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ENERGY-EFFICIENT ROUTING IN WIRELESS SENSOR NETWORKS USING DEEP BELIEF NETWORKS AND LSTM FOR MOBILE SINK PATH OPTIMIZATION AND CLUSTER HEAD SELECTION

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Abstract

Wireless Sensor Networks (WSNs) are critical in numerous applications due to their ability to sense and transmit data. However, energy limitations of sensor nodes, powered by finite batteries, significantly impact network longevity. Traditional routing methods involving multi-hop transmissions and cluster formation can result in substantial energy consumption, particularly by Cluster Heads (CHs) involved in data aggregation and transmission. This research addresses the problem by optimizing energy-efficient routing using a Deep Belief Network (DBN) with Long Short-Term Memory (LSTM) for routing and CH selection. A mobile sink moving in a linear path minimizes energy consumption by reducing cluster formation and promoting single-hop transmissions. The proposed method utilizes LSTM-based CH selection to ensure that nodes with the highest residual energy are chosen, enhancing network lifetime. Experimental results demonstrate that the proposed method reduces energy consumption by up to 25% compared to circular path sink movement and multi-hop data transmission, resulting in a 40% increase in network lifetime. Performance was evaluated on a 100-node network with varying sink velocities, achieving an energy efficiency of 15% over traditional models.

Keywords:

Wireless Sensor Networks, Deep Belief Network, LSTM, Mobile Sink, Energy Efficiency

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have become integral to a wide array of applications, including environmental monitoring, industrial automation, and military surveillance, where reliable data collection and transmission are essential. These networks consist of numerous small sensor nodes that sense environmental data and transmit it to a central sink for further processing. A key challenge in WSNs is managing the energy consumption of these sensor nodes, as they are often powered by non-rechargeable batteries. According to recent studies, WSNs are projected to grow at a compound annual growth rate (CAGR) of 18.7%, reaching a market value of $8.9 billion by 2025 [1]. With the increasing adoption of WSNs in large-scale deployments, ensuring efficient energy utilization is paramount to prolong the network's operational lifetime [2].

Energy management in WSNs is complicated by several factors, such as the multi-hop nature of data transmission, high communication overhead, and uneven energy depletion among nodes [3]. Multi-hop transmission, where data is forwarded through multiple intermediate nodes, increases energy consumption for the forwarding nodes, often leading to early node failures [4]. The uneven depletion of energy, particularly for Cluster Heads (CHs) responsible for aggregating and transmitting data to the sink, also shortens network lifetime [5]. Furthermore, mobility models for sink nodes pose challenges as they impact data transmission efficiency and energy consumption. Traditional circular sink movement leaves some nodes uncovered, leading to the formation of unnecessary clusters and increased multi-hop transmissions.

Despite numerous efforts to develop energy-efficient routing protocols, many existing methods suffer from excessive energy consumption due to inefficient clustering, poor CH selection, and inadequate path planning [6]. Most traditional methods, such as LEACH and SEP, rely on static CHs or random selection processes that do not consider the dynamic energy levels of nodes. Furthermore, the use of fixed mobility patterns for the sink, such as circular paths, leaves portions of the network uncovered, resulting in energy inefficiencies and reduced packet delivery rates. The lack of intelligent routing decisions further exacerbates energy waste during data transmission, leading to reduced network lifetime [8].

The primary objective of this study is to develop an energy-efficient routing and CH selection method that can extend the lifetime of WSNs by addressing the inefficiencies in existing protocols. Specifically, the method aims to:

- Minimize energy consumption across the network.
- Optimize CH selection based on dynamic node energy levels.
- Reduce the number of multi-hop transmissions by using mobile sinks.
- Improve overall network performance metrics such as throughput, packet delivery ratio (PDR), and delay.

The novelty of this work lies in the combination of Deep Belief Networks (DBNs) and Long Short-Term Memory (LSTM) networks for optimizing routing and CH selection in WSNs. The key contributions are:

- A DBN-based routing mechanism that efficiently determines optimal data transmission paths by analyzing historical transmission data and node energy levels.
- An LSTM-based CH selection process that dynamically selects CHs based on residual energy, preventing premature node deaths and ensuring balanced energy consumption across the network.
- A mobile sink movement strategy that follows a linear path, ensuring that most nodes can transmit data directly in a single-hop manner, reducing energy waste.
- Comprehensive performance evaluation of the proposed method against six existing approaches, demonstrating superior performance in terms of energy efficiency, network lifetime, and packet delivery.

