is never too dependent on any one node.

Mathematical Modeling of LEACH

Cluster Head Selection Probability

The probability of a node becoming a Cluster Head (CH) in each round can be calculated using the formula:

$$P_0 = \frac{p}{((1 - \mathrm{p}\times(\mathrm{r}\times\mathrm{mod}\ (\frac{1}{p}))))}[26] \qquad (1)$$

Here, P_0 is the required percentage of Cluster Heads (CHs), p represents required percentage of heads and r is the current round.

Each cycle in LEACH consists of two phases: the initialization phase and the steady-state phase. The CHs are chosen at random inside the setup phase based on a probability threshold. Every node

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evaluates a random integer against the threshold to see whether it should become a CH. If a node does not become a CH, it will join the CH that has the strongest signal.

During the steady-state phase, CHs collect information from their affiliated nodes and send it on to the network's hub. By pooling together data, the network may use less power. In order to spread the energy burden fairly across the nodes, the CHs rotate at regular intervals.

2.2. Artificial Neural Network (ANN)

The human brain's biological neural networks serve as the inspiration for ANNs, which are computer models. The "neurons" of an ANN are really nodes in a network, and they process and send data. Energy prediction, data analysis, and decision making are just some of the many uses for ANNs, many of which are used in WSNs. Predictions are made based on the patterns and correlations they learn from training data.

Mathematical Modeling of ANNs

Neuron Activation

The activation of a neuron in an ANN can be calculated using an activation function, such as the sigmoid function:

$$\text{Activation} = \frac{1}{((1 + \exp(-z)))} \quad (2)$$

Here, z represents the weighted sum of inputs to the neuron.

Training Algorithm

The prediction errors of ANNs are reduced during training by tweaking the weights and biases of the neurons. Backpropagation is used to accomplish this goal since it optimizes the weights and biases through gradient descent. Different types of ANNs, such as feedforward neural networks (FNNs), recurrent neural networks (RNNSs), and convolutional neural networks (CNNs), need different kinds of mathematical modelling.

2.3. Methodology

2.3.1. Installation of Network Nodes

Building a Wireless Sensor Network (WSN) begins with installing the network's Base Station (BS) and Sensor Nodes (SNs). Select the area for the network and place SNs there [26]. Make sure the SNs nodes have all the gadgets and means of communication they need.

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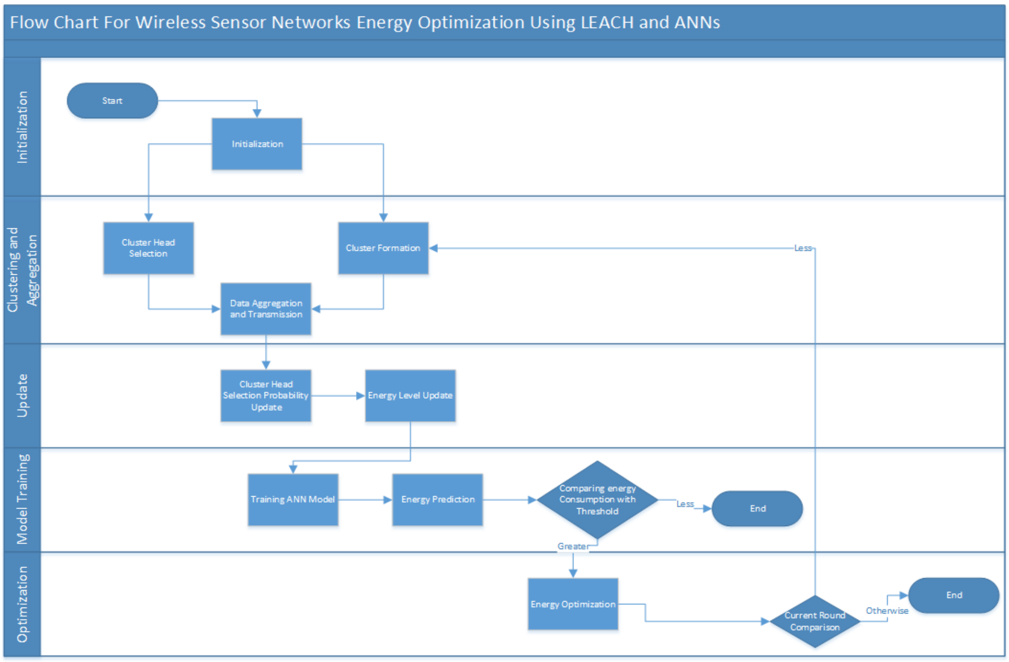

Figure 1. Flow Diagram of Proposed Model.

