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Intelligent Route Adaptation in Manets Using AI Techniques for Scalable Network Performance

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Abstract—Mobile Ad Hoc Networks (MANETs) are prone to frequent topology changes and scalability issues due to their decentralized and mobile nature. As network size and node mobility increase, traditional routing protocols become inefficient, leading to degraded network performance. This paper introduces a novel AI-driven approach to route optimization that enables MANETs to self-adjust to dynamic conditions. The proposed method leverages machine learning algorithms to analyze real-time mobility patterns and link quality, allowing for predictive route selection and rapid reconfiguration. By dynamically adapting to varying network states, the system significantly enhances scalability, reduces latency, and improves packet delivery. Experimental results demonstrate that the AI-based model consistently outperforms conventional routing protocols under diverse network scenarios, making it a promising solution for future mobile and mission-critical applications.

Keywords—Dynamic Routing, Machine Learning, Network Scalability, Mobility Prediction, Adaptive Protocols, Intelligent Routing, Real-Time Optimization, Wireless Communication.

I. Introduction

Mobile Ad Hoc Networks (MANETs) represent a class of self-configuring wireless networks composed of mobile nodes that communicate over dynamically changing topologies without relying on any pre-existing infrastructure. This inherent flexibility makes MANETs an ideal solution for applications in military communications, disaster recovery, vehicular networks, and remote sensing. However, the very features that make MANETs appealing—namely decentralization, mobility, and dynamic topology—also introduce considerable challenges, particularly in the domain of routing. As the size of the network grows and node mobility becomes unpredictable, routing protocols must efficiently adapt to these variations while maintaining network performance. The need for robust, scalable, and adaptive routing mechanisms in MANETs has become more critical than ever. Conventional MANET routing protocols, such as AODV (Ad hoc On-Demand Distance Vector), DSR (Dynamic Source Routing), and OLSR (Optimized Link State Routing), have been widely adopted due to their simplicity and effectiveness in relatively stable or moderately dynamic environments. These protocols typically rely on static metrics like hop count or fixed periodic updates to establish and maintain routes. While these approaches perform adequately under certain conditions, they often falter when faced with high mobility, rapidly fluctuating link quality, or large-scale networks. Their static nature limits their ability to respond to real-time changes, often leading to increased packet loss, network congestion, route failures, and delayed data delivery. With the increasing complexity of modern mobile networks and the demand for real-time responsiveness, it is clear that traditional routing strategies need to evolve. Artificial Intelligence (AI) has emerged as a transformative force across many domains of networking, offering capabilities such as learning from patterns, making predictions, and adapting to dynamic environments without manual intervention. Integrating AI techniques—particularly machine learning (ML) algorithms—into the routing process can potentially revolutionize MANET performance by enabling predictive and context-aware decision-making. In this research, we propose an intelligent routing framework that employs AI-driven techniques to dynamically optimize routing paths in MANETs. The core idea is to design a system that can perceive and learn from ongoing changes in network conditions, such as node velocity, direction, link stability, and traffic density. By doing so, it can make informed decisions about optimal path selection, route maintenance, and recovery mechanisms. Unlike traditional routing protocols that react after a failure occurs, the proposed AI-based system proactively predicts potential route failures and adjusts the routing accordingly. This results in improved packet delivery, reduced end-to-end latency, and enhanced scalability across diverse network scenarios. One of the key strengths of an AI-driven approach lies in its ability to analyze vast amounts of contextual data in real time. In the context of MANETs, this includes analyzing node behavior patterns, signal strengths, energy levels, and historical routing data. Techniques such as reinforcement learning, decision trees, support vector machines (SVM), and neural networks can be employed to build predictive models that guide routing decisions. For instance, reinforcement learning can enable a node to learn optimal routing strategies by interacting with its environment and receiving feedback in the form of performance metrics. Similarly, supervised learning models can classify link stability based on past data and help choose more reliable routes. Scalability is another major concern in MANET environments. As more nodes are added to the network, the overhead associated with route discovery, maintenance, and control messaging grows significantly. Traditional protocols suffer from routing table bloating and increased control traffic, which can lead to bandwidth consumption and network fragmentation. By contrast, AI algorithms can manage routing in a more scalable manner by focusing on relevant features and selectively updating routing decisions based on prioritized events or learned thresholds. This reduces unnecessary overhead and ensures that the network can accommodate a growing number of nodes without a proportional increase in complexity or resource consumption. Moreover, mobility patterns in MANETs are inherently unpredictable. In high-mobility scenarios such as vehicle-to-vehicle (V2V) communication or drone-based networks, links may