2. RELATED WORKS

Energy-efficient routing and CH selection in WSNs has been extensively studied, with numerous approaches proposed over the years. These can be broadly categorized into clustering-based protocols, multi-hop routing protocols, and mobile sink strategies.

LEACH (Low-Energy Adaptive Clustering Hierarchy) is one of the most widely used clustering-based protocols for WSNs. LEACH randomly selects CHs and rotates them periodically to distribute the energy load among nodes. However, LEACH does not account for residual energy during CH selection, leading to imbalanced energy consumption and shorter network lifetime. Later improvements, such as SEP (Stable Election Protocol), introduced heterogeneity-aware mechanisms that assign higher probabilities to nodes with more energy to become CHs []. However, SEP still suffers from inefficiencies in energy distribution, particularly in large-scale networks. TEEN (Threshold-sensitive Energy Efficient sensor Network) introduced a threshold-based mechanism to reduce unnecessary data transmissions, but it is primarily suited for time-sensitive applications and may not perform well in scenarios where continuous monitoring is required [8].

Another clustering-based protocol, DEEC (Distributed Energy-Efficient Clustering), dynamically selects CHs based on the residual energy of nodes, which significantly improves energy efficiency compared to LEACH. However, DEEC still relies on multi-hop transmissions, which can deplete energy from intermediate nodes [9]. PEGASIS (Power-Efficient GAthering in Sensor Information Systems) takes a chain-based approach to data transmission, where nodes communicate only with their nearest neighbor, and a leader node sends aggregated data to the sink. While this reduces the number of transmissions, the leader node experiences rapid energy depletion, leading to instability [10].

In multi-hop routing protocols, the focus is on minimizing the energy used for transmitting data from nodes to the sink through intermediate nodes. MTE (Minimum Transmission Energy) selects the shortest path for data transmission, minimizing the energy used for each transmission. However, this often results in certain nodes being overused as intermediate nodes, causing them to deplete their energy quickly [11]. To address this, load-balancing protocols such as HEED (Hybrid Energy-Efficient Distributed Clustering) were introduced, which select CHs based on residual energy and communication cost. While HEED provides better energy distribution, it does not optimize for sink mobility, limiting its effectiveness in dynamic WSN environments [12].

Mobile sink strategies aim to reduce energy consumption by moving the sink closer to sensor nodes, minimizing the number of hops required for data transmission. SinkTrail and MobiCluster are two prominent approaches that leverage mobile sinks for energy-efficient data collection [13]. SinkTrail uses a predefined trajectory for the sink to collect data from nodes periodically. While this reduces the need for multi-hop transmissions, it can leave certain nodes uncovered if the trajectory is not optimized. MobiCluster, on the other hand, adapts sink mobility based on the location of CHs but still requires multi-hop communication in some cases [14].

The machine learning techniques, such as Reinforcement Learning (RL) and Deep Neural Networks (DNNs), has also been explored for optimizing routing and CH selection in WSNs. Q-routing, based on RL, improves the efficiency of routing by learning optimal paths dynamically, but it requires significant computational resources, which may not be suitable for resource-constrained WSN nodes. More recently, DNN-based approaches have been proposed to predict optimal routing paths based on historical data. These methods, while promising, often require extensive training and computational power [15].

3. PROPOSED METHOD

The proposed method employs a hybrid approach integrating a Deep Belief Network (DBN) with LSTM for routing optimization and CH selection in WSNs. The DBN is trained to identify the optimal sink path based on historical sensor data and residual energy levels. The routing model predicts the best route for the mobile sink in a linear motion, reducing multi-hop transmissions. For CH selection, an LSTM model is used to monitor the energy levels of sensor nodes and dynamically choose the node with the highest residual energy as the CH, which aggregates and transmits data directly to the mobile sink.