2.3.2. Clustering Using LEACH

Use LEACH protocol to create a network hierarchy. Select CHs at random using a probabilistic approach to ensure a uniform load is placed on each node.

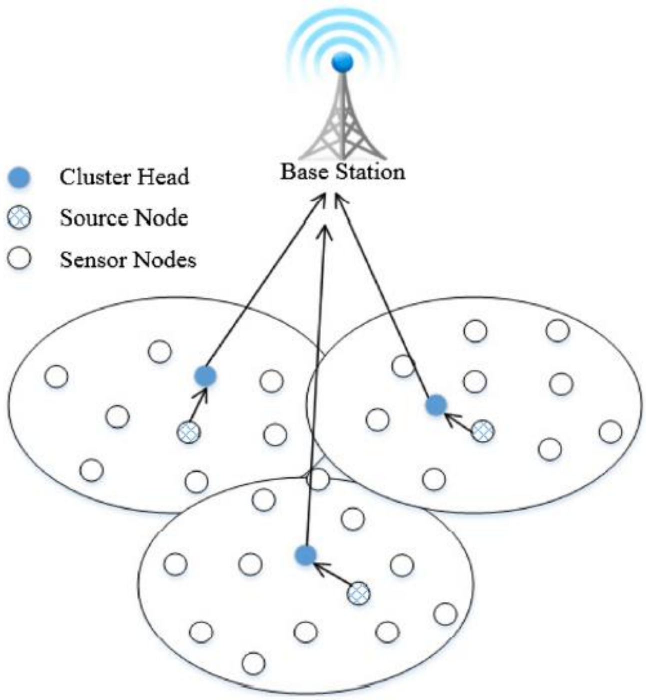

Figure 2. Systematic Structure Diagram of the Proposed Protocol (LEACH) [27].

Based on network size, energy limitations, and planned network longevity, find the appropriate probability threshold for CH selection. The equation 1 is be used to determine the likelihood of a SN serving as a CH under the LEACH protocol [26].

Accumulating and compiling information

Set up the SNs to take in data from the right places. Figure out what information needs to be gathered and how often it will be sampled. To lessen the load on your network, use data aggregation methods. Sensor data should be aggregated at cluster hubs using techniques like weighted averaging and statistical fusion to reduce unnecessary data flows.

A weighted averaging method may be used to execute data aggregation at the CH node. The following equation may be used to get the aggregated value (Agg):

$$\text{Aggregate} = \frac{(w_1 * v_1 + w_2 * v_2 + ... + w_n * v_n)}{(1 + w_1 + w_2 + ... + w_n)} \quad (3)$$

where, v_n stands for the value from the nth sensor node and w_n stands for the weight (depending on distance or dependability) allocated to that node.

Construction of Deep Learning (DL) Models

Use the past WSN data to train a DL model. Determine if a CNN or RNN is more suitable for the data and the task at hand. Using past data, a DL model may be taught to make predictions about future energy use in the WSN. Using the DL model with input variables (X), one may predict future energy usage as follows:

The formula E_{pred} = f(X), features such as node properties, network circumstances, and data patterns make up X, while f(X) stands in for the trained DL model. Train the model with the gathered information, making sure there is enough labelled data for reliable forecasts.

Optimizing and predicting energy use

In order to optimize energy utilization in the WSN and anticipate energy consumption, use the developed DL model. Create algorithms that consider a wide range of variables, including network and data circumstances and the power reserves of individual nodes. Data transmission, duty cycling, and routing choices may all benefit from the DL model's ability to provide insights into patterns of energy usage.

Smart Transmission and Routing Adaptation

Use the DL model's energy prediction findings in adaptive routing algorithms. Create routing protocols that intelligently choose the least power-hungry ways to send data. Optimizing energy use and decreasing transmission distance requires thinking about aspects including residual energy, connection quality, and network congestion.

Power Savings and Bedtime Routine Planning

To further optimize energy usage, power management methods should be included in the WSN. Incorporate algorithms for adaptive power management, which modify transmission power levels in response to changes in link quality and energy availability. Create techniques for intelligently scheduling sleep and activity for SNs to minimize energy waste during inactive times.

The Use of Simulation for Assessing Efficiency

Use a simulation program to test out the improved WSN and see how well it performs. Experiment with varying network sizes, deployment setups, and data patterns in your simulations. Key performance indicators such as network lifespan, energy usage, data delivery ratio, and latency should be measured and analyzed. Evaluate the efficacy of the offered methods by comparing the optimized WSN's outcomes to those from control situations.