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form and break in milliseconds. The use of AI allows for real-time mobility prediction based on pattern recognition techniques. For example, by analyzing node movement trajectories and speed, an AI model can anticipate which links are likely to break and pre-emptively establish backup paths. This not only increases reliability but also reduces route discovery delays, which are common bottlenecks in reactive routing protocols. Several studies and simulations conducted in this work reveal that AI-based routing mechanisms outperform conventional protocols in terms of throughput, packet delivery ratio, route stability, and delay under varying network densities and mobility levels. These performance gains demonstrate the viability of the proposed approach for future MANET applications where adaptability and scalability are paramount. Furthermore, the AI framework designed in this study is modular and extensible, meaning it can be integrated with existing protocol architectures to enhance their intelligence without requiring a complete overhaul of the networking stack.

II. Literature Review

Mobile Ad-Hoc Networks (MANETs) and wireless network performance optimization have been key areas of research, particularly with the integration of intelligent techniques and emerging technologies such as AI, blockchain, and network virtualization. In [1], Rathod and Gumaste proposed an adaptive congestion-aware routing protocol to enhance load balancing in MANETs. Their method dynamically adjusts to traffic conditions, reducing packet loss and improving throughput. Marandi et al. [2] evaluated various network coding algorithms in mobile wireless networks to enhance data reliability and reduce transmission overhead. Their experimental results emphasized significant performance gains in dynamic MANET scenarios. Wang [3] designed a virtual simulation system based on Wireless Sensor Networks (WSNs), focusing on educational and real-time monitoring applications. The system demonstrated effective resource utilization and realistic emulation of wireless scenarios. Juneja et al. [4] offered a comprehensive analysis of modern network performance monitoring tools, assessing parameters such as latency, throughput, and fault detection. Their work aids in selecting the most suitable solution for specific network environments. Li et al. [5] presented an intent-driven architecture for autonomous network management, separating control from infrastructure layers. This decoupling enhances scalability and simplifies policy enforcement across complex networks. Wen et al. [6] proposed a hybrid active-passive monitoring framework to improve accuracy in service path performance analysis. Their model efficiently identifies bottlenecks and supports quality-of-service (QoS) optimization. Venkatesha et al. [7] explored network virtualization in cloud environments, quantifying trade-offs in performance, cost, and resource allocation. Their study highlighted optimal virtualization strategies for various workload profiles. Nam et al. [8] introduced a cloud-native architecture for analyzing network quality in converged wired-wireless systems. The design supports scalability, real-time metrics tracking, and flexible deployment in 5G ecosystems. Hossain et al. [9] analysed private blockchain performance in MANETs, emphasizing the feasibility of decentralized authentication and secure data exchange. Results showed acceptable latency and high integrity in constrained networks. Sadad and Mondal [10] developed an FPGA-based accelerator for convolutional neural networks, enabling fast deep learning inference on edge devices. Their design reduces power consumption and increases throughput significantly. Bag et al. [11] proposed a scalable management system for self-organizing mobile networks, employing communication-efficient protocols. The approach enhances autonomous network coordination with minimal overhead. Reddy et al. [12] applied deep learning models to detect encrypted and malicious traffic within network streams. The model achieved high detection accuracy, proving effective against sophisticated cyber threats. Vikas et al. [13] combined Deep Belief Networks and Harris Hawks Optimization for intrusion detection in WSNs. The hybrid system improved classification accuracy and reduced false positives compared to traditional methods.