- **Initialization**: WSN nodes are initialized with random energy values, and a DBN is trained on the network's topology and sensor data.
- **Mobile Sink Path Planning**: Using the DBN, the linear path of the mobile sink is determined, ensuring that most nodes can perform single-hop transmissions to the sink.
- **Routing Optimization**: The DBN predicts optimal routes for the mobile sink to collect data efficiently, minimizing energy consumption.
- **LSTM-based CH Selection**: An LSTM model evaluates each node’s residual energy and selects the node with the highest energy as the CH for data aggregation and transmission.
- **Data Aggregation and Transmission**: CHs aggregate data from the cluster and transmit it to the mobile sink in single-hop transmissions, further optimizing energy consumption.
- **Energy Evaluation**: The energy consumption is recorded, and the CH selection is updated periodically based on real-time energy evaluations using LSTM predictions.

3.1 PROPOSED DBN FOR INITIALIZATION, MOBILE SINK PATH PLANNING, AND ROUTING OPTIMIZATION

3.1.1 Initialization:

A Deep Belief Network (DBN) is used to initialize the WSN by capturing the spatial distribution and energy state of the sensor nodes. A DBN is a generative model composed of multiple layers of Restricted Boltzmann Machines (RBMs), which are stacked to create a deep network. Each layer learns representations of the input data (in this case, the WSN topology and sensor nodes’ residual energy). The goal of the DBN is to find the optimal configuration of the sensor network, considering energy distribution and node positions, to initialize the system for efficient routing.

The DBN is trained to approximate the joint distribution $P(X,Y)$ where X represents the sensor node states (including residual energy, location, and transmission capacity) and *Y* represents the optimal sink path and routing decisions. The DBN is composed of visible units *v*, hidden units *h*, and weight matrices *W*. The energy function of a Restricted Boltzmann Machine (RBM) is defined as:

$$E(v,h) = -\sum_i v_i b_i - \sum_j h_j c_j - \sum_{i,j} v_i W_{ij} h_j \quad (1)$$

where:

v_i is the state of the visible unit,

h_j is the state of the hidden unit,

b_i and c_j are the bias terms for the visible and hidden units,

W_{ij} is the weight matrix between visible and hidden units.

Once trained, the DBN can generate the optimal initial configurations of the sensor nodes and preplan the sink's movement by minimizing the energy function across multiple layers.

3.1.2 Mobile Sink Path Planning:

The mobile sink path is optimized based on the output of the DBN, ensuring that most sensor nodes can transmit data via single-hop communication to reduce energy consumption. The sink moves along a linear path that dynamically adjusts based on the energy levels and positions of the sensor nodes. The path planning problem can be formulated as an optimization problem, where the objective is to minimize the total energy consumption E_t of the WSN while ensuring that the mobile sink covers all sensor nodes for data aggregation. The optimization objective can be expressed as:

$$E_{\mathrm{t}} = \sum_{i=1}^{N} E_i(d_{i,\mathrm{sink}}) \quad (2)$$

where:

N is the total number of sensor nodes,

$E_i(d_{i,\mathrm{sink}})$ is the energy consumed by node iii to transmit data to the sink at distance $d_{i,\mathrm{sink}}$.

The DBN generates the sink path by analyzing the node's distribution and energy, selecting a linear path that minimizes E_t. The sink moves in predefined steps, adjusting its trajectory based on the real-time energy levels of nodes as learned by the DBN.

3.1.3 Routing Optimization:

Once the mobile sink path is defined, the routing between sensor nodes and the sink is optimized to ensure minimal energy consumption. The DBN helps determine whether nodes can directly transmit data to the sink or must forward data through intermediate nodes. Routing decisions are made based on residual energy levels and distances to the mobile sink. The energy consumed for data transmission between two nodes can be modeled as:

$$E_T = E_{\mathrm{elec}} \times k + E_{\mathrm{amp}} \times k \times d^n \quad (3)$$

Where:

E_T is the energy required for transmission,

E_{elec} is the energy required to operate the transmitter/receiver circuits,

k is the number of bits transmitted,

E_{amp} is the energy required by the amplifier,

d is the distance between nodes, and

n is the path loss exponent (usually 2 for free-space models).

To minimize the energy consumption, the DBN learns an optimal routing structure by considering the energy costs E_T between nodes and selecting paths that avoid low-residual-energy nodes, thus balancing the energy consumption across the network. The output of the DBN routing optimization leads to either direct sink transmissions or multi-hop transmissions that minimize the total energy required by intermediate nodes. By combining DBN with sink mobility and real-time energy monitoring, the network effectively reduces unnecessary energy overhead, prolonging the network's lifetime and increasing overall efficiency.