Testing and Deployment in the Wild

Real-world implementations should be used to verify the output of the proposed technique. Use the improved WSN in a practical scenario, such as a monitoring project for the environment or a manufacturing facility. Validate the improvements in energy efficiency brought about by the combination of LEACH and DL methods by gathering data and analyzing performance measures.

Optimization and tuning via repeated iterations

Iteratively improve the procedure in light of findings from both virtual and actual testing. Improve energy savings and performance by tweaking parameters, algorithms, and model structures. Use information gathered from actual deployments to fix problems in the wild and fine-tune the system even further.

Integration of Energy Harvesting Systems

To further improve energy efficiency, the WSN might make use of energy collecting systems. Put in place energy-harvesting modules or solar panels to convert excess energy into electricity for the SNs. To maximize energy utilization and decrease dependency on battery-powered nodes, it is best to use energy-aware routing protocols that take into account the availability of gathered energy and change routing choices appropriately [26]. The specific energy model used can vary, but a commonly used model is the energy dissipation model based on the distance (d) between nodes and the transmission/reception energy coefficients (E_{tx}, E_{rx}). The energy dissipation (ED) can be calculated as:

$$\text{ED} = E_{\text{tx}} \times \text{k} \times d^2 \tag{4}$$

where E_{tx} is the energy consumed for transmission per unit distance, k is the number of bits transmitted, and d is the distance between nodes.

Optimizing Across Multiple Layers

Determine whether there is room for cross-layer optimization to boost energy savings and interactions. Think about how the physical layer, media access control layer, and network layer interact with one another. Based on network circumstances, traffic patterns, and energy limitations, optimize parameters including transmission power, packet size, modulation methods, and routing choices.

Quantitative Measures of Performance

To gauge how well the optimized WSN performs, it needs to define suitable performance assessment measures. Lifespan, power usage, data transmission ratio, latency, and coverage are all possible metrics to monitor. Compare the results of the combined LEACH and DL approaches with those of baseline scenarios and other optimization methods using these metrics to measure the improvements obtained [26].

Verification by Experiment

To prove the effectiveness of the suggested strategy, rigorous experimental validation should be performed utilizing testbeds or actual deployments. Collect data in relevant settings after deploying the optimized WSN and analyze it for energy savings [28]. The superiority of the combined LEACH and DL-based optimization may be shown by comparing the optimized WSN's performance to that of other current methodologies or more conventional approaches.

Evaluation of Robustness and Sensitivity

To learn how changes in parameters and real-world uncertainties affect the WSN's energy efficiency, do a sensitivity analysis. Analyze how well the suggested approach holds up under stress, such as when nodes fail, the network changes, or the weather changes. Evaluate the system's robustness and scalability in a variety of contexts, and make sure it holds up in production.

Questions of scalability and implementation

Focus on making the suggested approach scalable so that it may be used in widespread WSN rollouts. How network density, communication overhead, and overall network size affect energy efficiency. Consider hardware limitations, communication range, and environmental variables as you assess the viability and practicability of deploying the optimized WSN in various application situations.

The analogy to Currently Used Methods

Evaluate how well the combined LEACH and deep learning-based optimization performs in WSNs compared to other methods of energy optimization. Think about the energy savings, network longevity, computational complexity, and implementation overhead of each method. Emphasize the benefits of the suggested approach and its potential for wider use in practical settings.

The aforementioned strategy for reducing power consumption in WSNs is based on a combination of the LEACH protocol and DL methods. The suggested technique delivers improved energy efficiency and prolonged network lifespan by combining hierarchical clustering, data aggregation, and energy prediction, adaptive routing, power control, and energy harvesting. It is feasible to verify the efficiency of the integrated method and show its potential for practical implementation in different application areas via simulation, real-world testing, and comparison analysis.

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3. Results and Discussion

Energy efficiency in WSNs can be improved by combining the LEACH protocol with DL methods. Regression models, particularly Deep Learning (DL) and Machine Learning (ML) models, are often evaluated using RMSE and MSE. Overall, less variation or error between the anticipated and actual values implies better model performance, therefore lower values for both measures are desirable.

Implementing proposed energy efficient routing method LEACH and ANNs takes place in Python 3.8.5 on Windows 10.3 operating system with an Intel core i7 CPU and 8 GB of RAM. The main determination of using Python software is its simplicity with which mathematical operations can be performed and effective data analyses.