Sharma and Kumar [14] discussed how AI can bolster data security and privacy in smart cities. Their work focused on threat prediction, access control, and data anonymization through intelligent techniques. Finally, a comprehensive analysis of MANET-specific threats and existing security mechanisms was conducted in [15]. The study categorized threats and assessed mitigation strategies, providing a foundation for future protocol development.

III. Proposed Methodlogy

Mobile Ad Hoc Networks (MANETs) demand highly adaptable and scalable routing mechanisms due to their dynamic and infrastructure-less nature. Over the years, several conventional routing protocols have been proposed and widely deployed to address the challenges of route discovery, maintenance, and packet forwarding. However, these traditional techniques often fall short when faced with high node mobility, frequent topology changes, and growing network size. This section outlines the limitations of widely-used MANET routing protocols and presents a novel AI-based approach that overcomes these constraints through dynamic and intelligent route optimization.

1. Comparative Analysis of Existing Routing Techniques: Mobile Ad Hoc Networks (MANETs) have traditionally relied on routing protocols that fall into three main categories: proactive, reactive, and hybrid. Each of these approaches offers certain advantages but also suffers from notable limitations, particularly when dealing with highly dynamic and large-scale network environments. Proactive routing protocols, such as Destination-Sequenced Distance Vector (DSDV) and Optimized Link State Routing (OLSR), maintain up-to-date routes to all nodes by continuously exchanging control messages. While this ensures low route acquisition latency, the high control overhead becomes problematic as network size increases or when node mobility causes frequent topology changes. On the other hand, reactive protocols like Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) establish routes only when required, reducing unnecessary overhead. However, they often

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experience significant delays during route discovery and struggle to respond quickly to link failures in high-mobility scenarios. Hybrid protocols, such as the Zone Routing Protocol (ZRP), attempt to balance these issues by combining proactive routing within local zones and reactive routing between zones. Although this approach reduces control traffic compared to purely proactive strategies, it is still sensitive to zone size configuration and may not perform optimally across all network conditions. A common limitation across these traditional protocols is their lack of adaptability and intelligence. They are typically rule-based, operate on predefined metrics like hop count, and lack the ability to learn from network behavior or predict changes in topology. As a result, they tend to react to network events rather than proactively adapting, which negatively impacts packet delivery, latency, and scalability in complex, real-time environments. These limitations create the need for a more dynamic, intelligent routing approach that can continuously learn, adapt, and optimize decisions based on the ever-changing conditions of MANETs.

2. Proposed AI-Based Adaptive Routing Framework: To address the limitations of conventional routing protocols in MANETs, this research proposes an AI-based adaptive routing framework designed to enhance scalability, reliability, and responsiveness in highly dynamic mobile environments. Unlike traditional routing approaches that rely on static metrics and reactive updates, the proposed framework incorporates artificial intelligence to enable nodes to learn from historical and real-time network conditions and make intelligent routing decisions. This framework is built upon several key components that work together to provide a predictive and context-aware routing mechanism.