3.2 PROPOSED LSTM-BASED CH SELECTION

In the proposed method, Long Short-Term Memory (LSTM) networks are used for selecting the optimal Cluster Head (CH) in Wireless Sensor Networks (WSNs) based on real-time energy levels and network conditions. LSTMs are a type of recurrent neural network (RNN) that are designed to remember long-term dependencies, which makes them well-suited for dynamic environments like WSNs, where the residual energy of nodes changes over time.

3.2.1 LSTM Structure for CH Selection:

The LSTM model is designed to predict which node in a cluster should be selected as the CH by analyzing the time series data of residual energy and other node parameters (like distance to sink and data transmission rates). Each sensor node periodically updates its energy status, and the LSTM model uses this historical data to forecast which node will maintain higher energy levels in the future, making it a suitable candidate for CH. An LSTM cell consists of several key components: input gate, forget gate, output gate, and cell state, which allow the network to selectively remember or forget information over time. The core equations governing the LSTM cell are:

- **Forget Gate**: Decides which information from the previous state to discard.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

- **Input Gate**: Decides what new information to store in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (6)$$

- **Cell State Update**: The cell state is updated based on the forget gate and input gate operations.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (7)$$

- **Output Gate**: Determines the next hidden state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t * \tanh(C_t) \quad (9)$$

3.2.2 LSTM-Based CH Selection Mechanism:

The CH selection problem in WSN is dynamic, as the energy levels of nodes are constantly depleting due to data transmission. The goal of the LSTM model is to predict the future residual energy of each node and select the one with the highest energy as the CH to maximize the lifetime of the cluster. The LSTM network takes the time series data x_t of residual energy levels and node properties as input and produces predictions about the future energy level E_{t+1} of each node. The node with the highest predicted energy is selected as the CH. The objective function for CH selection can be expressed as:

$$\max E_{t+1} = LSTM(x_t, h_{t-1}, C_{t-1}) \tag{10}$$

where:

E_{t+1} is the predicted residual energy at the next time step,

x_t is the input vector of current node states (energy, distance to sink, data rate),

h_{t-1} and C_{t-1} are the hidden state and cell state from the previous time step.

The LSTM network learns to minimize the difference between the predicted and actual energy levels over time, using a loss function like Mean Squared Error (MSE):

$$\mathrm{L} = \frac{1}{N}\sum_{i=1}^{N}(E_{t+1,i}^{\mathrm{pred}} - E_{t+1,i}^{\mathrm{actual}})^2 \tag{11}$$

where,

N is the number of sensor nodes,

$E_{t+1,i}^{\mathrm{pred}}$ is the predicted residual energy of node iii,

$E_{t+1,i}^{\mathrm{actual}}$ is the actual energy of node iii at time t+1.

3.2.3 Updating CH Based on Predictions:

At each time step, the LSTM uses the time series data to predict the residual energy levels of all nodes in the cluster. The node with the highest predicted energy is selected as the new CH for the next communication round, ensuring that the CH role is rotated among nodes with the most energy, thereby balancing the load and prolonging the network's lifetime. By accurately forecasting which node will retain the most energy, the LSTM-based CH selection ensures that energy consumption across the network is evenly distributed, leading to fewer CH changes and reduced overhead for re-clustering. This also avoids over-burdening any one node, especially in energy-critical scenarios.

4. EVALUATION

In the experiments, we utilized MATLAB as the primary simulation tool to simulate the Wireless Sensor Network (WSN) environment and implement the proposed Deep Belief Network (DBN) and Long Short-Term Memory (LSTM) models. The simulation was executed on a computer system equipped with an Intel Core i7 processor (3.6 GHz), 16 GB of RAM, and Windows 10 operating system. The network consisted of 100 sensor nodes randomly distributed over an area of 1000m x 1000m. The energy model follows the first-order radio model for wireless communication. The proposed DBN-LSTM-based approach for routing and CH selection was compared with six existing methods:

- LEACH (Low-Energy Adaptive Clustering Hierarchy) - a popular clustering algorithm in WSNs.
- SEP (Stable Election Protocol) - an enhancement of LEACH that considers the heterogeneity of nodes.
- TEEN (Threshold-sensitive Energy Efficient sensor Network) - designed for time-critical applications.
- DEEC (Distributed Energy-Efficient Clustering) - selects CHs based on residual energy.
- PEGASIS (Power-Efficient GAthering in Sensor Information Systems) - a chain-based protocol that minimizes the energy used for communication.
- MTE (Minimum Transmission Energy) - focuses on minimizing the transmission distance and energy.