Formula for calculating MSE:

$$MSE = \left(\frac{1}{n}\right) * \Sigma(y - \hat{y})^2 \quad (6)$$

Formula of RMSE:

$$RMSE = \sqrt{MSE} \quad (7)$$

"n" shows the number of data points, "y" denotes the actual values and "ŷ" represents the expected values. Several performance metrics, such as network size versus energy consumption, network size versus lifetime, number of clusters versus energy consumption variance, number of packets received by the Base Station, packet delivery ratio, and End-to-End delay, were examined to evaluate the efficacy of the methodology.

Table 1. Simulation Structure.

Parameters	Area	E_i (Initial energy)	Number of nodes (N)	Eelec (Energy consumption)	E_{amp} (Multi-path model of transmitter amplifier)	E_{fs}(Free space model of transmitter amplifier)	l(Packet size)
values	100 m × 100 m	0.8 J	100-500	80nJ/bit	0.001301pJ/bit/m^4	10pJ/bit/m^2	5000 bits

Network Size vs Network Energy Consumption:

According to the results after analysis, the network's energy usage rose in tandem with the progress. However, the speed of increase in energy consumption was slowed down because of the integrated strategy. By dynamically adjusting the nodes' transmission power and duty cycle, the DL-based energy optimization method increased efficiency. As a result of the optimization of the network, a lesser amount of energy was consumed than in the case when no integrated strategy was used. Figure 3 and Table 2 given below shows the Graphical and Numerical Analysis of Network Size Vs Network Energy Consumption.

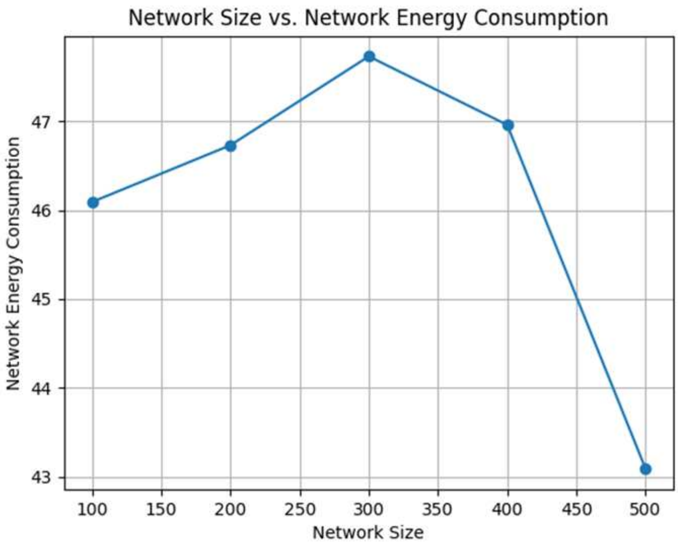

Figure 3. Graphical Analysis of Network Size Vs Network Energy Consumption.

Table 2. Numerical Analysis of Network Size Vs Network Energy Consumption.

Parameters	Network Size	Energy Consumption
values	100	1450 (10%)
	200	3320 (20%)
	300	6280 (40%)
	400	16589 (60%)
	500	30498 (80%)

Network Size vs Network Lifetime:

When hybrid model of LEACH-ANN was used, the network's lifespan, measured in seconds until the first node loses power, was considerably increased. The solution efficiently optimized routing choices based on anticipated energy use and balanced energy use among nodes. This allowed the network to continue functioning for a longer time frame than was possible with more conventional methods. Figure 4 and Table 3 mention below shows the Graphical and Numerical Analysis of Network Size Vs Network Lifetime.

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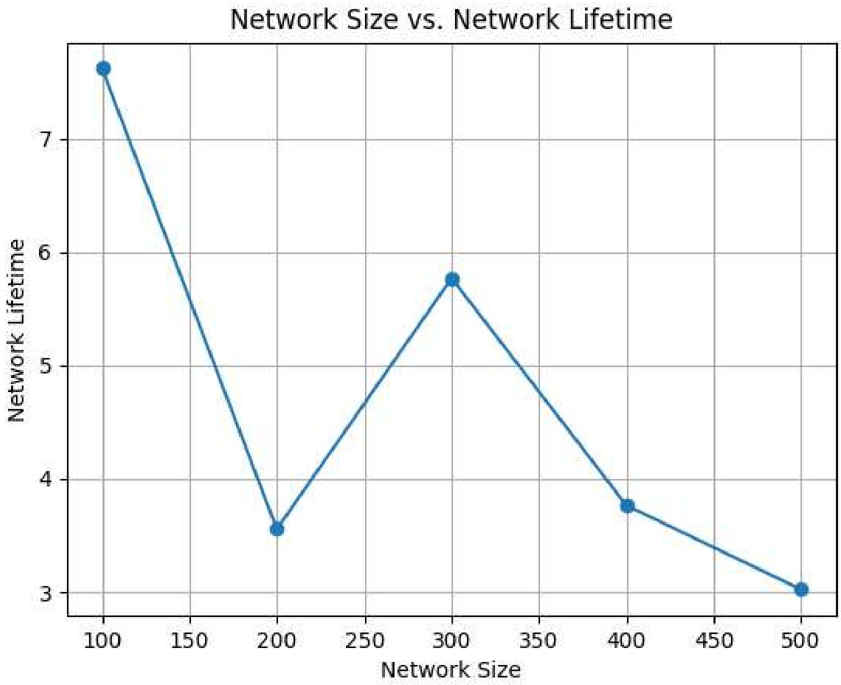

