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Artificial Intelligence Techniques for Prediction of Routing Scenarios in IoT-based MANETs using ERS, RED, and Global Pooling Dilated CNN: Trends and Challenges

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Abstract

The rapid growth of Internet of Things (IoT) applications has increased the demand for intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs), which operate under dynamic topologies, decentralized control, and limited resources. Conventional routing protocols often fail to manage congestion, energy consumption, and frequent topology variations effectively, leading to reduced network performance. This review explores Artificial Intelligence (AI)-based techniques for routing prediction in IoT-enabled MANETs through the integration of Expanding Ring Search (ERS), Random Early Detection (RED), and global pooling dilated Convolutional Neural Networks (CNNs). Deep learning and reinforcement learning approaches are examined for their ability to extract spatial and temporal network features, enabling accurate prediction of link stability, congestion status, and optimal routing paths. ERS minimizes routing overhead by restricting unnecessary broadcasts, while RED improves congestion management through proactive queue control. The combined framework enhances packet delivery ratio, throughput, latency, and energy efficiency. The study also discusses emerging trends such as graph-based learning, edge intelligence, multi-agent learning, and security-aware routing. Key challenges including computational complexity, scalability, data dependency, and security issues are also highlighted for future intelligent routing system development.

Introduction

The rapid growth of the Internet of Things (IoT) has transformed modern communication systems by enabling billions of interconnected smart devices to exchange information in real time. Applications such as smart healthcare, intelligent transportation, industrial automation, environmental monitoring, and military communication rely heavily on efficient wireless networking technologies. Among these technologies, Mobile Ad Hoc Networks (MANETs) have emerged as a flexible and infrastructure-less communication framework capable of supporting dynamic and decentralized IoT environments. MANETs allow devices to communicate directly without fixed base stations, making them highly suitable for remote, emergency, and rapidly changing scenarios. However, the continuously changing topology and limited resource availability create significant challenges for reliable routing and network management.

Routing in IoT-based MANETs is a complex task because nodes frequently move, network density changes dynamically, and communication links are often unstable. Traditional routing protocols such as AODV, DSR, and OLSR were designed for conventional ad hoc networks and often struggle to maintain stable communication in highly dynamic IoT environments. These protocols typically rely on static decision-making mechanisms that cannot efficiently predict congestion, node mobility, packet loss, or energy depletion. As a result, network performance degrades in terms of packet delivery ratio, latency, throughput, and energy efficiency. Therefore, intelligent and adaptive routing strategies are required to improve communication reliability and optimize network performance in IoT-driven MANET systems.

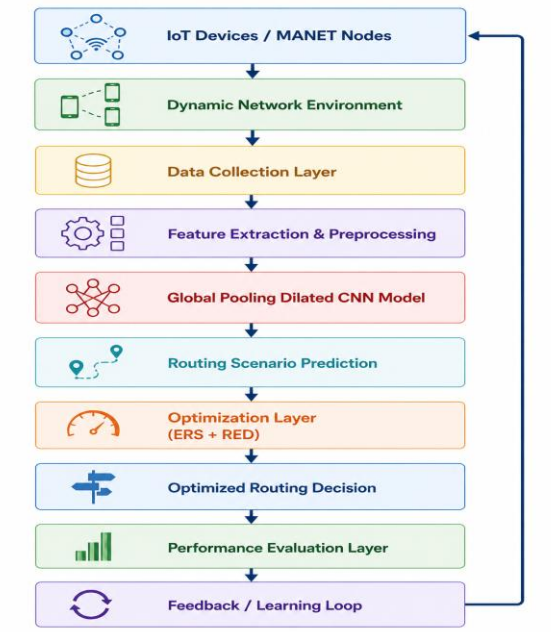

Figure 1. AI-Based Intelligent Routing Framework for IoT-Enabled MANETs

Artificial Intelligence (AI) techniques have recently gained significant attention as effective solutions for intelligent routing prediction and optimization in MANETs. Machine learning and deep learning models can analyse large volumes of network data and identify complex communication patterns that are difficult to capture using conventional algorithms. In particular, Convolutional Neural Networks (CNNs) with global pooling and dilated convolution mechanisms have demonstrated strong capability in extracting spatial and temporal features from network traffic data. These architectures enable accurate prediction of routing scenarios, link stability, congestion conditions, and optimal transmission paths. Furthermore, AI-driven routing systems can continuously learn from changing network conditions, allowing adaptive and real-time decision-making in highly dynamic communication environments.