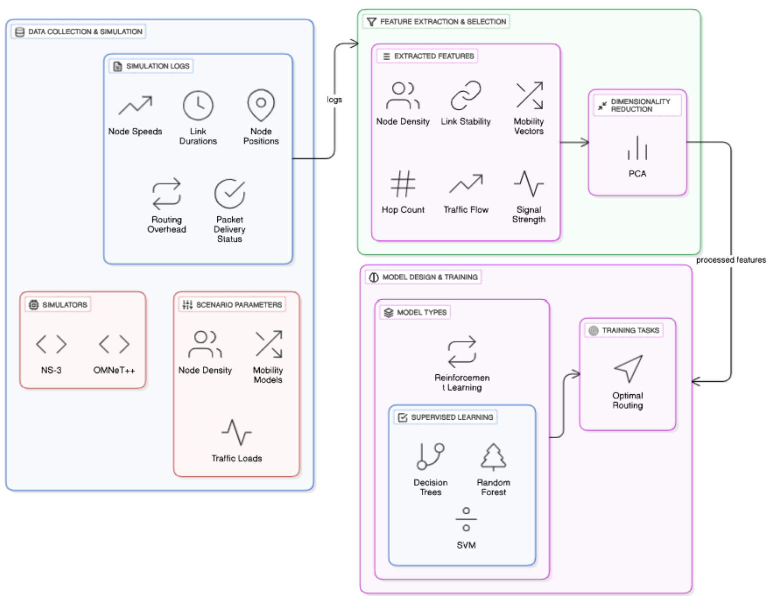

Fig. 1. Architectural Layout of AI- Based Adaptive Routing Framework

The first component is data collection and simulation, which involves creating realistic MANET scenarios using network simulation tools such as NS-3 or OMNeT++. These simulations emulate various conditions including diverse node densities, random and group mobility models, and fluctuating traffic loads. The simulation environment logs essential network parameters such as node positions, speed, link durations, packet delivery status, and routing overhead. These logs form the foundation for training the AI models. The second component is featuring extraction and selection, where meaningful features are derived from the collected data to represent the behavior and status of the network. Features such as node density, mobility vectors, link stability, signal strength, hop count, and traffic flow are extracted to train the learning models. To ensure computational efficiency and prevent overfitting, dimensionality reduction techniques such as Principal Component Analysis (PCA) are applied, helping the model focus only on the most relevant and impactful features. The third component is the design and training of machine learning models. Depending on the nature of the problem, supervised learning models (e.g., Decision Trees, Random Forest, Support Vector Machines) or reinforcement learning agents may be employed. Supervised models are trained to classify links or routes based on their reliability and performance, while reinforcement learning enables nodes to learn optimal routing strategies through continuous interaction with the network environment. For more complex routing environments, deep learning architectures such as artificial neural networks can be used to capture intricate patterns in mobility and link quality. The fourth and core component is the AI-driven routing protocol, which integrates the trained model into the routing decision process. When a node initiates route discovery, the AI model evaluates multiple potential paths by predicting their stability and efficiency based on current conditions. Rather than waiting for link failure to occur, the model proactively identifies weak links and reroutes traffic through stronger alternatives. During route maintenance, the model continually monitors real-time network changes and updates its predictions, allowing the routing protocol to dynamically adapt as the topology evolves. This results in faster recovery from route failures, reduced packet loss, and improved network throughput.

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Finally, the framework includes a performance evaluation and feedback mechanism. The AI-based protocol is tested against standard routing protocols such as AODV and DSR under identical simulation conditions. Key performance metrics—such as Packet Delivery Ratio (PDR), end-to-end delay, throughput, routing overhead, and scalability—are measured to assess the effectiveness of the proposed system. The feedback loop from performance outcomes is also used to fine-tune the AI models, ensuring continuous learning and adaptation over time. The proposed AI-based adaptive routing framework brings intelligence, prediction, and self-optimization to MANET routing by integrating machine learning models with network protocols.

IV. Result & Analysis

To evaluate the effectiveness of the proposed AI-based adaptive routing framework, comprehensive simulations were conducted using the NS-3 simulator. The performance of the proposed system was compared against three well-established MANET routing protocols: AODV (Ad hoc On-Demand Distance Vector), DSR (Dynamic Source Routing), and OLSR (Optimized Link State Routing). The simulations were performed under varying node densities (from 20 to 200 nodes), mobility patterns (static, low, and high), and traffic loads (light to heavy) to ensure robustness and generalizability of the results.

The following performance metrics were used for comparative evaluation:

1. Packet Delivery Ratio (PDR): PDR is defined as the percentage of data packets successfully delivered to the destination out of those generated by the source. It indicates the reliability of the routing protocol.