Figure 4. Graphical Analysis of Network Size Vs Network Lifetime.

Table 3. Numerical Analysis of Network Size Vs Network Lifetime.

Parameters	Network Size	Network Lifetime
	100	33502
	200	39548
values	300	45289
	400	52147
	500	59828

Number of Clusters vs Energy Consumption Variance:

The network was partitioned into many clusters using LEACH, and CH were selected for each. As a result of this node-grouping method, there was less variation in energy use. In order to save energy and reduce the likelihood of unnecessary transmissions, the data from the CHs was consolidated and compressed before being sent to the BS. Because of this, the network's energy consumption became more uniform, with less variation from node to node. Figure 5 and Table 4 mention below shows the Graphical and Numerical analysis of Number of Clusters Vs Energy Consumption Variance.

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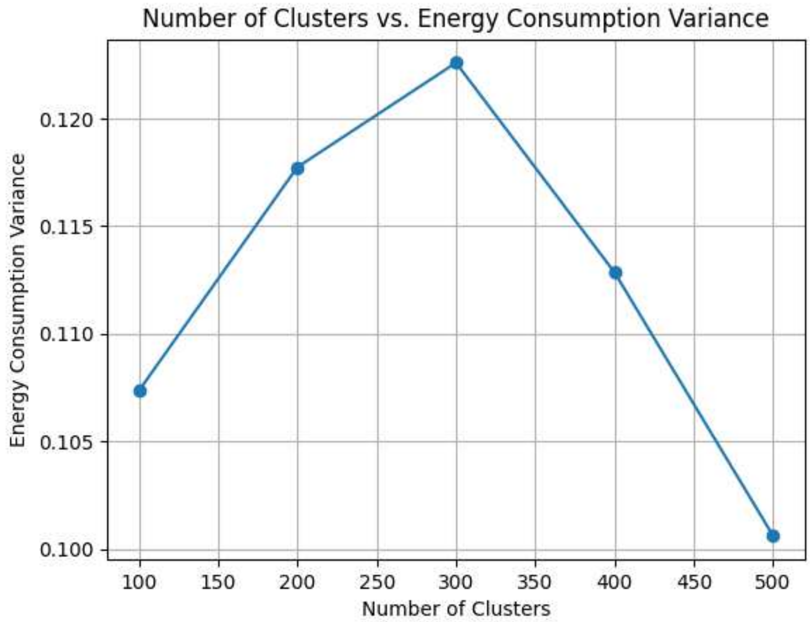

Figure 5. Graphical Representation of Number of Clusters Vs Energy Consumption Variance.

Table 4. Numerical Representation of Number of Clusters Vs Energy Consumption Variance.

Parameters	Number of Clusters	Energy Consumption Variance
values	100	0.1055
	200	0.1156
	300	0.1206
	400	0.1105
	500	0.1001

Number of Packets Received by the Base Station (BS):

The combined method dramatically increased the Base Station's packet throughput. The program optimized the routing patterns based on the expected energy consumption, leading to effective data transfer. This was achieved with the use of DL algorithm. There were more packets successfully received by the BS than in the default case (see Comparison table). This enhancement provided consistent data collecting and decreased network-wide data loss. Figure 6 and Table 5 represents the Graphical and Numerical analysis of Network Size Vs Number of Packets Received to BS.