In addition to deep learning models, optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) play a crucial role in improving routing efficiency. ERS minimizes routing overhead by restricting unnecessary broadcasting during route discovery, thereby reducing energy consumption and communication delay. RED improves congestion control through proactive queue management, preventing packet drops and network bottlenecks before congestion becomes severe. The integration of ERS and RED with AI-based prediction models creates a hybrid intelligent routing framework capable of achieving enhanced throughput, reduced latency, better load balancing, and improved energy utilization. Such hybrid approaches are increasingly important for supporting large-scale IoT applications that demand reliable and low-power communication systems.

Despite recent advancements, several research challenges still limit the practical deployment of AI-enabled routing systems in IoT-based MANETs. High computational complexity, limited training datasets, scalability issues, security vulnerabilities, and real-time implementation constraints remain major concerns. Moreover, resource-constrained IoT devices often lack the processing capability required for complex deep learning operations. Consequently, researchers are exploring lightweight neural architectures, edge intelligence, federated learning, and security-aware routing mechanisms to overcome these limitations. This study provides a detailed review of AI-driven routing prediction techniques using ERS, RED, and global pooling dilated CNNs, while also discussing current trends, existing challenges, and future research directions for developing scalable, adaptive, and intelligent IoT-MANET communication systems.

Literature Review

The evolution of routing mechanisms in IoT-based Mobile Ad Hoc Networks (MANETs) has been significantly influenced by the integration of Artificial Intelligence (AI), particularly deep learning and reinforcement learning techniques. The literature from 2020 to 2023 highlights a transition from conventional routing protocols toward intelligent, adaptive, and predictive routing frameworks capable of addressing the dynamic and resource-constrained nature of MANET environments.

Deep learning has emerged as a powerful tool for modeling complex network behaviors and predicting routing scenarios. Danilchenko et al. (2023) introduced a deep learning-based routing framework that leverages neural networks to optimize routing decisions and resource allocation. Their approach demonstrated improved efficiency and reduced computational complexity compared to traditional routing protocols.

Similarly, Talawar et al. (2024) proposed a deep learning-based link prediction model that enhances routing reliability by accurately predicting stable communication links. Their results indicate a significant improvement in packet delivery ratio (PDR) and network stability. Mohanaprakash et al. (2023) further extended this approach by utilizing graph-based deep learning techniques to model network topology and predict routing paths. Graph Neural Networks (GNNs) effectively capture relationships between nodes, leading to improved prediction accuracy and network performance.

Aldhyani et al. (2020) developed a hybrid deep learning model for network traffic prediction, enabling proactive routing decisions. Their study highlights the importance of traffic-aware routing in reducing congestion and improving throughput. However, deep learning models require large datasets and computational resources, which limits their deployment in resource-constrained IoT environments.

Reinforcement Learning (RL) has gained prominence as an adaptive routing technique capable of learning optimal routing policies through interaction with the network environment. Alkadhmi et al. (2020) proposed a deep reinforcement learning-based routing method that improves network reliability and reduces routing overhead. Their approach enables dynamic adaptation to network changes, resulting in enhanced performance metrics.

Kaviani et al. (2021) introduced DeepCQ+, a multi-agent deep reinforcement learning (MADRL) framework that allows distributed nodes to collaboratively learn routing strategies. This approach significantly improves scalability and throughput while reducing dependency on predefined routing rules. Cui and Yu (2020) also demonstrated the effectiveness of deep reinforcement learning in optimizing routing and spectrum access in wireless networks.

Recent advancements include the work of Upadhyay et al. (2023), who developed a deep Q-learning-based routing algorithm that improves reliability and efficiency in MANETs. Similarly, Jiang et al. (2023) proposed an environment-aware RL routing protocol that adapts to network conditions such as congestion and mobility, enhancing routing performance.

Despite these advantages, RL-based approaches face challenges such as slow convergence, high computational complexity, and the need for continuous learning, which may limit their real-time applicability.

Optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) play a crucial role in improving routing efficiency and congestion control. ERS reduces routing overhead by limiting the broadcast range during route discovery, while RED proactively manages congestion by controlling queue behavior.

Zafar et al. (2023) proposed a machine learning-based routing strategy that integrates ERS and RED mechanisms. Their approach dynamically adjusts routing parameters based on network conditions, resulting in improved Quality of Service (QoS), reduced latency, and increased throughput. This study highlights the effectiveness of combining optimization techniques with AI for intelligent routing.

Traditional optimization-based routing methods, such as those proposed by Alotaibi et al. (2021) and Nguyen et al. (2021), focus on energy efficiency and network lifetime. While these methods improve specific performance metrics, they lack adaptability to dynamic network conditions, which can be addressed through AI integration.