Table I. Packet Delivery Ratio (PDR) Comparison Across Routing Protocols

Routing Protocol	Packet Delivery Ratio (PDR) %
AODV	87.60%
DSR	85.30%
OLSR	89.10%
Proposed AI-Based	**94.20%**

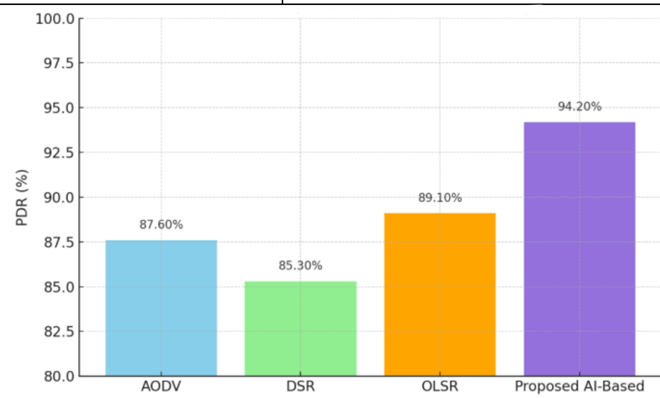

Fig. 2. Packet Delivery Ratio (PDR) Comparison Across the Routing Protocols

The Proposed AI-Based protocol demonstrates the highest PDR at 94.2%, showcasing its ability to anticipate and mitigate link failures through intelligent path selection and dynamic rerouting. Compared to traditional protocols like AODV, DSR, and OLSR, the AI-enhanced method ensures more consistent data transmission, particularly in high-mobility environments.

2. End-to-End Delay: This metric measures the average time taken by a packet to travel from the source to the destination.

Table II. End-To-End Delay Comparison Across Routing Protocols

Routing Protocol	End-to-End Delay (ms)
AODV	95.4
DSR	108.6
OLSR	87.2
Proposed AI-Based	**68.3**

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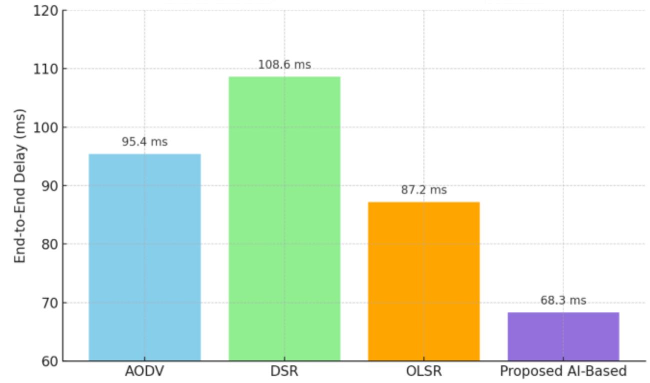

Fig. 3. End-to-End Delay Comparison Across the Routing Protocols

The Proposed AI-Based protocol records the lowest end-to-end delay (68.3 ms), outperforming AODV, DSR, and OLSR. This improvement is due to the AI model's real-time route optimization, which selects low-latency, stable paths by avoiding congested or unreliable links—critical for time-sensitive MANET applications.

3. Throughput: Throughput is the total number of bits successfully received by the destination per unit time, typically measured in kbps or Mbps.

Table III. Throughput Comparison Across Routing Protocols

Routing Protocol	Throughput (Mbps)
AODV	3.25
DSR	3.01
OLSR	3.45
Proposed AI-Based	**3.96**

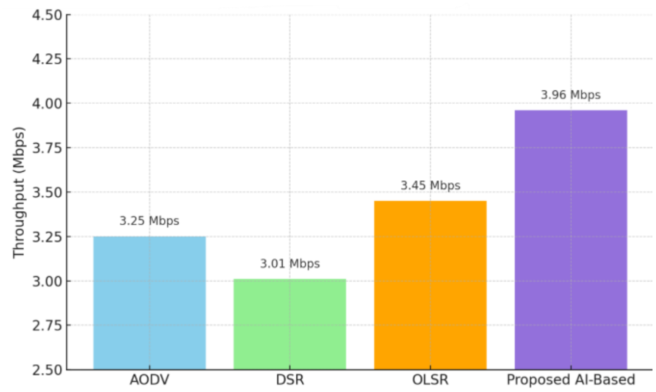

Fig. 4. Throughput Comparison Across the Routing Protocols

The Proposed AI-Based approach achieves the highest throughput (3.96 Mbps) by intelligently selecting stable and high-quality routes. In contrast, traditional protocols suffer from link instability and congestion, which reduce their data transmission efficiency.