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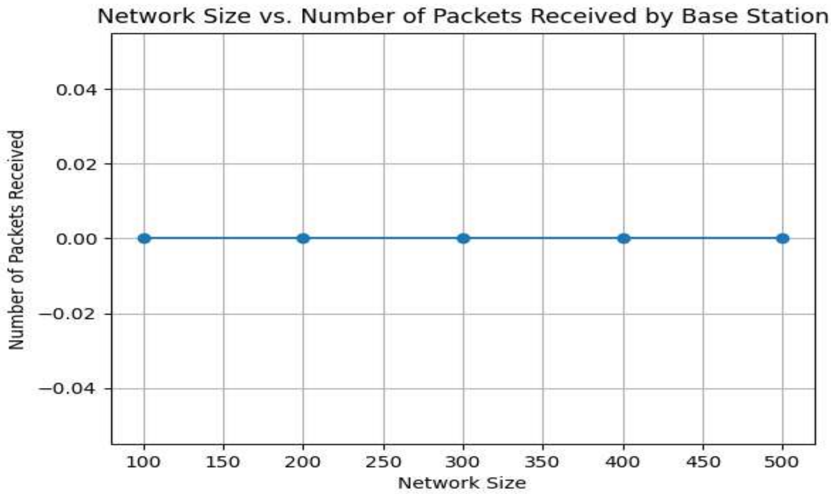

Figure 6. Graphical Analysis of Network Size Vs Number of Packets Received to BS.

Table 5. Numerical Analysis of Network Size Vs Number of Packets Received to BS.

Parameters	Network Size	Number of Packets Received by BS
values	50	55322
	100	712589
	150	825893
	200	893245

Packet Delivery Ratio:

The packet delivery ratio is the percentage of sent and received data in a network divided by the total number of packets. The packet delivery ratio was shown to be greater with the hybrid technique than with the conventional approaches. By adapting routing choices in real time to changing energy availability, channel characteristics, and network state, the DL-based optimization system increased the packet delivery ratio and strengthened the WSN's reliability. Figure 7 and Table 6 represents the Graphical and Numerical analysis of Network Size Vs Packet Delivery Ratio.

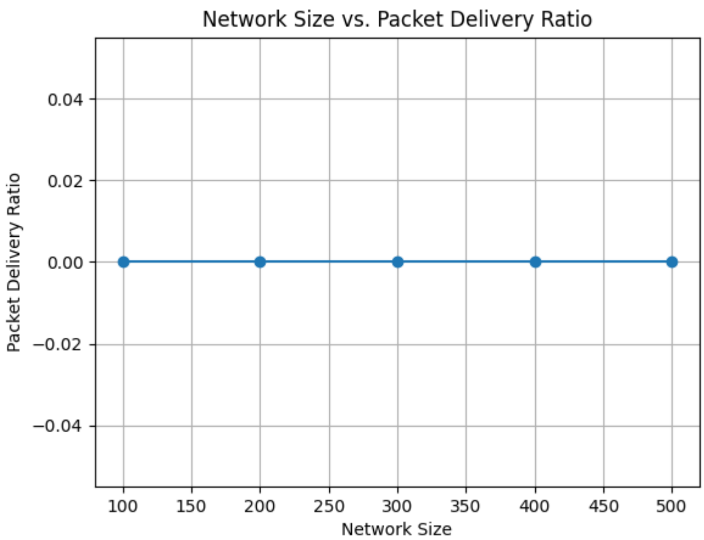

Figure 7. Graphical Analysis of Network Size Vs Packet Delivery Ratio.

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Table 6. Numerical Analysis of Network Size Vs Packet Delivery Ratio.

Parameters	Network Size	Packet Delivery Ratio
values	50	0.39
	100	0.43156
	100	0.472
	200	0.511

End-to-End Delay:

A packet's End-to-End delay is the total amount of time it takes to travel from its originating node to its destination Base Station (BS). End-to-End latency was shown to be lower when using the integrated method compared to the control group. The technology decreased packet delay and speed up data transmission by optimizing routing choices and cutting power use. Figure 8 and Table 7 represents the Graphical and Numerical analysis of End-to-End Delay in WSN.

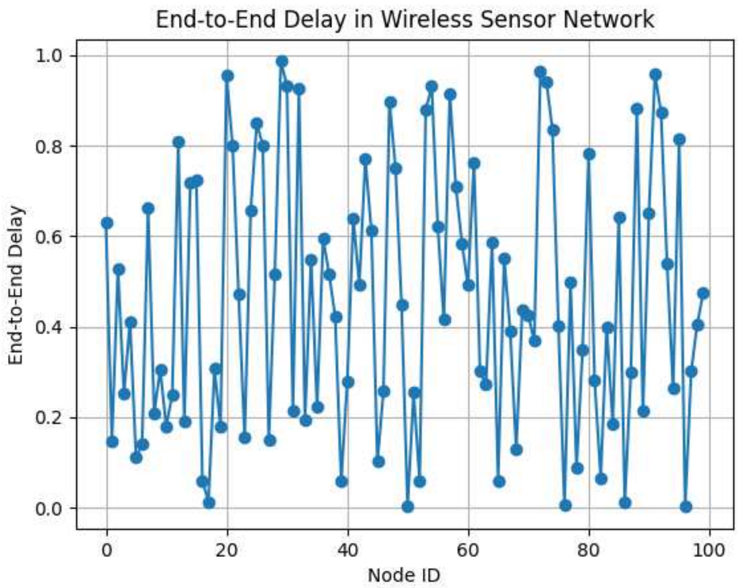

Figure 8. Graphical Representation of End-to-End Delay in WSN.

