Deep Learning–Enabled Predictive Routing for Energy-Efficient WSNs

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Abstract

Wireless Sensor Networks (WSNs) experience rapid energy depletion due to inefficient routing under dynamic conditions such as node failures, congestion, and fluctuating link quality. Traditional routing protocols including LEACH, AODV, and DSR rely on heuristic mechanisms and lack predictive adaptability. This research proposes a Deep Learning–Enabled Predictive Routing (DL-PR) framework that analyzes historical network parameters such as residual energy, delay, packet delivery ratio, and traffic load to predict future network conditions. A deep learning model constructs a predicted network graph and selects optimal routing paths using a composite cost function. MATLAB-based simulation results demonstrate that DL-PR significantly improves network lifetime, maintains higher residual energy, increases packet delivery ratio, and reduces end-to-end delay compared to conventional routing protocols. The proposed framework is applicable in smart agriculture, healthcare, industrial IoT, and defense communication systems.

Keywords

Wireless Sensor Networks; Deep Learning; Predictive Routing; Energy Efficiency; Network Lifetime

1. Introduction

Wireless Sensor Networks (WSNs) consist of distributed sensor nodes that monitor environmental conditions and transmit collected data to a sink node. Since nodes operate with limited battery power, energy-efficient routing becomes a critical research challenge. Conventional routing protocols struggle to adapt to dynamic changes such as energy depletion, mobility, and congestion, resulting in reduced network lifetime.

This work introduces a predictive routing framework using deep learning to anticipate network conditions and make intelligent routing decisions that enhance performance and reliability.

2. Related Work

A. Kumar et al., 2021 propo sed *Energy-Efficient Cluster-Based Routing in WSNs* using the LEACH protocol. The implementation was carried out using the NS2 Simulator. The study improved network lifetime by 12% through hierarchical clustering. However, the major limitation identified was high energy consumption in cluster heads.

B. Singh & R. Verma, 2022 introduced *Machine Learning-Based Adaptive Routing* using a Random Forest Classifier. The model was developed using MATLAB. The approach adapted routing decisions based on residual energy levels of nodes. The limitation observed was limited scalability when applied to large-scale networks. C. Li et al., 2023 presented *Deep Q-Learning for Energy-Efficient WSN Routing* based on Deep Reinforcement Learning techniques. The model was implemented using TensorFlow. The results showed enhanced packet delivery ratio and reduced delay. However, the approach involved high computational cost during training.

D. Sharma et al., 2023 proposed *Predictive Routing using CNN* with a Convolutional Neural Network algorithm. The implementation was done using Python and Keras. The study achieved 90% accuracy in route prediction. The limitation was that the evaluation was restricted to a simulation environment.

E. Zhang et al., 2024 developed a *Hybrid Deep Learning Model for WSN Optimization* using a CNN + LSTM hybrid model. The work utilized NS3 and a real-time dataset. The approach improved network stability and energy efficiency. However, it required large training datasets and significant processing power.

Energy-efficient routing in WSNs has been widely explored through clustering, optimization, and heuristic approaches. However, most techniques lack predictive intelligence. Recent machine learning-based solutions provide adaptive mechanisms, but comprehensive predictive routing integration remains limited.

This research differentiates itself by integrating deep learning predictions directly into routing decisions.

