Energy-Efficient Routing in IoT Networks using Reinforcement Learning

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Abstract— **IoT networks suffer from rapid battery depletion, unstable link quality, and dynamic topologies that make traditional routing inefficient. Existing energy-aware routing protocols rely on static rules and cannot adapt to real-time variations in node energy, traffic load, or link reliability. This paper proposes an adaptive Reinforcement Learning-based routing framework that integrates multi-factor reward design, topology awareness, and predictive energy modeling to extend IoT network lifetime. The model evaluates residual energy, link quality, node stability, and estimated future consumption to select optimal routes. Experiments conducted in NS-3 demonstrate improved network lifetime, balanced energy consumption, and higher packet delivery ratio compared to LEACH, AODV-Energy, and basic RL models. The novelty lies in combining multi-factor reward shaping with dynamic learning, enabling IoT nodes to autonomously adapt routing policies under changing conditions.**

Index Terms—**IoT Routing, Reinforcement Learning, Energy Efficiency, Multi-Agent RL, Network Lifetime Optimization.**

I. INTRODUCTION

The evolution of IoT technologies has led to extensive deployments of battery-powered sensing and monitoring devices. These devices operate in unpredictable physical environments and must maintain operation for extended durations without frequent maintenance. Energy consumption becomes a critical parameter in determining the overall viability and reliability of IoT systems. Among various energy-consuming processes, wireless communication accounts for the highest proportion, making routing strategies essential for prolonging network lifespan.

Traditional routing protocols such as AODV, DSR, and LEACH were developed for mobile ad-hoc or clustered networks, but their static decision rules limit their effectiveness in dynamic IoT scenarios. Wireless interference, varying node workloads, environmental disruptions, and energy disparities often lead to imbalanced network usage and premature failure of critical nodes.

Reinforcement Learning (RL), with its ability to learn from interaction and improve over time, provides a strong foundation for adaptive routing. RL agents learn optimal behaviors by receiving rewards or penalties based on their actions. However, existing RL-driven routing approaches often simplify environmental conditions and overlook key metrics such as link stability, node congestion, and predicted energy drain.

To address these limitations, this paper presents a new adaptive RL routing framework capable of:
• Analyzing multi-factor network states,
• Predicting short-term battery depletion trends,
• Adjusting routing policies autonomously,
• and balancing energy consumption across nodes.
The system enhances overall network lifetime while maintaining a stable communication structure.

II. LITERATURE REVIEW

A. Traditional Energy-Aware Routing Protocols
Several traditional routing protocols aim to reduce energy consumption in IoT networks. LEACH uses clustering to reduce communication overhead but suffers from uneven cluster head distribution. AODV-Energy introduces energy awareness but still employs static decision-making. These protocols lack real-time adaptability.

B. Reinforcement Learning for Routing
RL-based routing methods have gained traction due to their adaptability. Q-learning has been applied for next-hop selection, but its performance deteriorates in

large networks due to state explosion. Deep RL models address scalability but require high computational power, which is often unavailable in IoT devices.

C. Multi-Agent Reinforcement Learning (MARL)

MARL techniques allow nodes to cooperate but face challenges such as convergence instability and high overhead. Their application in IoT routing is still limited and requires lightweight implementations.

D. Energy Prediction in IoT Networks

Studies highlight that energy prediction enhances routing performance. Most approaches use fixed forecasting models without integrating predictions into RL routing decisions.

E. Research Gaps

The literature reveals key gaps:

- Limited use of multi-factor RL (battery, link quality, queue length, energy forecast).
- Lack of adaptive reward mechanisms.
- Poor performance in dynamic or heterogeneous networks.
- Minimal integration of predictive analytics into routing decisions.

The proposed framework addresses all these gaps through an integrated RL-based routing model.

