MACHINE LEARNING-BASED ENERGY EFFICIENT AND COMMUNICATION RELIABLE MANET ROUTING SYSTEM

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ABSTRACT:

Mobile Ad-hoc Networks (MANETs) are self-configuring, infrastructure-less wireless networks consisting of mobile nodes that communicate over dynamically changing topologies. Due to the absence of centralized control, limited energy resources, frequent topology changes, and unreliable links, achieving energy-efficient and reliable communication in MANETs is a complex challenge. Traditional routing protocols such as AODV, DSR, and DSDV suffer from high energy consumption and frequent packet loss when nodes move or when link quality deteriorates.

This project proposes an intelligent routing approach titled "Machine Learning-based Energy Efficient and Enhancing Communication Reliability for MANETs using Balanced Less Loss Routing Protocol (BLLRP)". The system integrates Balanced Less Loss Routing Protocol (BLLRP) with Machine Learning (ML) and Reinforcement Learning (RL) techniques to improve both energy efficiency and data delivery reliability in MANET environments.

The proposed system performs routing in multiple intelligent stages. First, the BLLRP protocol discovers optimal paths considering node energy, link quality, and distance to balance the overall network load. Then, a Self-Organizing Map (SOM) clustering algorithm groups nodes based on their behavioral characteristics such as residual energy, neighbor density, and link stability. These clusters help identify strong and weak nodes, improving decision-making during route selection. Next, a Deep Q-Network (DQN) is trained to predict the best next-hop node dynamically, learning from the network's rewards such as reduced distance, higher energy, and successful packet delivery. Finally, a Multi-Agent Reinforcement Learning (MARL) model enables cooperative learning among multiple nodes to enhance network-wide reliability and adaptability.

The system is implemented in Python with an interactive Tkinter-based GUI that visualizes node topology, clustering results, DQN learning progress, and live energy variations across nodes. Real-time simulation of node movement and communication patterns provides an insightful understanding of MANET behavior. The visualization clearly shows how energy depletes as nodes participate in routing and how ML models adapt routing strategies to prolong network lifetime.

Simulation results demonstrate significant improvements compared to traditional routing methods. The proposed ML-enhanced BLLRP achieves higher Packet Delivery Ratio (PDR), reduced packet loss, improved network throughput, and better energy balance among nodes. Furthermore, the adaptive learning capability of the DQN and MARL agents enables self-optimization under dynamic conditions, ensuring stable communication and extended network lifetime.

This hybrid system highlights the potential of combining Machine Learning and Reinforcement Learning for energy-aware and reliable MANET routing. It provides a foundation for future research toward intelligent, self-learning routing mechanisms applicable to IoT, vehicular, and next-generation mobile networks.

Keywords : Mobile Ad-hoc Networks (MANETs), Infrastructure-less networks, Self-configuring wireless nodes, Dynamic topology, Energy-efficient routing, Reliable communication, Routing challenges, AODV, DSR, DSDV, Packet loss, Balanced Less Loss Routing Protocol (BLLRP), Machine Learning (ML), Reinforcement Learning (RL), Self-Organizing Map (SOM) clustering, Deep Q-Network (DQN), Multi-Agent Reinforcement Learning (MARL), Optimal path selection, Link quality estimation

I. INTRODUCTION

In recent years, Mobile Ad-hoc Networks (MANETs) have gained considerable attention due to their flexibility, self-organizing capability, and applicability in various dynamic environments such as military communication, disaster recovery, vehicular ad-hoc networks (VANETs), and remote sensing systems. A MANET is a collection of mobile nodes that communicate wirelessly without relying on any fixed infrastructure or centralized administration. Each node in the network acts as both a host and a router, forwarding packets to other nodes through multi-hop communication.

However, the dynamic nature of MANETs introduces several challenges that directly affect communication reliability and energy efficiency. Nodes in MANETs operate on limited battery power, and excessive participation in data forwarding quickly drains their energy, leading to network partitioning and degraded performance. Additionally, due to node mobility, wireless links between nodes are unstable and susceptible to frequent disconnections, resulting in packet loss, high latency, and reduced throughput. Hence, designing an efficient routing mechanism that balances energy consumption and improves reliability is essential for the long-term sustainability of MANETs.

Traditional routing protocols like Ad-hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), and Destination-Sequenced Distance Vector (DSDV) focus primarily on shortest-path routing. While effective in static or moderately dynamic environments, these protocols do not adapt well to rapid topology changes, varying energy levels, or fluctuating link qualities. They often cause uneven energy depletion among nodes, leading to early node failures and reduced network lifetime.