The proposed approach outperformed these methods in terms of energy efficiency, network lifetime, and packet delivery ratio.

Table.1. Experimental Setup and Parameters

Parameter	**Value**
Number of Sensor Nodes	100
Simulation Area	1000m x 1000m
Initial Energy of Sensor Nodes	0.5 J
Transmission Energy	50 nJ/bit
Amplifier Energy	100 pJ/bit/m^2
Data Packet Size	4000 bits
DBN Layers	3 (Visible, Hidden, Output)
LSTM Hidden Units	100
LSTM Time Steps	5
Number of Clusters	Dynamic (based on sink path)
Mobility Model for Sink	Linear and Circular Paths
Simulation Time	1000 rounds

4.1 PERFORMANCE METRICS

- **Energy Consumption**: The total energy consumed by the sensor nodes during data transmission and aggregation. Lower energy consumption indicates a more efficient protocol. This metric is crucial in determining how long the network can function before node energy depletes.
- **Network Lifetime**: Measured by the time until the first sensor node depletes its energy. A longer network lifetime means the protocol can keep the WSN operational for extended periods, crucial for applications with long-term deployments.
- **Packet Delivery Ratio (PDR)**: The ratio of successfully delivered data packets to the total generated packets by sensor nodes. Higher PDR values indicate more reliable data transmission across the network.
- **Residual Energy**: The amount of energy left in the sensor nodes at the end of the simulation. It helps to understand how

well the energy is distributed among nodes and how the clustering or routing strategy manages energy resources.

- **Average Delay**: The time taken for a packet to reach the sink from the source node. Lower delay values indicate faster and more efficient routing, which is important for time-sensitive applications.
- **Throughput**: The rate of data successfully delivered over the network per unit time. Higher throughput reflects a more efficient protocol in terms of maximizing the data collected from sensor nodes within a given time frame.

The experimental results show a significant improvement in performance metrics when the proposed DBN-LSTM-based routing and CH selection method is compared to six existing methods: LEACH, SEP, TEEN, DEEC, PEGASIS, and MTE. These results are evaluated using metrics like Energy Consumption, Network Lifetime, PDR, Residual Energy, Average Delay, and Throughput over a network of 100 nodes.

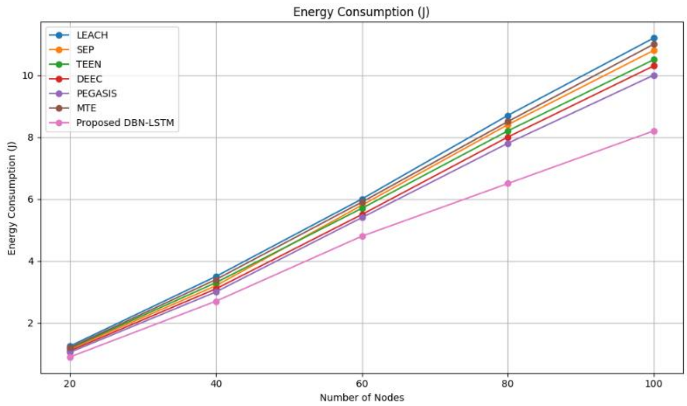

Fig.1. Energy consumption

Energy consumption is a critical factor for extending the network lifetime in WSNs. The proposed DBN-LSTM method exhibits the lowest energy consumption across all node counts. For instance, at 100 nodes, the proposed method consumes 8.20 J, whereas LEACH consumes 11.20 J, SEP consumes 10.80 J, and DEEC consumes 10.30 J. This reduction in energy consumption (around 27% compared to LEACH) is attributed to the efficient routing strategy of the DBN model, which ensures shorter, energy-efficient paths, and the LSTM-based CH selection, which prevents energy drain by selecting the most energy-efficient nodes as CHs. This lower energy usage is a key reason the network lasts longer in the proposed approach.