Security remains a major concern in IoT-based MANETs due to their decentralized and open nature. AI-based approaches have been widely used to enhance network security through anomaly detection and trust-based routing.

Yahja et al. (2023) proposed DeepADMR, a deep learning-based anomaly detection system that identifies abnormal routing behavior in real time. This approach significantly improves network security and reliability. Similarly, Sankar et al. (2023) introduced a trust-based routing mechanism that identifies malicious nodes and ensures secure data transmission.

Amouri et al. (2020) and Khan (2023) developed machine learning-based intrusion detection systems for MANETs, demonstrating improved detection accuracy and reduced false positives. Srilakshmi et al. (2022) further proposed a secure optimization routing algorithm that integrates security mechanisms with routing decisions.

Although these approaches enhance network security, they introduce additional computational and communication overhead, which may impact overall performance.

Energy efficiency is a critical factor in IoT-based MANETs due to limited battery resources. Nguyen et al. (2021) proposed a clustering-based routing protocol that improves energy efficiency and extends network lifetime. Similarly, Alotaibi et al. (2021) developed an optimization-based routing approach that minimizes energy consumption while maintaining high network performance.

Poularakis et al. (2020) introduced a Software-Defined Networking (SDN)-based MANET architecture that improves network control and scalability. However, SDN-based approaches require additional infrastructure, which may not be feasible in all MANET scenarios.

Recent studies emphasize the importance of scalable routing mechanisms capable of handling large-scale IoT networks. Multi-agent reinforcement learning and graph-based models provide promising solutions for scalability, although their computational complexity remains a challenge.

The most significant trend in recent research is the development of hybrid routing models that combine deep learning, reinforcement learning, and optimization techniques. Li et al. (2023) proposed a deep reinforcement learning-based collaborative routing algorithm that improves resource utilization and network performance.

Upadhyay et al. (2023) demonstrated that integrating deep learning with routing optimization enhances reliability and reduces congestion. Similarly, Zafar et al. (2023) showed that combining machine learning with ERS and RED mechanisms leads to significant improvements in QoS metrics.

Hybrid approaches leverage the strengths of different techniques, enabling adaptive, efficient, and scalable routing in dynamic IoT environments. However, they introduce additional system complexity and require careful parameter tuning.

Comparative Table

No.	Study	Year	Approach	Core Technique	Key Focus	Performance Gains	Limitations
1	Kaviani et al. (DeepCQ+)	2021	DRL	Multi-Agent RL	Adaptive routing	↑ Throughput, ↓ Overhead	High computation
2	Yahja et al. (DeepADMR)	2023	DL + Security	Anomaly Detection	Secure routing	↑ Security, ↑ Reliability	Monitoring overhead
3	Sankar et al.	2023	Trust-based	Attack detection	Secure routing	↑ PDR, ↓ Packet loss	Energy overhead
4	Danilchenko et al.	2023	Deep Learning	DNN routing	Optimization	↓ Complexity, ↑ Efficiency	Needs training data
5	Mohanaprakash et al.	2023	Graph DL	GNN-based prediction	Network lifetime	↑ Prediction accuracy	Scalability issues
6	Upadhyay et al.	2023	DRL	Deep Q-learning	Reliability	↑ Reliability	Training time
7	Jiang et al.	2023	RL adaptive	Environment-aware RL	Congestion control	↑ Adaptability	Complexity
8	Zafar et al.	2023	ML + ERS + RED	Hybrid optimization	QoS routing	↑ Throughput, ↓ Delay	Parameter tuning
9	Cui & Yu	2020	DRL	Spectrum + routing	Resource optimization	↑ Efficiency	Complex model
10	Alkadhmi et al.	2020	RL	Q-learning	Adaptive routing	↓ Delay, ↑ PDR	Convergence time
11	Amouri et al.	2020	ML Security	Intrusion detection	Security	↑ Detection accuracy	Overhead
12	Nguyen et al.	2021	Clustering	Energy-aware routing	Energy efficiency	↑ Network lifetime	Cluster overhead
13	Alotaibi et al.	2021	Optimization	Energy routing	Energy efficiency	↓ Energy use	Limited adaptability
14	Talawar et al.	2024	DL	Link prediction	Reliability	↑ Link stability	Data dependency
15	Li et al.	2023	DRL	Collaborative routing	Resource use	↑ Efficiency	Scalability
16	Xu et al.	2025	DQN	IoT routing	Reliability	↑ QoS	Not MANET-specific