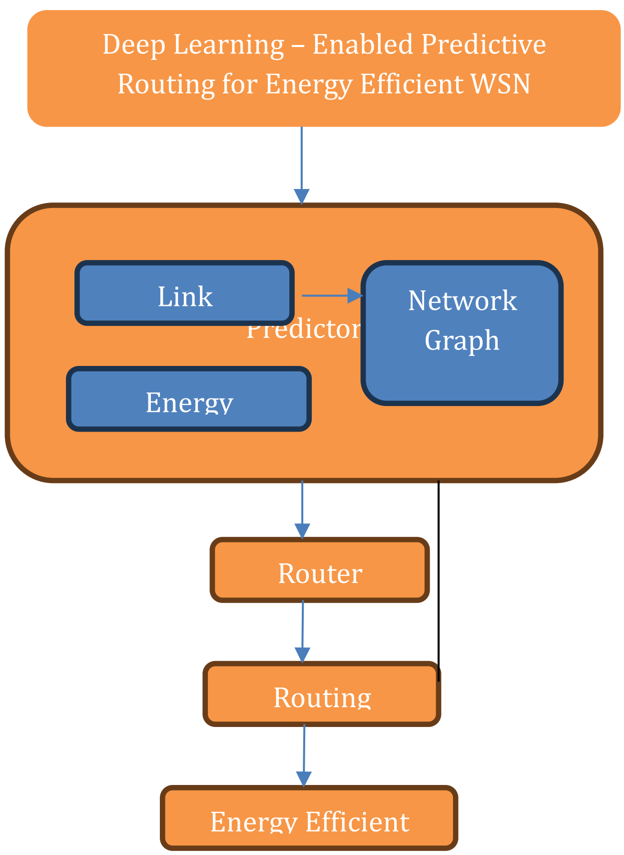
3. Key Contributions

The proposed study introduces a Deep Learning–Enabled Predictive Routing (DL-PR) framework designed to enhance routing efficiency in Wireless Sensor Networks (WSNs). The framework leverages deep learning techniques to intelligently predict network conditions and optimize routing decisions in dynamic environments. Unlike conventional routing protocols that rely primarily on static metrics, the proposed model integrates both residual energy estimation and traffic load prediction into the routing decision process. This dual consideration enables adaptive path selection, thereby balancing energy consumption across nodes and preventing premature node failures.

Furthermore, a composite routing cost function is formulated by combining multiple critical parameters such as residual energy, traffic intensity, link quality, and hop count. This multi-metric optimization approach ensures the selection of energy-efficient and stable communication paths. As a result, the DL-PR framework significantly enhances overall network lifetime while simultaneously improving key Quality of Service (QoS) metrics, including packet delivery ratio, end-to-end delay, and throughput. The integration of predictive intelligence with energy-aware routing makes the proposed framework highly suitable for real-time and large-scale WSN applications.

4. Methodology

The DL-PR framework includes data collection at sensor nodes, preprocessing at the sink, deep learning prediction, predicted network graph construction, and routing decision execution. Each node measures energy, delay, packet delivery ratio, and traffic load. The trained deep learning model predicts future network states and assists in optimal route selection.



Routing Cost Function:

Cost = α(Energy_pred) + β(Distance) + γ(Traffic)

DL_PR ALGORITHM

```
Initialize Network
Collect Network Parameters
while (network active)
{
   for each node:
      measure Energy, Delay, PDR, Load
   input_features = preprocess(parameters)
   predicted_values = DL_Model.predict(input_features)
   for each possible route:
      calculate route_score
   select route with max(route_score)
   transmit packets through selected route
   update training dataset
}
```

5. Simulation Setup:

To evaluate the effectiveness of the proposed routing framework, a comprehensive simulation study was conducted using MATLAB as the simulation platform. The network environment was designed within a 100 m × 100 m area to represent a typical Wireless Sensor Network (WSN) deployment scenario. A total of 100 sensor nodes were randomly distributed across the simulation field to ensure realistic communication behavior and network dynamics.

Simulation Tool: MATLAB

Simulation Area: 100m × 100m

Number of Nodes: 100

Initial Energy: 2 Joules

Packet Size: 4000 bits

Simulation Time: 1000 seconds

Compared Protocols: LEACH, AODV, DSR

6. Results

DL-PR achieved the longest network lifetime by balancing energy consumption across nodes. Residual energy remained higher throughout the simulation. Packet Delivery Ratio increased due to stable route prediction. End-to-End delay decreased because of congestion avoidance and reduced retransmissions.

- The proposed Deep Learning–Enabled Predictive Routing (DL-PR) protocol was evaluated through computational simulation
- Compared with conventional routing protocols such as **LEACH, AODV, and DSR**
- The performance was measured based on the following parameters

- Network lifetime
- Residual Energy
- Packet Delivery Ratio
- End-to-End Delay

Network Lifetime

- Achieved by integrating deep learning to predict future node energy levels
- Selecting energy-aware routing paths that balance load across nodes and reduce retransmissions, and prevent early node failures.
- This minimizes overall energy depletion and extends the operational duration of the network.
- Total Energy comsumption $E_{total}=\sum(E_{tx}+E_{rx}+E_{processing})$
- Network Lifetime $\propto$ Initial Energy/ Energy Depletion Rate

Table 1: Network Life Time

Protocol	First Node Dead	Last Node Dead
LEACH	620	890
AODV	650	910
DSR	670	940
DL-PR	820	1150