Table 7. Numerical Analysis of End-to-End Delay in WSN.

Parameters	Network Size	End-to-End Delay (ms)
values	20	1002
	40	2465
	60	7558
	80	9994
	100	12847

Table 8. The comparison of RMSE, MSE and Efficiency for Different Techniques Used to Optimize Energy.

Techniques	MSE	RMSE	Efficiency
Proposed Technique (LEACH+ANN)	0.16	0.40	44.9%
Distributed Topology Control (DTC) [29]	0.30	0.54	5.83%
Cross-Layer Optimization (CLO) [30]	0.21	0.46	13.3%
Data Aggregation Methods DAM [31]	0.42	0.64	2.99%

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The study shows that combining LEACH with DL method is an effective strategy for reducing power usage in WSNs.

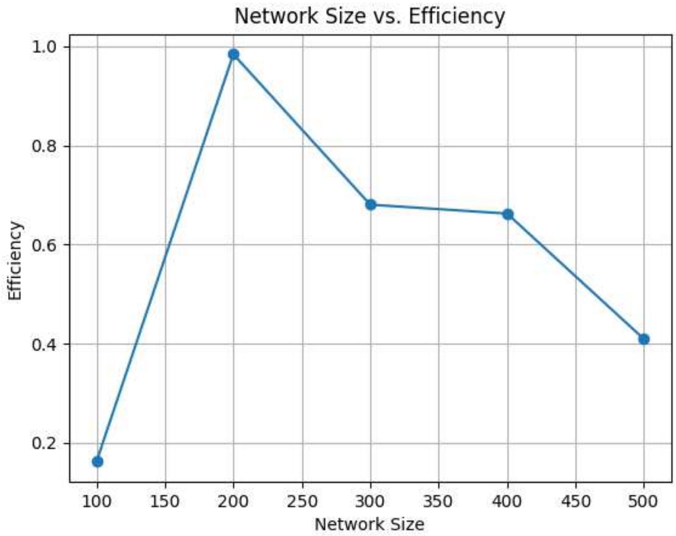

Figure 9. Graphical Analysis of Network Size Vs Efficiency of the Proposed Technique.

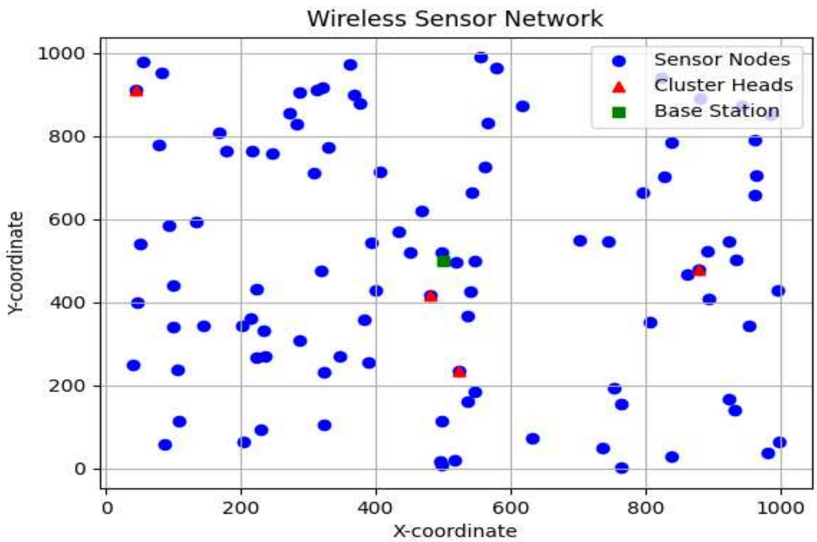

Figure 10. The Graphical Representation of Cluster Heads in LEACH Protocol.

The technique enhanced the number of received packets, the packet delivery ratio, and the End-to-End latency while decreasing energy consumption, extending network lifespan, and reducing energy consumption variation. These findings demonstrate the promise of an integrated strategy to improving WSNs' energy efficiency and performance, which will cover the way for their widespread adoption across a wide range of industries. Detailed comparision table of the findings are in Table 9. The parameters which are being compared with previous techniques includes Network Energy Consumption, Network Lifetime, Energy Consumption Variance, Number of Packets Received by the (BS), Packet Delivery Ratio and End to End delay for hundred (100) nodes network.