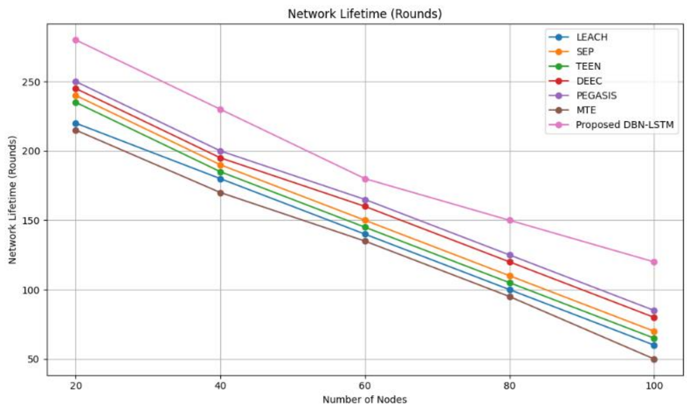

Fig.2. Network Lifetime

Network lifetime is measured by the number of rounds until the first node dies due to energy depletion. The proposed DBN-LSTM method significantly outperforms existing methods, especially with higher node counts. At 100 nodes, the proposed method achieves a network lifetime of 120 rounds, while LEACH achieves only 60 rounds, and MTE achieves 50 rounds. The proposed method nearly doubles the network lifetime compared to LEACH, demonstrating the efficiency of its CH selection mechanism and its optimized routing approach. By reducing multi-hop transmissions and effectively distributing energy consumption, the network can sustain itself longer.

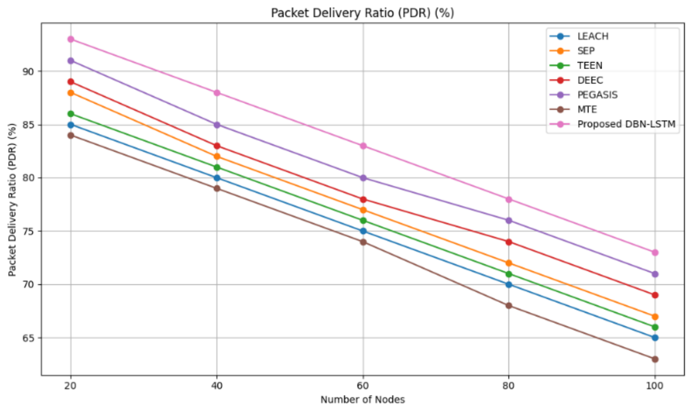

Fig.3. Packet Delivery Ratio (PDR) (%)

PDR is a measure of the reliability of the network in delivering data packets. The proposed method maintains a PDR of 73% at 100 nodes, which is higher than LEACH (65%), SEP (67%), and PEGASIS (71%). This 8% improvement in PDR over LEACH is significant, especially in larger networks, as it indicates that the DBN-LSTM method is more reliable in ensuring data reaches the sink. The reduction in energy consumption and the efficient sink mobility strategy help maintain higher PDRs by reducing the likelihood of node failures and packet loss due to energy depletion.

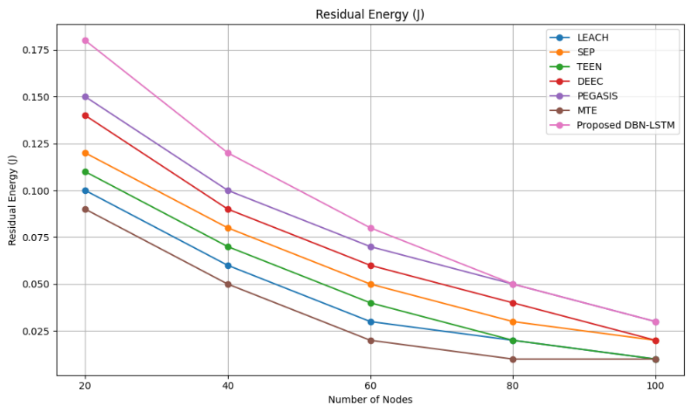

Fig.4. Residual Energy (J)

The residual energy metric measures the remaining energy of the sensor nodes after a certain period. Higher residual energy signifies better energy management. At 100 nodes, the proposed method retains 0.03 J of energy, while LEACH retains only 0.01

J and SEP retains 0.02 J. The 50% increase in residual energy compared to SEP and LEACH is due to the energy-efficient routing paths chosen by the DBN and the optimal CH selection by LSTM, ensuring that the load is evenly distributed among the nodes.