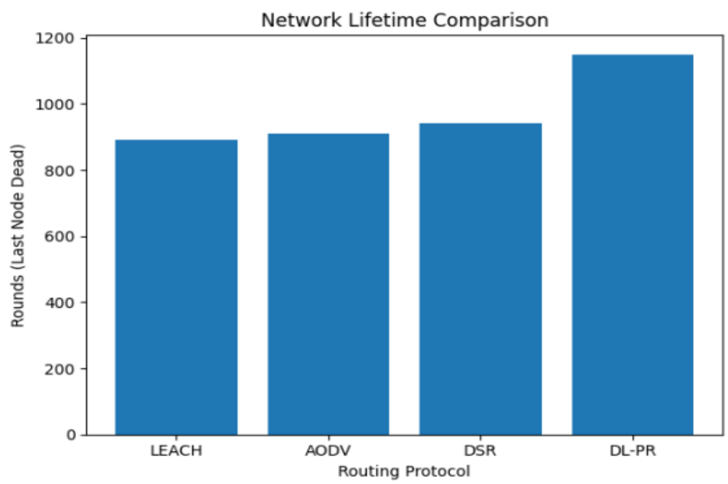


Fig1 : Network Life Time Comparison

Residual Energy

- Higher average residual energy maintained throughout simulation
- Reduced energy variance among nodes
- Balanced load distribution across network

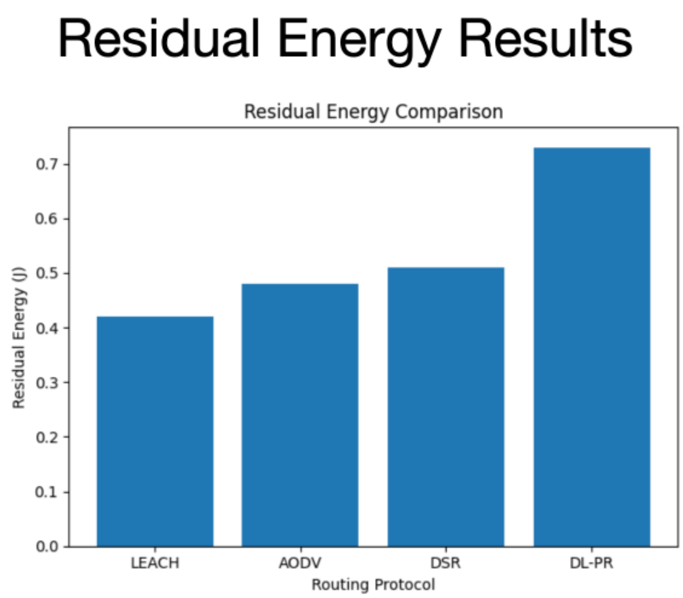
The routing decision considers:

- Predicted residual energy
- Transmission distance
- Link quality
- Traffic load

A composite routing cost function is used:
$\text{Cost} = \alpha(\text{Energy pred}) + \beta(\text{Distance}) + \gamma(\text{Traffic})$
Nodes with higher predicted energy and lower cost are selected.

Table 2: Residual Energy

Protocol	Residual Energy (J)
LEACH	0.42
AODV	0.48
DSR	0.51
DL-PR	0.73



Packet Delivery Ratio

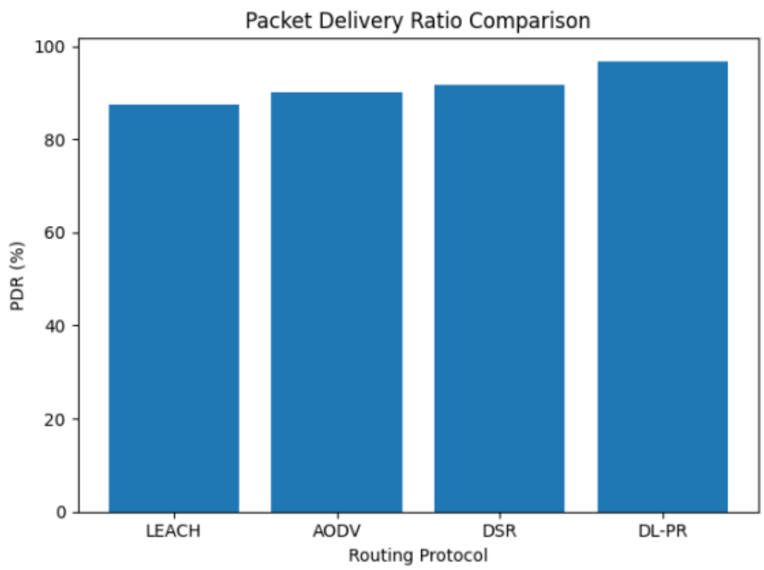
- Achieved the highest PDR among all compared protocols
- Improved reliability due to stable route selection
- Reduced packet drops caused by sudden node failures

