Deep Learning-Enabled Predictive Routing for Energy-Efficient Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are extensively used in fields like smart agriculture, healthcare, industrial automation and environmental monitoring. Energy-efficient routing continues to be one of the main issues influencing network longevity and Quality of Service (QoS) because sensor nodes run on limited battery power. Conventional routing protocols such as LEACH, AODV and DSR typically rely on static routing algorithms and are unable to efficiently adjust to dynamic network situations such as varying connection quality, traffic congestion and node energy depletion. The Deep Learning-Enables Predictive Routing (DL-PR) system proposed in this research uses past data such as residual energy, packet delivery ratio, traffic load and communication delay to forecast future network conditions. A composite routing cost function is used to determine dependable and energy-efficient routing paths based on the anticipated network condition. When compared to traditional routing protocols, simulation experiments using MATLAB show that the suggested architecture greatly boosts network lifetime, maintains higher residual energy, raises packet delivery ratio and lowers end-to-end delay. For the future generation of IoT-enabled Wireless Sensor Networks, the suggested framework provides an intelligent routing solution.

Keyword: Wireless Sensor Networks, Deep Learning, Predictive Routing, Energy Efficiency, Network Lifetime, Internet of Things

Introduction

Wireless Sensor Networks (WSNs) are made up of many battery-operated sensor nodes that work together to gather and send data to a base station. The need for dependable and energy-efficient communication protocols has grown as a result of their extensive use in smart cities, environmental monitoring, healthcare systems, industrial automation and military surveillance. Reducing energy usage is crucial for extending network lifetime because it is frequently impractical to replace or recharge batteries.

Conventional routing protocols such as LEACH, AODV and DSR are unable to effectively adapt to dynamic changes in node energy, traffic conditions or connection quality since they mostly rely on predetermined routing metrics. As a result, the network’s overall performance is decreased by frequent route failures, packet loss and increased communication delay.

This paper suggests a Deep Learning-Enabled Predictive Routing (DL_PR) framework that anticipates future network conditions intelligently before making routing decisions in order to get around these restrictions. The suggested architecture balances energy usage among sensor nodes while enhancing communication reliability through the integration of deep learning and energy-aware routing.

Related Work

For WSNs, a number of researchers have suggested energy-efficient routing strategies. Through hierarchical communication, cluster-based routing protocols like LEACH increase energy efficiency, however they frequently experience unequal energy depletion among cluster heads. Although adaptive routing based on network characteristics has been introduced via machine learning techniques, their scalability for large sensor networks is still constrained. More recently, gains in packet delivery ratio and network stability have been shown via hybrid CNN-LSTM models and deep reinforcement learning. However, a lot of current approaches need a lot of processing power and big training sets.

In contrast to earlier methods, the suggested DL-PR framework minimizes overall energy usage while enabling intelligent route selection by combining deep learning-based prediction with several routing criteria such as residual energy, traffic load, communication delay and link quality.

Proposed Deep Learning-Enabled Predictive Routing Framework

Figure 1 illustrated the five main phases of the suggested framework:

- Gathering network data from sensor nodes.
- Preparing and normalizing data
- Using a deep learning model, future network conditions are predicted.
- Building a projected network graph
- Using a composite routing cost function to determine the best routing path.

The sink node received constant reports from each sensor node regrading remaining energy, packet delivery ratio, communication delay and traffic load. In order to predict future network circumstances, the trained deep learning model processes these parameters. The routing algorithm chooses routes with greater residual energy, improved link quality and less congestion based on the projected values.

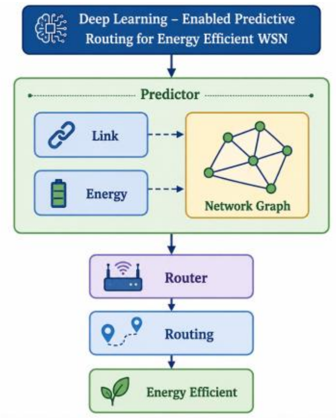

Figure 1: Deep Learning Enabled Predictive Routing for Energy Efficient WSN

The routing cost function is expressed as

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

where α, β, and γ represent weighting coefficients that prioritize energy efficiency, communication distance and traffic conditions respectively.

The predictive routing strategy distributes communication load evenly among sensor nodes, reducing premature node failures and improving overall network performance.

Simulation Setup

The effectiveness of the proposed framework was evaluated using MATLAB simulation

Table 1: Simulation Parameters

Parameter	Value
Simulation Area	100 × 100 m
Number of Nodes	100
Initial Energy	2 Joules
Packet Size	4000 bits
Simulation Time	1000 seconds
Compared Protocols	LEACH, AODV, DSR

The proposed DL-PR protocol was compared with three widely used routing protocols based on four performance metrics as shown in Table 1: Network Lifetime, Residual Energy, packet Delivery Ratio (PDR) and End-to-End Delay.

Results and Discussion

Simulation results demonstrate that the proposed DL-PR framework consistently outperforms conventional routing protocols as shown in Table 2.

The first node in the DL-PR network becomes inactive only after 820 rounds, whereas LEACH experiences its first node failure at 620 rounds. Similarly, the last node services until 1150 rounds, indicating a significant improvement in network lifetime due to balanced energy utilization.

The average residual energy achieved by DL-PR is 0.73 J, considerable higher than LEACH (0.42 J), AODV (0.48 J) and DSR (0.51 J). This demonstrates the effectiveness of predictive routing in minimizing unnecessary energy consumption.

The Packet Delivery ratio reached 96.8% exceeding the performance of all conventional protocols. Accurate route prediction, minimizes packet drops caused by congestion and node failures, thereby improving communication reliability.

Similarly, the average End-to-End Delay decreases to 175 ms, compared with 220 ms in LEACH, resulting in faster transmission and improved Quality of Service.

Table 2 Comparative Performance

Protocol	Network Lifetime	Residual Energy (J)	PDR (%)	Delay (ms)
LEACH	620	0.42	87.5	220
AODV	650	0.48	90.2	205
DSR	670	0.51	91.6	198
DL-PR	**820**	**0.73**	**96.8**	**175**

Conclusion

This paper presented a Deep Learning-Enabled Predictive Routing (DL-PR) framework for improving energy efficiency in Wireless Sensor Networks. Unlike conventional routing techniques, the proposed method predicts future network conditions before route selection, enabling intelligent and adaptive communication decisions. Simulation results demonstrate significant improvements in network lifetime, residual energy, packet delivery ratio and communication delay compared with LEACH, AODV and DSR. The proposed framework effectively balanced energy consumption while maintaining reliable communication, making it suitable for IoT-based applications such as smart agriculture, healthcare monitoring, industrial automation and intelligent transportation systems. Future work will focus on real-time deployment using edge computing platforms and lightweight deep learning models for large-scale sensor networks.

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