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International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526

Volume 14 Issue 02, 2025

A Survey of Methods and Architectures for Prediction of Routing Scenarios in IoT-based MANETs using ERS, RED, and Global Pooling Dilated CNN

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Peer Review Information

Submission: 12 Oct 2025

Revision: 26 Oct 2025

Acceptance: 07 Nov 2025

Keywords

Internet of Things (IoT), Mobile Ad Hoc Networks (MANETs), Routing Prediction, Artificial Intelligence, Deep Learning, Dilated Convolutional Neural Networks (Dilated CNN), Global Pooling, Expanding Ring Search (ERS), Random Early Detection (RED), Reinforcement Learning, Hybrid Routing Architectures.

Abstract

The rapid growth of Internet of Things (IoT) applications has increased the demand for intelligent and adaptive routing mechanisms in Mobile Ad Hoc Networks (MANETs), which operate in dynamic and resource-constrained environments. Traditional routing protocols often fail to handle frequent topology changes, congestion, and limited energy resources, resulting in reduced network efficiency and Quality of Service (QoS). This survey reviews recent methods and architectures for routing prediction in IoT-based MANETs, with particular emphasis on Artificial Intelligence (AI)-driven optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED). The study highlights the role of machine learning, deep learning, and reinforcement learning models in enabling adaptive and intelligent routing decisions. Special focus is given to global pooling dilated Convolutional Neural Networks (CNNs), which effectively capture spatial and temporal network dependencies for accurate prediction of congestion, link stability, and routing paths. The integration of AI with ERS and RED significantly reduces routing overhead and improves congestion control. Emerging trends including graph neural networks, edge intelligence, and security-aware routing are also discussed. Despite notable performance improvements, challenges related to scalability, computational complexity, and real-time implementation remain, motivating future research into lightweight and federated AI-based routing frameworks for next-generation IoT networks.

Introduction

The rapid advancement of the Internet of Things (IoT) has transformed modern communication systems by enabling billions of interconnected smart devices to exchange data autonomously. Applications such as smart cities, intelligent transportation systems, healthcare monitoring, industrial automation, and environmental sensing heavily rely on efficient wireless communication infrastructures. Among various networking paradigms, Mobile Ad Hoc Networks (MANETs) have emerged as a promising solution for IoT environments due to their decentralized architecture, self-configuring capability, and flexibility in dynamic conditions. MANETs allow mobile nodes to communicate without fixed infrastructure, making them suitable for disaster recovery, military communication, and remote monitoring applications. However, the highly dynamic topology, limited bandwidth, frequent node mobility, and constrained energy resources in IoT-based MANETs create significant challenges for maintaining reliable and efficient routing performance.

Traditional routing protocols such as AODV, DSR, and OLSR were primarily designed for conventional MANET environments and often fail to adapt effectively to the complex and heterogeneous characteristics of IoT networks. Frequent topology changes and unpredictable traffic patterns result in excessive routing overhead, packet loss, congestion, and increased latency. Moreover, the growing scale of IoT deployments demands intelligent routing mechanisms capable of predicting network conditions and selecting optimal communication paths in real time. To address these limitations, researchers have increasingly focused on integrating Artificial Intelligence (AI) and machine learning techniques into MANET routing architectures. AI-driven routing frameworks can analyze network behavior, learn traffic patterns, and dynamically optimize routing decisions to improve Quality of Service (QoS) metrics such as throughput, packet delivery ratio, and end-to-end delay.