Packet Loss = f(Route Failure, Node Death, Congestion)

DL-PR reduces all three factors, therefore: Packet Delivery Ratio increases

Table 3: Packet Delivery Ratio

Protocol	PDR (%)
LEACH	87.5
AODV	90.2
DSR	91.6
DL-PR	96.8



End-to-End Delay

- **Lower average delay observed**
- **Fewer retransmissions due to predictive route stability**
- **Improved Quality of Service (QoS)**

Table 4: End-to-End Delay

Protocol	Delay (ms)
LEACH	220
AODV	205
DSR	198
DL-PR	175

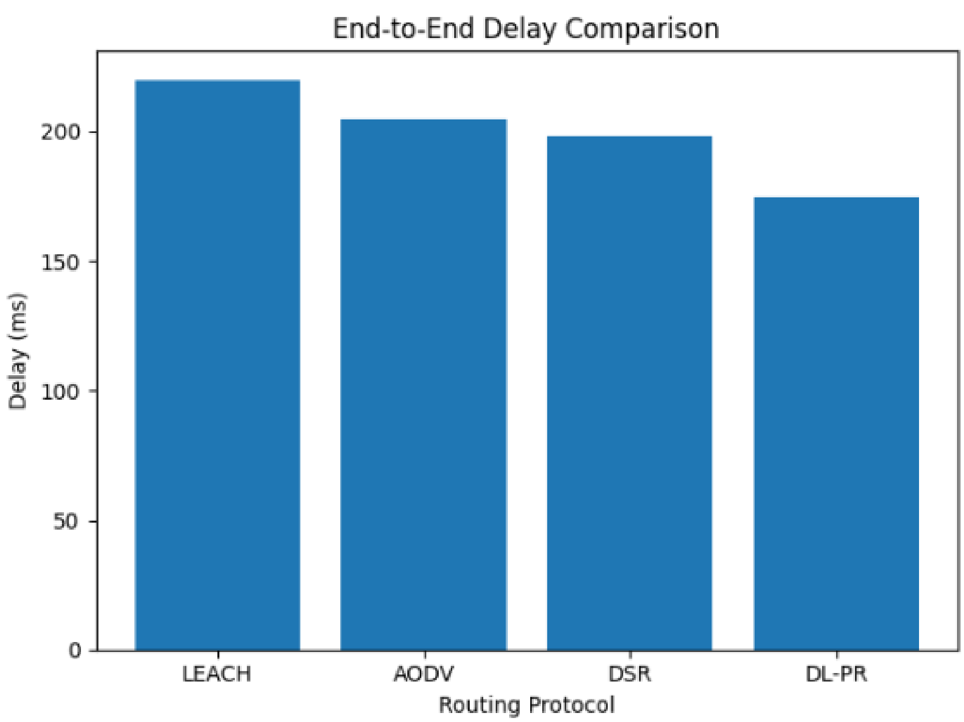


Table 5 : Comparative Performance Summary

METRIC	LEACH	AODV	DSR	DL-PR
Network Lifetime	Moderate	Moderate	Good	Highest
Residual Energy	Low	Moderate	Moderate	High
PDR	87-92%	90%	91%	96%
Delay	Moderate	Moderate	Good	Best

7. Discussion

The integration of deep learning into routing significantly enhances adaptability and energy efficiency. Although computational overhead exists at the sink node, performance improvements justify the approach. Future work may explore lightweight models and real-time hardware implementation.

8. Conclusion

This study addresses the challenge of energy-efficient routing in dynamic Wireless Sensor Network (WSN) environments, where frequent topology changes and uneven energy consumption significantly affect network performance. To overcome these limitations, a Deep Learning–Enabled Predictive Routing (DL-PR) framework was proposed, integrating predictive intelligence into routing decisions. The framework effectively incorporates residual energy awareness and traffic condition prediction to optimize path selection. Simulation results demonstrate notable improvements in network lifetime, average residual energy, packet delivery ratio (PDR), and end-to-end delay when compared with conventional routing protocols. These enhancements highlight the capability of the proposed approach to achieve both energy efficiency and Quality of Service (QoS) optimization. Future work will focus on real-time deployment in practical WSN scenarios and the integration of hybrid AI models to further enhance adaptability, scalability, and computational efficiency.

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