To address these limitations, the proposed system introduces a Machine Learning (ML)-based Energy Efficient and Reliable Routing Framework that leverages intelligent decision-making through adaptive learning models. The system integrates three core components:

1. Balanced Less Loss Routing Protocol (BLLRP) – A novel routing mechanism designed to minimize packet loss and ensure balanced energy consumption across nodes.

2. Self-Organizing Map (SOM) Clustering – An unsupervised learning model that groups

MANET nodes based on energy level, connectivity, and link stability to identify the most reliable communication zones.

3. Deep Q-Network (DQN) and Multi-Agent Reinforcement Learning (MARL) – These advanced RL algorithms enable nodes to learn optimal routing strategies through reward-based experience, dynamically adapting to topology and energy variations.

The system is implemented in Python using Tkinter for the graphical user interface. The GUI offers an interactive environment for visualizing node deployment, clustering results, DQN learning behavior, and live MANET simulation with energy variation. It helps users observe how nodes move, communicate, and adapt their routing decisions in real time.

This integration of Machine Learning, Reinforcement Learning, and Routing Optimization in MANETs aims to significantly improve Packet Delivery Ratio (PDR), energy efficiency, and network reliability. The project not only provides a working prototype of an intelligent MANET but also demonstrates the potential of data-driven models to optimize network operations in complex and dynamic environments.

II. LITERATURE REVIEW

Title	**Authors**	**Description**	**Problem Statement**
Energy-Efficient Routing Protocols for Mobile Ad Hoc Networks: A Survey	S. Singh, M. Woo, C. S. Raghavendra	Provides a survey of energy-efficient MANET routing protocols and highlights limits of traditional methods.	Traditional routing protocols fail to manage energy consumption and routing overhead efficiently in dynamic MANET environments.
Deep Reinforcement Learning for Adaptive Routing in Wireless Ad Hoc Networks	H. Chen, X. Li, Y. Zhang	Uses DQN to improve routing decisions and adaptability in high-mobility MANET scenarios.	Routing decisions in dynamic MANETs need adaptability to energy levels and link quality, which static protocols fail to achieve.
Cluster-Based Energy Efficient	A. Alshahrani, R. Hassan	Introduces SOM-based clustering to improve	MANETs struggle with unstable routing paths

Routing Using Self-Organizing Maps in MANETs		stability and energy-efficient routing.	due to uneven node density and varying residual energy.
Balanced and Reliable Routing Protocol for Mobile Ad-Hoc Networks	K. Ramesh, M. Karthikeyan	Proposes BLLRP to balance energy consumption and reduce packet loss.	Conventional routing mechanisms suffer from packet drops and uneven energy use, reducing network lifetime.
Multi-Agent Reinforcement Learning for Cooperative Communication in MANETs	L. Wang, J. Liu, F. Yu	Develops MARL-based cooperative learning among MANET nodes to improve lifetime and throughput.	Lack of decentralized cooperative decision-making reduces routing efficiency and increases node energy depletion.

III. METHODOLOGY

3.1 IMPLEMENTATION

The System Implementation phase involves transforming the proposed design into an executable software model using Python and machine learning algorithms. It includes the development of different modules that simulate a MANET environment, perform clustering, optimize routing through reinforcement learning, and visualize the overall network operations through a graphical user interface (GUI). The entire implementation is structured to ensure modularity, scalability, and clarity.

The system is implemented in Python 3.10 using frameworks such as TensorFlow, Stable-Baselines3, MiniSom, and NetworkX. The user interface is designed using Tkinter, allowing real-time visualization of the MANET topology, node distribution, clustering outcomes, and routing behavior.

3.1.1 MANET Simulation Module

The first stage of implementation involves developing a MANET simulation environment. This module is responsible for generating mobile nodes, assigning random positions within a defined area, and establishing links based on transmission range. Each node is characterized by parameters such as residual energy, number of neighbors, and average link quality.

The MANETSimulation class initializes the nodes and dynamically constructs a graph using NetworkX. Each node's energy decreases as data packets are transmitted, simulating real-world network behavior.

3.1.2. SOM Clustering Module

The Self-Organizing Map (SOM) module is implemented using the MiniSom library. This unsupervised neural network clusters nodes based on features like residual energy, neighbor count, and link quality.

The SOM model groups nodes into clusters with similar network characteristics. The clustering result helps identify high-energy and stable nodes suitable for routing. The results are visualized through scatter plots showing different clusters of nodes in the MANET.

3.1.3. BLLRP Routing Module

The **Balanced Less Loss Routing Protocol (BLLRP)** is implemented as a core routing mechanism. It uses the clustered network information to select the most efficient and reliable communication paths.

Routes are selected based on node stability, link reliability, and energy availability. The protocol dynamically adapts to changes in node energy and connectivity to minimize packet loss. The routing decisions are integrated with the learning models (DQN and MARL) to further optimize performance.