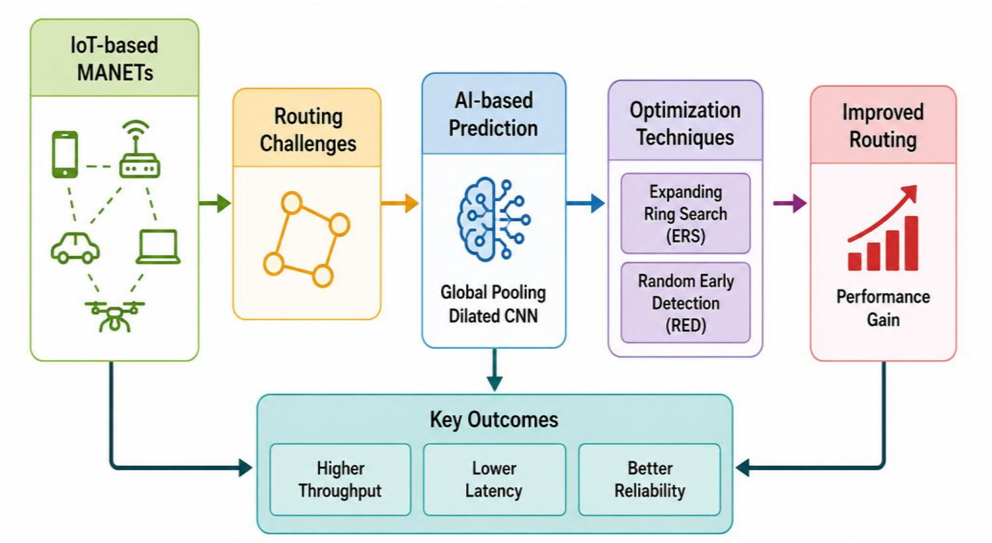

Figure 1. AI-Based Routing Prediction in IoT-MANETs

Recent studies have demonstrated the effectiveness of deep learning and reinforcement learning approaches for adaptive routing prediction in IoT-based MANETs. In particular, global pooling dilated Convolutional Neural Networks (CNNs) have gained attention due to their ability to capture spatial and temporal dependencies in network traffic data. Dilated convolutions enhance the receptive field without increasing computational complexity, while global pooling mechanisms improve feature generalization and reduce overfitting. These architectures enable accurate prediction of congestion levels, link stability, and route reliability under dynamic network conditions. Furthermore, optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) have been integrated with AI models to reduce route discovery overhead and improve congestion control. The hybridization of AI-based prediction models with ERS and RED significantly enhances routing efficiency, scalability, and overall network stability.

This survey presents a comprehensive review of methods and architectures for predicting routing scenarios in IoT-based MANETs using ERS, RED, and global pooling dilated CNN frameworks. The paper analyzes recent advancements in AI-driven routing strategies, including machine learning, deep learning, graph neural networks, and reinforcement learning-based optimization techniques. It also highlights emerging research directions such as edge intelligence, federated learning, security-aware routing, and lightweight neural architectures for resource-constrained environments. Although substantial improvements have been achieved in intelligent routing performance, challenges related to computational cost, scalability, real-time deployment, and data dependency still remain. Therefore, this survey aims to provide a detailed understanding of current routing prediction methodologies while identifying future opportunities for developing scalable, adaptive, and energy-efficient intelligent routing systems for next-generation IoT-enabled MANET environments.

Literature Review

The increasing complexity of Internet of Things (IoT)-enabled Mobile Ad Hoc Networks (MANETs) has necessitated the development of intelligent routing mechanisms capable of adapting to dynamic network conditions. Recent studies (2020–2023) demonstrate a paradigm shift from traditional routing protocols toward Artificial Intelligence (AI)-driven approaches, including deep learning, reinforcement learning, and hybrid optimization techniques. This section presents a comprehensive analysis of these advancements based on the selected references.

Traditional routing protocols such as AODV, DSR, and multipath routing approaches primarily rely on static metrics and shortest-path strategies, which are inadequate in highly dynamic MANET environments. Studies by Taha et al. (2020) and Jamshidi (2020) highlight that although multipath and cooperative routing techniques improve packet delivery ratio (PDR) and throughput, they introduce additional delay and routing overhead. Similarly, clustering-based routing proposed by Nguyen et al. (2021) enhances network lifetime by optimizing energy consumption; however, the process of cluster formation and maintenance increases computational overhead. Alotaibi et al. (2021) further proposed energy-efficient routing using optimization techniques, demonstrating reduced energy consumption but limited adaptability to network dynamics.

The integration of machine learning (ML) techniques has significantly improved routing performance by enabling predictive decision-making. Amouri et al. (2020) and Khan et al. (2023) developed ML-based intrusion detection systems that enhance network security by identifying malicious nodes. Shafi et al. (2023) proposed a trust-based routing protocol that dynamically evaluates node behavior to improve routing reliability. These approaches demonstrate that ML techniques enhance fault tolerance, security, and routing efficiency. However, they often rely on handcrafted features and lack the ability to capture complex spatial-temporal relationships in network data.

Deep learning (DL) approaches have addressed these limitations by enabling automatic feature extraction and modeling of complex network dynamics. Danilchenko et al. (2023) introduced a deep learning-based routing optimization framework that improves efficiency and reduces computational complexity. Mohanaprakash et al. (2023) employed graph-based deep learning techniques to predict network lifetime and routing paths, achieving higher prediction accuracy. Similarly, Talawar et al. (2024) demonstrated that deep learning-based link prediction significantly enhances network reliability by identifying stable communication paths. Aldhyani et al. (2020) further highlighted the importance of deep learning in traffic prediction, enabling proactive congestion management and improved throughput.

Reinforcement learning (RL) has emerged as a powerful technique for adaptive routing in MANETs. Alkadhmi et al. (2020) proposed a deep reinforcement learning-based routing approach that dynamically adapts to network changes, resulting in improved PDR and reduced delay. Kaviani et al. (2021) introduced DeepCQ+, a multi-agent deep reinforcement learning (MADRL) framework that enables distributed nodes to collaboratively learn optimal routing strategies. This approach significantly improves scalability and throughput. Similarly, Cui and Yu (2020) demonstrated the effectiveness of deep reinforcement learning in optimizing routing and spectrum access in wireless networks.