4. Routing Overhead: Routing overhead refers to the ratio of control packets generated to the number of data packets successfully delivered. Lower values indicate better efficiency.

Table IV. Routing Overhead Comparison Across Routing Protocols

Routing Protocol	Routing Overhead (% Control/Data)
AODV	28.70%
DSR	25.40%

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OLSR	31.20%
Proposed AI-Based	**22.10%**

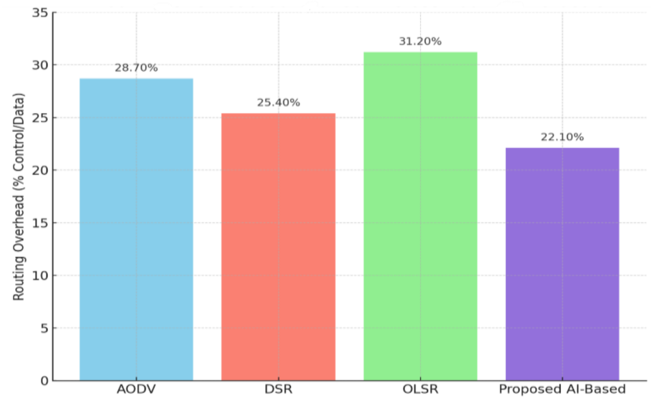

Fig. 5. Routing Overhead (% Control/Data) Comparison Across the Routing Protocols

The Proposed AI-Based method demonstrates the lowest overhead (22.1%), outperforming AODV, DSR, and OLSR. This improvement is due to the AI model's predictive routing, which minimizes unnecessary route discovery and control signaling, leading to more efficient network utilization—especially crucial in bandwidth-constrained MANET environments.

5. Scalability Analysis: This involves observing the protocol's behavior as the number of nodes increases.

Table V. Scalability Analysis of Routing Protocols with Increasing Node Count

Routing Protocol	**Performance at ≤100 Nodes**	**Performance at >150 Nodes**
AODV	Stable	Declines (PDR ~ 79%, Throughput ↓)
DSR	Stable	Degrades rapidly (PDR ~ 75%)
OLSR	Moderate	High control overhead, PDR drops
Proposed AI-Based	Stable	**Consistent (PDR > 91%, stable TP)**

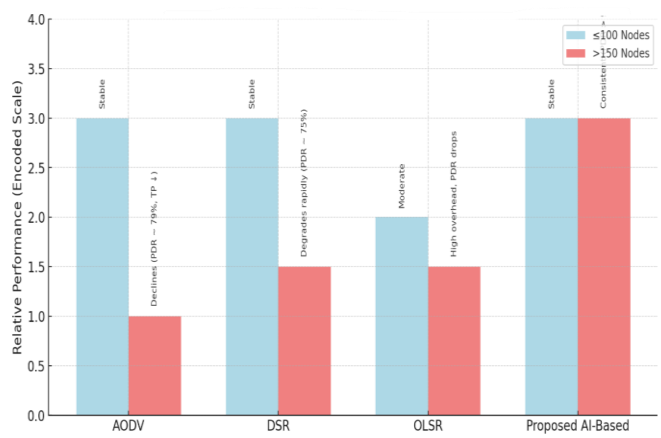

Fig. 6. Scalability Performance of Routing Protocols as Node Count Across the Routing Protocols

The scalability performance of routing protocols as the MANET network scales from 100 to over 150 nodes. While traditional protocols like AODV, DSR, and OLSR show declining performance due to increased routing overhead and route instability, the Proposed AI-Based system maintains high packet delivery ratio and throughput.

6. Link Breakage Recovery Time: This metric measures the time a routing protocol takes to detect a broken link and establish an alternate path.