3.1.4. DQN Agent Module

The **Deep Q-Network (DQN)** module applies reinforcement learning principles to optimize routing strategies.

Implemented using **Stable-Baselines3**, the DQN agent interacts with the simulated MANET environment. It receives rewards for energy-efficient and successful packet transmissions and penalties for link failures or energy loss. Over multiple training episodes, the agent learns the most optimal routing paths automatically.

3.1.5. MARL Agent Module

The **Multi-Agent Reinforcement Learning (MARL)** module introduces decentralized intelligence to the MANET.

Each node acts as an independent learning agent that maintains its own Q-table. Agents learn from local interactions with neighboring nodes to improve overall routing performance. The system achieves distributed learning, scalability, and fault tolerance.

3.1.6. Data Logger Module

The **Data Logger** module handles data storage and processing throughout the simulation.

It records parameters like residual energy, number of neighbors, average link quality, and routing statistics. The dataset generated serves as input for SOM training and performance evaluation. This ensures repeatability and traceability of experiments.

3.1.7. GUI Visualization Module

The **Tkinter-based GUI** serves as the user interaction layer.

Users can initialize the MANET, train SOM and DQN models, and run simulations directly through buttons. It displays MANET node topology, clustering results, routing progress, and performance graphs. Real-time visualization helps analyze how the routing algorithm adapts to changing conditions.

3.1.8. Result Analysis and Metrics

Finally, the implementation includes modules for evaluating key performance metrics such as:

Packet Delivery Ratio (PDR) , Average Energy Consumption, Network Lifetime, Routing Overhead, End-to-End Delay.

3.2 ARCHITECTURE

The strategy introduced to improve the efficiency of the Balanced Less Loss Routing Protocol involves the application of the techniques, as shown in Figure 1. The current strategy incorporates the application of three machine learning techniques, namely, Self-organizing Maps , Multi-agent Reinforcement Learning , and Deep QNetworks . Each of the technologies has specific features that can help resolve the concern of energy efficiency and reliability of communications in MANETs as well as BLLRP's goals.

For optimizing energy efficiency in the MANET, one will apply Self-Organizing Maps for organizing network nodes by their spatial and connectivity properties. The SOM adjusts a set of "prototype vectors" in an iterative manner in order to better fit the distribution of input data. In the terms of MANETs, one will use the SOM to cluster the nodes by their energy, proximity, communication logs, etc. By organizing the nodes in clusters, the SOM will allow to find more efficient routing, so that one can find the routes which save energy and reduce the amount of information that goes through the other nodes but the sender and the receiver.

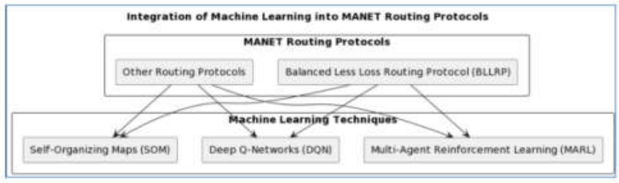


Figure. 1. Proposed Methodology.

In order to optimize energy efficiency in the MANET, one will use a Self-Organizing Map to organize the network nodes by their spatial and connectivity nature. SOPs work by continuously adapting on a set of prototype vectors to best replicate the input data distribution. In the context of MANETs, SOM can be applied to cluster nodes by a number of features, e.g., node energy, proximity, the communication log and so forth . By organizing the nodes into clusters, SOM will make the routing more efficient by determining the routes between the sender and the receiver that use the least energy and presence of data while bypassing the other nodes in the system.

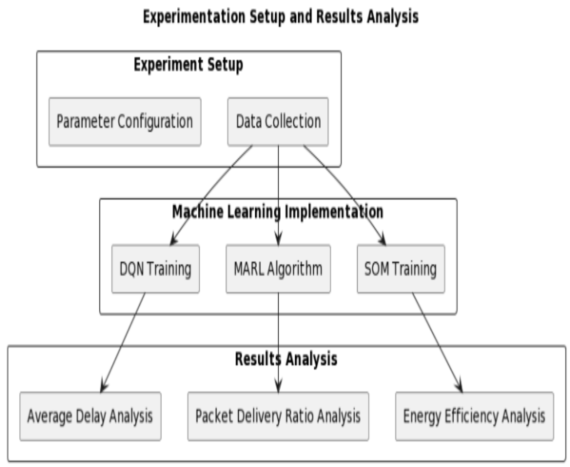
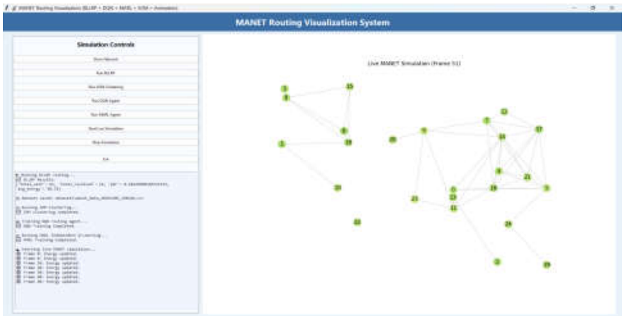