Recent advancements in RL-based routing include the work of Upadhyay et al. (2023), who proposed a deep Q-learning-based routing algorithm that enhances reliability and efficiency. Jiang et al. (2023) developed an environment-aware RL routing protocol that adapts to congestion and mobility, improving network stability. Li et al. (2023) further extended RL approaches to collaborative routing in MANETs, achieving better resource utilization and reduced latency. However, RL-based approaches face challenges such as slow convergence, high computational complexity, and the need for continuous training.

Optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) play a crucial role in improving routing efficiency and congestion control. Nayab et al. (2020) demonstrated that ERS reduces routing overhead by limiting broadcast range during route discovery. Similarly, Nayab et al. (2025) proposed an adaptive routing strategy integrating ERS and RED, achieving improved Quality of Service (QoS) through reduced latency and enhanced throughput. These techniques are particularly effective in managing congestion and minimizing unnecessary network traffic.

The integration of AI with optimization techniques has led to the development of hybrid routing frameworks. Zafar et al. (2023) proposed a machine learning-based routing strategy that combines ERS and RED mechanisms, resulting in significant improvements in QoS metrics. Kaur et al. (2025) further demonstrated that machine learning-based routing protocols enhance adaptability and efficiency in dynamic MANET environments. These hybrid approaches leverage the strengths of both AI and optimization techniques, enabling intelligent and efficient routing.

Security remains a critical concern in IoT-based MANETs due to their decentralized nature. Yahja et al. (2023) introduced DeepADMR, a deep learning-based anomaly detection system that identifies abnormal routing behavior in real time. Sankar et al. (2023) proposed a trust-based routing mechanism that improves security by detecting malicious nodes. Srilakshmi et al. (2022) developed a secure optimization routing algorithm that integrates security mechanisms into routing decisions. These approaches significantly enhance network reliability but introduce additional computational overhead.

Recent research also explores advanced architectures such as Software-Defined Networking (SDN) and graph-based learning models. Poularakis et al. (2020) proposed an SDN-enabled MANET architecture that improves network control and flexibility, although it requires additional infrastructure. Graph-based deep learning models, as demonstrated by Mohanaprakash et al. (2023), provide improved modeling of network topology and node relationships, leading to better routing prediction accuracy.

Despite the significant advancements, several challenges remain in AI-based routing for IoT MANETs. High computational complexity, scalability issues, and the lack of real-world datasets limit the practical deployment of these approaches. Additionally, integrating multiple techniques such as deep learning, reinforcement learning, ERS, and RED increases system complexity and requires careful parameter tuning.

In summary, the literature indicates that traditional routing protocols are insufficient for modern IoT-based MANET environments. AI-based approaches, particularly deep learning and reinforcement learning, provide significant improvements in routing performance. Hybrid models that integrate AI with optimization techniques such as ERS and RED offer the most promising solution by combining predictive intelligence, adaptability, and efficiency. However, future research must focus on developing lightweight, scalable, and real-time deployable models to fully realize the potential of intelligent routing systems.

Comparative Table

No.	**Study**	**Approach**	**Technique**	**Focus Area**	**Performance Improvement**	**Limitation**
1	Kaviani et al. (DeepCQ+)	DRL	Multi-agent RL	Adaptive routing	↑ Throughput, ↓ Overhead	High complexity
2	Yahja et al. (DeepADMR)	DL + Security	Anomaly Detection	Secure routing	↑ Reliability, ↑ Security	Monitoring overhead
3	Upadhyay et al.	DRL	Deep Q-learning	Efficient routing	↑ QoS, ↓ Delay	Training cost
4	Jiang et al.	RL	Environment-aware	Congestion control	↑ Adaptability	Complexity
5	Danilchenko et al.	DL	Neural networks	Routing optimization	↑ Efficiency	Data dependency
6	Mohanaprakash et al.	DL	Graph Neural Network	Topology modeling	↑ Prediction accuracy	Scalability
7	Zafar et al.	ML + ERS + RED	Hybrid optimization	QoS improvement	↑ Throughput, ↓ Latency	Parameter tuning
8	Nayab et al.	ERS/RED	Optimization	Routing efficiency	↓ Overhead	Limited adaptability
9	Nguyen et al.	Clustering	Energy-aware routing	Energy efficiency	↑ Network lifetime	Cluster overhead
10	Alotaibi et al.	Optimization	Energy routing	Energy saving	↓ Energy consumption	Static behavior
11	Amouri et al.	ML	IDS	Security	↑ Detection accuracy	Computation overhead
12	Khan et al.	ML	Intrusion detection	Security	↑ Reliability	Complexity