III. PROBLEM STATEMENT

IoT nodes operate in unpredictable environments with limited energy resources. Current routing solutions are insufficient due to:

- Static routing that does not adapt to real-time energy variations,
- Inefficient load balancing leading to early battery drainage of central nodes,
- Poor routing decisions resulting from ignoring link quality and queue status,
- Lack of predictive modeling for energy usage,
- Inability of existing RL models to generalize across dynamic topologies.

There is a clear need for an adaptive RL-based routing method capable of analyzing multi-dimensional network states and optimizing routing decisions to extend overall network lifetime.

IV. METHODOLOGY

A. Research Approach

A simulation-based experimental methodology was used, combining RL modeling with detailed IoT network emulation.

B. Simulation Environment

- Simulator: NS-3 (Energy, Mobility, Propagation models)
- Topologies: Grid, random, clustered, and mixed IoT nodes
- Node capacity: 200–500 mAh battery models
- Traffic: Periodic sensing + random event-based traffic

C. State Representation

Each IoT node observes the following parameters:

1. Residual energy
2. Link quality (RSSI, packet loss rate)
3. Queue length
4. Node degree (connectivity)
5. Predicted short-term energy consumption
6. Neighbor stability index

D. Actions

The RL agent selects:

- Optimal next-hop node
- Optional sleep/wake scheduling for energy saving

E. Reward Design

The reward includes multiple components:

- Positive reward for successful delivery
- Penalty for high energy usage
- Penalty for draining low-energy nodes
- Bonus for load balancing
- Penalty for selecting unstable or unreliable links

F. Tools and Technologies

- Python (RL agent implementation)
- Stable Baselines3 (PPO / DQN)
- NS-3 Python bindings
- Pandas + Matplotlib for analytics

G. Evaluation Metrics

1. Packet Delivery Ratio (PDR)
2. Network Lifetime
3. Average Residual Energy

4. Energy Fairness Index
5. End-to-End Delay
6. Routing Overhead

V. PROPOSED ARCHITECTURE

The architecture includes:
1. State Observation Module
Collects node-level parameters and updates them continuously.

2. Energy Prediction Engine
Uses past consumption trends to estimate near-future battery drain.

3. Reinforcement Learning Agent
An actor-critic model processes state inputs and outputs optimal routing decisions.

4. Reward Shaping Module
Dynamically adjusts rewards based on network performance and energy distribution.

5. Routing Decision Executor
Enforces forwarding decisions and updates RL agent state.

6. Feedback Loop
State and reward information are fed back into the RL model for continuous improvement.

VI. DISCUSSION

The adaptive RL-based routing model provides significant advantages over traditional routing. It reduces energy consumption by intelligently balancing load across nodes while avoiding overuse of high-energy nodes. The RL model adapts to failures, energy drops, and varying link conditions, making it suitable for harsh and dynamic environments.
However, RL training can be computationally intensive. Lightweight RL implementations may be required for deployment on resource-constrained nodes. Simulations may not fully capture real-world hardware limitations, suggesting the need for physical testbed validation.

VII. CONCLUSION

This paper presents an adaptive RL-based routing framework that effectively improves energy efficiency and network performance in IoT deployments. By integrating multi-factor state modeling, predictive analytics, and dynamic reward shaping, the proposed system outperforms conventional routing protocols. Future work will explore hardware implementation, federated RL for privacy-preserving routing, and GNN-based topology reasoning for enhanced scalability.

REFERENCES

[1] A. Shinde, "Intelligent Routing Models for Low-Power IoT Networks," Journal of Emerging Communication Systems, 2022.
[2] R. Kulkarni, "Energy Trends and Optimization Methods in IoT," International Sensor Technology Review, 2021.
[3] M. Lonkar, "Learning-Based Wireless Routing Approaches," Advanced Computing Studies, 2023.
[4] P. Thombre, "Adaptive Mechanisms for IoT Connectivity," Global Networks Journal, 2020.
[5] S. Rathi, "Resource-Aware Algorithms for Distributed IoT Devices," Modern Engineering Innovations, 2024.