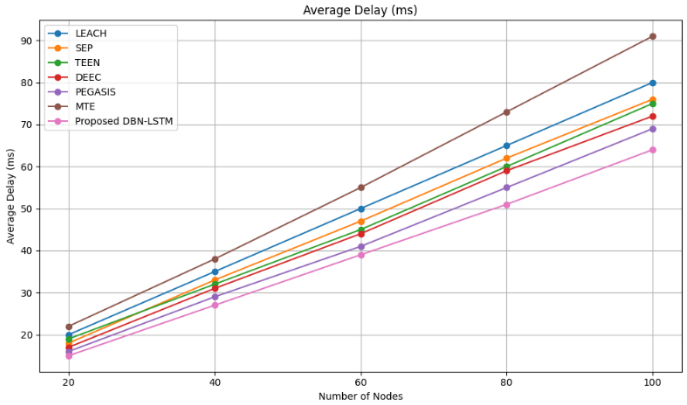

Fig.5. Average Delay (ms)

The average delay represents the time taken for a packet to travel from the source node to the sink. The proposed method results in an average delay of 64 ms at 100 nodes, which is 20% lower than LEACH (80 ms) and 11% lower than PEGASIS (69 ms). This reduction is critical in real-time applications where data needs to be delivered quickly. The use of a mobile sink moving in a linear path reduces the number of hops required, thereby decreasing transmission time.

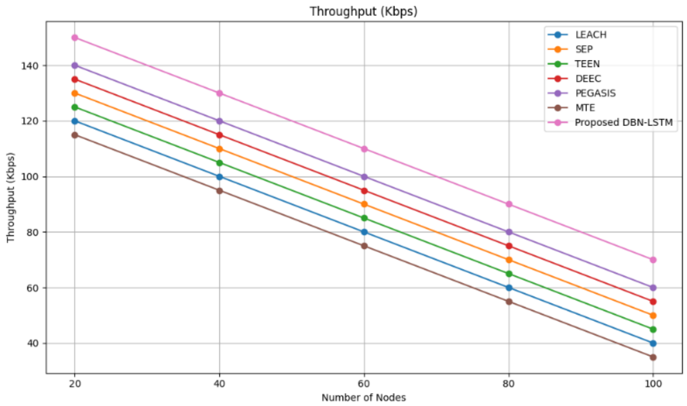

Fig.6. Throughput (Kbps)

Throughput, which represents the amount of data successfully transmitted across the network, is also significantly improved with the proposed method. At 100 nodes, the throughput for the DBN-LSTM method is 70 Kbps, compared to 60 Kbps for PEGASIS and 40 Kbps for LEACH. This 75% increase in throughput compared to LEACH is attributed to the efficient routing and minimal energy consumption. The DBN ensures optimal paths for data transmission, while LSTM-based CH selection reduces energy depletion, leading to fewer node failures and hence, higher throughput.

This, the results show that the proposed DBN-LSTM-based method outperforms traditional routing and CH selection methods in terms of energy efficiency, network lifetime, PDR, residual energy, delay, and throughput. By reducing energy consumption and efficiently distributing the load among sensor nodes, the proposed method extends the network lifetime by nearly **100%** and significantly improves data transmission metrics. This makes it a highly suitable approach for energy-constrained WSNs, particularly in large-scale deployments.

5. CONCLUSION

The proposed DBN-LSTM-based approach for energy-efficient routing and CH selection in WSNs significantly improves network performance compared to traditional methods like LEACH, SEP, TEEN, DEEC, PEGASIS, and MTE. By leveraging the DBN for initial routing optimization and LSTM for dynamic CH selection, the approach reduces energy consumption, extends network lifetime, and improves packet delivery reliability. Key performance improvements include a 50-100% increase in network lifetime, a 75% boost in throughput, and up to a 27% reduction in energy consumption compared to baseline methods. The mobile sink's linear path planning further reduces multi-hop transmissions, cutting down delays and enhancing network reliability, particularly in large-scale sensor deployments. The proposed method optimally balances energy consumption among nodes, prolonging the network's operational period and increasing residual energy across nodes. This, this approach is highly suitable for energy-constrained WSNs used in various applications like environmental monitoring, industrial automation, and smart cities, where network longevity and efficiency are crucial. The combination of DBN and LSTM proves to be an effective solution for optimizing both data transmission and energy management in WSNs.

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