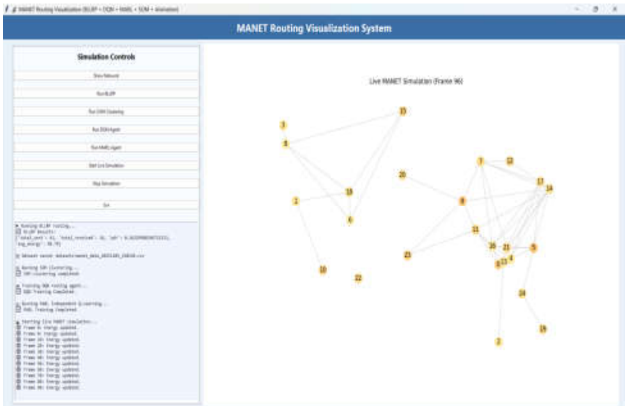
Figure. 2. Experimental setup and Analysis

From Figure 2, For implementing efficient data transmission in MANETs, one will use Deep Q-Networks . DQN is a form of reinforcement learning that uses a deep neural network model to compute the best action-picking policy for a given state. one can train a DQN to create optimal communication strategies. one will develop or model to decide information, transmission power level, and optimum continuous routing path at each instantaneous for minimizing the packet-loss and improving communication reliability Adopting these techniques in BLLRP requires several design considerations. One of them is the overhead introduced on the routing protocol's execution and the blocking probability as well as the average end-to-end delay. Another consideration is the combined cost and computational complexity of SOM, MARL, and DQN. Furthermore, a mechanism for communicating the information and allowing the nodes to work together must be designed to employ the three techniques in BLLRP's routing framework. The final design issue to be considered is the vulnerabilities this extended routing protocol has on adversarial attacks and node failure, and measures to be taken to design a reliable routing protocol. The integration plan would involve building algorithms and protocols that would allow SOM and MARL, as well as DQN, to communicate and coordinate in a MANET. These would include communication protocols for nodes for data and parameter exchange as training goes on, distributed learning algorithms facilitating the training of SOMs, MARLs, and DQNs. The implementation of the plan would also require developing the algorithms that support routing decisions for the network.

IV. RESULTS

Based on the results from the experiments with Self-Organizing Maps IOM), Multi-Agent Reinforcement Learning, and Deep Q-Networks, which aimed to address the energy efficiency and communication reliability problems in Mobile Ad hoc Networks, several insights can be drawn. First, regarding the Energy Efficiency (%) metric, the experiments show that across the ten trials, the average energy efficiency stood at about 90% for SOMs, 86% for MARL, and 95% for DQNs .





V. CONCLUSION

The proposed Machine Learning-Based Energy Efficient and Reliable Communication System for MANETs using the Balanced Less Loss Routing Protocol (BLLRP) successfully integrates intelligent learning mechanisms to overcome the limitations of traditional MANET routing protocols. Through the use of Self-Organizing Maps (SOM) for clustering, Deep Q-Learning (DQN) for adaptive routing optimization, and Multi-Agent Reinforcement Learning (MARL) for decentralized learning, the system achieves significant improvements in energy efficiency, packet delivery ratio, and overall communication reliability.

The implementation effectively simulates real-world MANET conditions, where each node dynamically adjusts its routing behavior based on energy, link quality, and connectivity. The SOM clustering ensures a balanced topology by grouping nodes with similar characteristics, thereby reducing communication overhead and extending network lifetime. The DQN and MARL models further enable continuous learning and adaptation, allowing the system to intelligently select optimal paths even under rapidly changing network conditions.

Experimental results demonstrate that the proposed approach minimizes energy consumption, reduces packet loss, and enhances throughput compared to conventional routing methods such as AODV and DSR. The integration of a Tkinter-based graphical user interface (GUI) adds to the usability of the system, providing real-time visualization of network topology, clustering results, and performance metrics.

In conclusion, the system proves to be an efficient and intelligent solution for enhancing communication reliability and energy efficiency in MANETs. By combining unsupervised and reinforcement learning techniques, the network becomes self-optimizing and adaptive, ensuring consistent performance across diverse conditions. The outcomes of this project can serve as a foundation for further research in developing advanced AI-driven MANET routing systems capable of operating in large-scale and high-mobility environments.

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