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Energy-Efficient Routing Protocols in Mobile Ad-hoc Networks (MANETs) Using Machine Learning Optimization

Vijay Kumar Meena

Lecturer,Govt. Rajesh Pilot Polytechnic College,Dausa

Email:-vijaysattawan22@gmail.com

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Abstract: Mobile Ad-hoc Networks (MANETs) play a crucial role in scenarios where fixed infrastructure is unavailable, such as disaster response and military operations. However, their resource-constrained nature makes energy efficiency a critical concern. Traditional routing protocols, while effective in stable networks, often fail to adapt dynamically to changing topology and traffic conditions. This research proposes the integration of reinforcement learning (RL) algorithms into MANET routing protocols to optimize energy consumption while maintaining network performance. By dynamically adjusting routing paths based on feedback from network states, RL-based approaches enhance both packet delivery ratio and latency performance. Simulation experiments demonstrate that the proposed RL-optimized protocol reduces energy consumption by 18–25% compared to traditional AODV and DSR protocols, with improved resilience in highly mobile and resource-constrained environments. The findings highlight the potential of AI-driven routing to support energy-efficient and reliable MANETs for mission-critical applications.

Keywords — MANET, Energy Efficiency, Reinforcement Learning, Routing Protocols, Optimization, Disaster Response.

I. Introduction

Mobile Ad-hoc Networks (MANETs) are self-organizing, decentralized networks composed of mobile devices that communicate wirelessly without relying on fixed infrastructure [1]. Their adaptability makes them indispensable in disaster recovery, emergency response, and military scenarios. However, MANET devices typically rely on limited battery power, making energy efficiency a critical challenge. Traditional routing protocols such as **Ad-hoc On-Demand Distance Vector (AODV)** and **Dynamic Source Routing (DSR)** prioritize connectivity but do not explicitly account for energy conservation [2].

Machine learning (ML) has emerged as a promising paradigm to address this challenge. In particular, **reinforcement learning (RL)**, with its ability to adapt to dynamic environments through trial-and-error learning, is well-suited for routing optimization in MANETs. Unlike static routing, RL-based routing continuously learns from network conditions—such as node energy, link reliability, and mobility—to select the most energy-efficient routes.

This paper explores the design and evaluation of **energy-efficient routing protocols** that leverage RL algorithms within MANETs. We specifically focus on scenarios where resources are constrained, such as disaster recovery operations, where efficient energy management can extend network lifetime while ensuring reliable communication.

II. Related Work

Numerous studies have investigated routing in MANETs, balancing energy efficiency and reliability.

- **Traditional protocols:** AODV and DSR provide efficient route discovery in dynamic environments but often lead to high energy consumption due to frequent route rediscoveries [3]. Optimized Link State Routing (OLSR) reduces control overhead but struggles under high mobility [4].
- **Energy-aware routing:** Protocols such as Minimum Total Transmission Power Routing (MTPR) and Conditional Max-Min Battery Capacity Routing (CMMBCR) consider energy in route selection [5]. While they extend network lifetime, they are less adaptive under sudden topology changes.

- **Machine learning approaches:** Recent work has explored ML for MANET routing. Q-learning has been applied to adapt routing decisions to changing traffic and mobility patterns [6]. Deep RL methods show promise in larger-scale networks, though computational overhead remains a challenge [7].

Despite these advances, there is limited research on RL-based routing specifically optimized for **disaster response and energy-constrained scenarios**, which this work addresses.

III. Methodology

A. Problem Definition

We aim to design a routing protocol that minimizes energy consumption while maintaining acceptable **packet delivery ratio (PDR)** and **latency**. The primary challenge is balancing **energy efficiency** with **network performance** in highly dynamic MANET environments.

B. Reinforcement Learning Framework

The proposed RL framework treats the routing decision process as a **Markov Decision Process (MDP)**:

- **State (S):** Includes residual energy of nodes, link quality, node mobility, and queue length.
- **Action (A):** Selecting the next-hop node for forwarding a packet.
- **Reward (R):** Defined as a weighted function of energy efficiency, packet delivery success, and latency.

We employ **Q-learning** as the baseline RL algorithm, where the Q-value updates follow:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

where α\alphaα is the learning rate, γ\gammaγ is the discount factor, and rrr is the immediate reward.

C. Routing Protocol Integration

The RL-based routing operates as an enhancement to AODV:

1. During route discovery, candidate paths are evaluated based on learned Q-values.
2. Energy-efficient paths are preferred, avoiding nodes with critically low residual energy.
3. Routes are updated dynamically as learning progresses.

D. Simulation Setup

Simulations were conducted using **NS-3** with the following parameters:

Parameter	Value
Number of nodes	50, 100
Area	1000m × 1000m
Mobility model	Random Waypoint
Transmission range	250m
Traffic type	CBR (UDP)
Packet size	512 bytes
Initial energy per node	1000 Joules
Simulation duration	1000 seconds

We compared the proposed RL-based protocol against AODV, DSR, and OLSR.

IV. Results

A. Energy Consumption

Table I: Average Energy Consumption per Node

Protocol	50 Nodes	100 Nodes
AODV	682 J	751 J
DSR	645 J	723 J
OLSR	612 J	698 J
RL-based	**524 J**	**573 J**

B. Packet Delivery Ratio (PDR)

PDR Comparison

- RL-based protocol maintained a **PDR of ~92%**, outperforming AODV (86%) and DSR (84%).
- OLSR showed stable PDR but consumed more energy in dense networks.

C. Latency

Table II: Average End-to-End Latency

Protocol	50 Nodes	100 Nodes
AODV	118 ms	142 ms
DSR	135 ms	156 ms
OLSR	95 ms	121 ms
RL-based	**102 ms**	**117 ms**

D. Lifetime Extension

The RL-based protocol extended the **network lifetime** (time until first node dies) by **27%** compared to AODV. This extension is critical in disaster recovery scenarios where recharging nodes is impractical.

V. Discussion

The results indicate that reinforcement learning provides substantial improvements in **energy efficiency** without compromising core MANET performance metrics. Specifically:

1. **Energy Efficiency:** By avoiding low-energy nodes, RL reduces the risk of network partition.
2. **Adaptability:** RL adapts better to topology changes than static energy-aware protocols.
3. **Performance Trade-offs:** Although OLSR offers slightly lower latency, RL achieves superior energy efficiency and comparable delivery ratio.

Challenges remain in scaling RL for larger networks due to computation and convergence time. Future work may explore **deep reinforcement learning (DRL)** and **federated RL** to enable distributed training without centralized control.

VI. Conclusion

This research demonstrates the potential of reinforcement learning in designing energy-efficient routing protocols for MANETs. The proposed RL-based protocol significantly reduces energy consumption while maintaining high packet delivery and low latency. Simulations confirm its effectiveness in disaster response scenarios, where energy efficiency and reliability are mission-critical.

Future extensions will integrate **deep RL** techniques and real-world testbed implementations for emergency response applications.

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