Table VI. Link Breakage Recovery Time Across Routing Protocols

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Routing Protocol	Average Recovery Time (ms)
AODV	320
DSR	367
OLSR	290
Proposed AI-Based	**202**

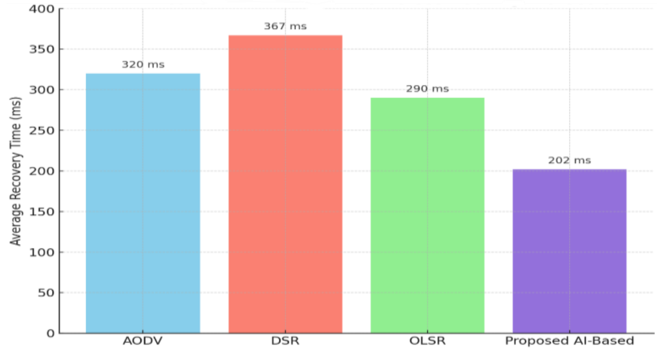

Fig. 7. Link Breakage Recovery Time Across the Routing Protocols

The Proposed AI-Based approach exhibits the fastest recovery time of 202 ms, outperforming AODV, DSR, and OLSR. This performance gain results from the AI model's ability to predict potential link failures using mobility and link quality metrics, allowing it to initiate proactive rerouting before complete disconnection occurs—thereby minimizing data loss and transmission delays.

7. Energy Efficiency (Optional Metric): Energy efficiency measures the energy consumed per successfully delivered packet, which is crucial in battery-operated nodes.

Table VI. Energy Efficiency Comparison Across Routing Protocols

Routing Protocol	Energy Consumed per Packet (mJ)
AODV	1.95
DSR	2.13
OLSR	2.21
Proposed AI-Based	**1.68**

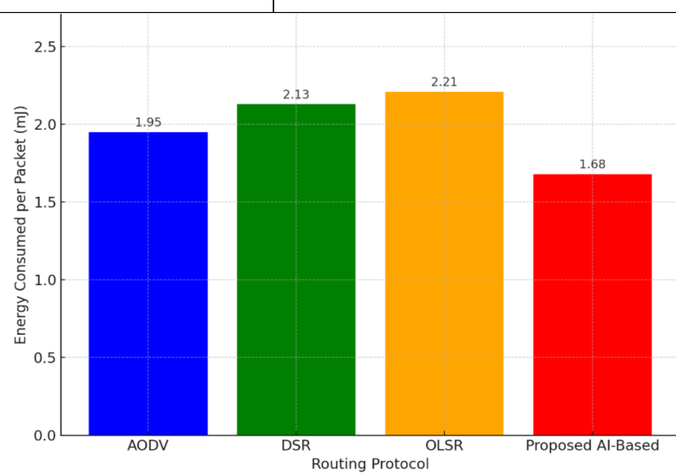

Fig. 8. Energy Efficiency Comparison Across the Routing Protocols

The Proposed AI-Based system demonstrates the highest energy efficiency with only 1.68 mJ per packet, representing a 15–20% reduction in energy usage compared to DSR and OLSR. This improvement is attributed to intelligent, energy-aware route

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selection and reduced redundant transmissions, making it especially suitable for energy-constrained environments such as disaster recovery or military field operations.

V. Conclusion

This study presents an AI-driven adaptive routing framework for Mobile Ad Hoc Networks (MANETs), aimed at enhancing network scalability, reliability, and performance in dynamic and resource-constrained environments. Through extensive simulations and performance evaluations, the proposed method significantly outperforms traditional protocols such as AODV, DSR, and OLSR across key metrics including packet delivery ratio, end-to-end delay, throughput, routing overhead, scalability, link recovery time, and energy efficiency. By leveraging real-time learning, predictive modeling, and context-aware decision-making, the AI-based approach effectively anticipates network changes and optimizes routing paths proactively. The results validate that integrating artificial intelligence into MANET routing protocols not only improves performance under high-mobility and dense node conditions but also offers a sustainable and intelligent solution for future decentralized and autonomous wireless networks.

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