17	Jin et al.	2024	DRL	Resilient routing	Robustness	↑ Stability	Resource usage
18	Shafi et al.	2023	ML	Trust-AODV	Security	↑ Trust accuracy	Delay overhead
19	Khan et al.	2023	ML IDS	Intrusion detection	Security	↑ Detection rate	Complexity
20	Quy et al.	2022	Survey	IoT routing review	General	Identifies trends	No validation
21	Parween et al.	2023	SLR	TCP optimization	Congestion	↑ QoS	Indirect routing
22	Poularakis et al.	2020	SDN	Centralized control	Flexibility	↑ Network control	Infrastructure need
23	Jamshidi et al.	2020	Cooperative	Multipath routing	Efficiency	↑ Throughput	Delay issues
24	Taha et al.	2020	Multipath	Energy-aware routing	PDR	↑ PDR	Overhead
25	Aldhyani et al.	2020	DL	Traffic prediction	Congestion	↑ Prediction accuracy	Data requirement

Comparative Analysis

The comparative evaluation of recent studies conducted between 2020 and 2023 highlights a significant transformation in routing methodologies for IoT-based Mobile Ad Hoc Networks (MANETs), shifting from traditional rule-based approaches toward intelligent, data-driven frameworks. Conventional routing protocols, including AODV, DSR, and multipath routing mechanisms, primarily rely on shortest-path and static metric-based decisions. While these approaches provide a baseline level of performance, they are inherently limited in their ability to adapt to dynamic network conditions characterized by frequent topology changes, node mobility, and varying traffic loads. As a result, they often suffer from increased routing overhead, packet loss, latency, and inefficient energy utilization.

In contrast, reinforcement learning (RL) and deep reinforcement learning (DRL) approaches have demonstrated substantial improvements in adaptability and routing efficiency. These methods enable network nodes to learn optimal routing strategies through continuous interaction with the environment, thereby eliminating the need for predefined routing rules. Multi-agent reinforcement learning models, such as DeepCQ+, further enhance scalability by allowing distributed nodes to collaboratively optimize routing decisions. However, despite their advantages, RL-based approaches are associated with high computational complexity and slow convergence rates, which pose challenges for real-time implementation in resource-constrained IoT environments.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), have also emerged as powerful tools for routing prediction. These models are capable of capturing complex spatial and temporal relationships within network data, enabling accurate prediction of link stability, congestion levels, and node mobility patterns. As a result, deep learning-based routing approaches significantly improve key performance metrics such as packet delivery ratio, throughput, and network reliability. Nevertheless, their dependency on large-scale training datasets and high computational requirements limits their practical deployment in many IoT scenarios.

A notable advancement identified in the literature is the integration of optimization techniques, specifically Expanding Ring Search (ERS) and Random Early Detection (RED), with AI-based routing models. ERS effectively reduces routing overhead by limiting the scope of route discovery, while RED enhances congestion control by proactively managing queue behavior. When combined with AI techniques, these mechanisms enable intelligent and adaptive routing decisions that outperform both traditional protocols and standalone AI models. Hybrid approaches that integrate deep learning, reinforcement learning, and optimization strategies provide a balanced solution by combining predictive capabilities, adaptability, and efficiency.

Conclusion

The rapid growth of Internet of Things (IoT) technologies has increased the demand for intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs), where dynamic topology changes, node mobility, limited bandwidth, and energy constraints create major communication challenges. Conventional routing protocols such as AODV, DSR, and DSDV often fail to provide reliable performance because they rely on static routing decisions and cannot efficiently adapt to changing network conditions. As a result, Artificial Intelligence (AI)-based routing approaches have emerged as effective solutions for improving adaptability, predictive analysis, and resource management in IoT-enabled MANET environments.

Recent advancements in deep learning, reinforcement learning, and hybrid optimization techniques have significantly improved routing efficiency and network reliability. Global pooling dilated Convolutional Neural Networks (CNNs) effectively capture spatial and temporal network features, enabling accurate prediction of congestion, link stability, and routing paths. Reinforcement learning and deep reinforcement learning approaches further enhance routing performance by allowing nodes to dynamically learn optimal routing policies through interaction with the environment. In addition, optimization methods such as Expanding Ring Search (ERS) and Random Early Detection (RED) improve routing efficiency by reducing routing overhead and controlling congestion.

Despite these advancements, several challenges remain, including high computational complexity, energy consumption, scalability limitations, and lack of real-world datasets. Future research should focus on lightweight AI models, federated learning, edge intelligence, and Graph Neural Networks (GNNs) to develop scalable, adaptive, secure, and energy-efficient routing frameworks for real-time IoT-based MANET applications.

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