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. Inclusion/Exclusion criteria

- **Inclusion Criteria:**
    - Sensor nodes with **adequate battery power** (above a certain threshold).
    - **Active nodes** participating in data transmission.
    - **Data packets** with valid timestamps and routing metadata.

    - **Simulation scenarios** that meet minimum network density or connectivity requirements.
    - **Deep Learning models** trained on relevant features such as node energy, distance, or link quality.
- **Exclusion Criteria:**
    - **Dead or inactive nodes** with no residual energy.
    - **Corrupted or incomplete data packets**.
    - **Outlier readings** caused by hardware malfunction or noise.
    - **Scenarios** where network topology is unstable or not representative.
    - **Routing cases** not applicable to predictive or energy-efficient models.

3. Databases for conducting search:

Database	Relevance to Topic
IEEE Xplore Digital Library	Highly relevant — most WSN and deep learning routing papers are published here (e.g., IEEE IoT Journal, IEEE Sensors Journal).
ScienceDirect (Elsevier)	Provides extensive peer-reviewed journal papers on AI models and energy-efficient networking.
ACM Digital Library	Offers papers on machine learning-based routing, edge computing, and network protocols.
Scopus	Excellent for identifying citation trends and filtering high-impact articles.
Web of Science (Clarivate)	Enables advanced citation analysis and tracking of emerging research in predictive networking.

4. Review & Analyze Results | Synthesize- Strength, Limitations

Aspect	Observation/Findings

Result Analysis	**The deep learning routing model will achieve higher energy efficiency and better routing accuracy**
Strengths	**Adaptive routing, reduced energy consumption, scalability, improved prediction accuracy**
Limitations	**High training overhead, dependency on data quality, limited real-world validation.**

5. 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.

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