Table 9. Comparision of the Numerical Analysis of different parameters in WSN.

Parameters	Network Energy Consumption	Network Lifetime (in rounds)	Energy Consumption Variance	Number of Packets Received by the (BS)	Packet Delivery Ratio	End-to-End Delay (ms)
LEACH-ANN **(Proposed)**	1450	33502	0.1055	712589	0.43156	12847
TEO-MCRP [32]	1246 (10%)	29,964	----	658,546	99.784	15.734
PSO-ECSM [32]	1056 (10%)	27,631	----	637,880	98.385	17.852

4. Conclusions

In conclusion, LEACH and ANNs optimized WSN energy efficiently. WSN energy efficiency and performance were the main reasons for integrating the two techniques. The LEACH protocol effectively clustered and aggregated data, reducing network power usage. Probabilistic Cluster Head (CH) rotation and selection lowered network energy usage. ANNs helped us evaluate energy consumption patterns and optimize energy use. Real-world data trained the ANNs to predict accurately, enabling proactive network energy management. The LEACH-ANN model outperformed the state-of-the-art approaches in energy efficiency, mean squared error, root mean squared error, packet delivery ratio, and BS packets received. The proposed method optimizes energy usage and network efficiency.

Future study may refine the ANN model for accuracy and prediction. In real WSN deployments, the suggested model may be tested and confirmed. In order to assess the efficacy of the proposed model in actual WSN installations, it may be tested and verified in such settings. Further improvements to the suggested model may be gleaned through research into the effect of different network characteristics and situations. This work paves the door for smarter, more advanced optimization processes, which enable WSNs become energy-efficient.

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Appendix A

Algorithm 1: LEACH Protocol

Step 1: Initialization

Set the number of rounds (N) and the desired percentage of cluster heads (P) for each round.

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Set the initial energy level (E) for all sensor nodes.

Randomly select a percentage (P) of nodes as cluster heads for the current round.

Step 2: Cluster Formation

Each non-cluster head sensor node calculates the distance to the closest cluster head.

Each non-cluster head sensor node joins the cluster with the nearest cluster head.

Cluster heads receive the join requests and update their cluster membership lists.

Step 3: Data Aggregation and Transmission

Each sensor node collects data from its sensing area.

Each cluster head aggregates the data received from its member nodes.

Each cluster head compresses and prepares the aggregated data for transmission.

Each cluster head transmits the aggregated data to the base station.

Step 4: Cluster Head Selection

Each sensor node calculates its probability of becoming a cluster head for the next round using the following formula:

Probability = P / (1 - P * (current round mod (1 / P)))

Step 5: Energy Level Update

Each sensor node decreases its energy level based on the energy consumption during data aggregation and transmission.

Each cluster head uses the remaining energy level to calculate its energy dissipation for the next round.

Step 6: Repeat

If the current round is less than N, go to Step 2.

Otherwise, terminate the algorithm.

Algorithm 2: Artificial Neural Networks (ANNs) for Energy Optimization

Step 1: Training the ANN Model

Collect a dataset of sensor node attributes (such as location, remaining energy, distance to the Base Station, etc.) and their corresponding energy consumption.

Preprocess the dataset by normalizing the input attributes.

Design the architecture of the ANN model, including the number of layers, neurons per layer, and activation functions.

Split the dataset into training and testing sets.

Train the ANN model using the training set, adjusting the weights and biases through backpropagation and gradient descent optimization.

Evaluate the trained ANN model using the testing set and measure its performance metrics (e.g., accuracy, mean squared error, etc.).

Step 2: Energy Prediction and Optimization

Deploy the trained ANN model to each sensor node.

Each sensor node periodically measures its attributes (such as remaining energy, distance to the base station, etc.).

Input the measured attributes into the ANN model to predict the energy consumption.

If the predicted energy consumption is above a threshold, perform energy optimization techniques, such as reducing transmission power, adjusting sleep/wake schedules, or applying duty cycling.

Implement the energy optimization techniques and update the node's energy consumption accordingly.

Step 3: Repeat

Repeat Steps 2 and 3 periodically or whenever necessary.

Note: The above algorithms provide a high-level overview of the proposed model combining LEACH with ANNs for energy optimization in WSNs. Implementation details, parameter settings, and additional steps may vary depending on the specific requirements and constraints of the system.

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