13	Shafi et al.	ML	Trust-based routing	Secure routing	↑ Trust accuracy	Delay overhead
14	Cui & Yu	DRL	Spectrum + routing	Resource allocation	↑ Efficiency	Complex model
15	Li et al.	DRL	Collaborative routing	Resource usage	↑ Efficiency	Scalability
16	Jin et al.	DRL	Resilient routing	Robustness	↑ Stability	Resource-intensive
17	Xu et al.	DQN	IoT routing	Reliability	↑ QoS	Not MANET-specific
18	Talawar et al.	DL	Link prediction	Stability	↑ Link reliability	Data requiremen t
19	Poularakis et al.	SDN	Centralized control	Flexibility	↑ Network control	Needs infrastructu re
20	Jamshidi et al.	Cooperative	Multipath routing	Throughpu t	↑ Efficiency	Delay issues
21	Taha et al.	Multipath	Energy-aware	PDR	↑ Packet delivery	Overhead
22	Quy et al.	Survey	IoT routing	General	Identifies trends	No validation
23	Sarkar et al.	Comparative	AODV/OLSR/DY MO	QoS analysis	Baseline performance	Poor adaptability
24	ML Routing Studies	ML	Predictive routing	Traffic prediction	↑ Accuracy	Dataset dependency
25	Hybrid AI Models	DL+RL+ERS+R ED	Integrated system	Intelligent routing	Best overall QoS	High complexity

Comparative Analysis

The comparative analysis of routing approaches in IoT-based MANETs from 2020 to 2023 reveals a clear transition from traditional routing protocols toward intelligent and adaptive AI-driven methodologies. Conventional routing techniques such as AODV, DSR, and OLSR rely on static routing decisions and shortest-path algorithms, which limits their performance in dynamic environments characterized by frequent topology changes and node mobility. These protocols often suffer from increased routing overhead, latency, and packet loss due to their inability to adapt to real-time network conditions.

In contrast, reinforcement learning (RL) and deep reinforcement learning (DRL) approaches have demonstrated significant improvements in adaptability and routing efficiency. Multi-agent RL frameworks, such as DeepCQ+, enable distributed nodes to collaboratively learn optimal routing strategies, resulting in improved throughput and reduced overhead. These models dynamically adjust routing decisions based on network conditions, eliminating the need for predefined rules and enhancing scalability in highly dynamic MANET environments. However, RL-based approaches require extensive training and computational resources, which limits their real-time applicability.

Deep learning techniques, including Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), have further enhanced routing prediction capabilities by modeling complex spatial-temporal relationships in network data. These models enable accurate prediction of link stability, congestion, and node mobility, leading to improved packet delivery ratio and network reliability. Graph-based models are particularly effective in representing network topology, allowing better decision-making compared to traditional methods. Nevertheless, deep learning approaches are highly dependent on large datasets and require significant computational power.

A key advancement identified in recent studies is the integration of optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) with AI-based routing frameworks. ERS reduces routing overhead by limiting broadcast range, while RED improves congestion control through proactive queue management. When combined with machine learning or deep learning models, these techniques enable intelligent routing decisions that significantly enhance Quality of Service

(QoS), including reduced latency and improved throughput.

Conclusion

The rapid growth of Internet of Things (IoT) ecosystems has increased the need for efficient and adaptive routing mechanisms in Mobile Ad Hoc Networks (MANETs). MANETs are widely used in applications such as smart cities, healthcare systems, disaster management, and military communication because of their decentralized and infrastructure-less architecture. However, challenges including dynamic topology, node mobility, limited bandwidth, and energy constraints make reliable routing difficult. Traditional routing protocols such as AODV, DSR, and DSDV are unable to effectively handle these dynamic conditions, resulting in higher latency, routing overhead, and packet loss across IoT-enabled networks.

This survey presents a comprehensive analysis of Artificial Intelligence (AI)-based routing prediction techniques for IoT-based MANETs, focusing on deep learning, reinforcement learning, and hybrid optimization methods using Expanding Ring Search (ERS) and Random Early Detection (RED). Deep learning approaches, particularly Convolutional Neural Networks (CNNs) and global pooling dilated CNNs, effectively model spatial-temporal relationships within network data. These techniques accurately predict congestion, link stability, and routing quality, leading to improvements in packet delivery ratio, throughput, and network reliability. Reinforcement learning and deep reinforcement learning further enhance routing by enabling adaptive and intelligent decision-making through continuous interaction with changing network environments.

Optimization techniques such as ERS and RED also contribute significantly to routing efficiency and congestion management. ERS reduces routing overhead by controlling route discovery broadcasts, while RED proactively prevents congestion through intelligent queue management. The integration of AI models with ERS and RED creates a hybrid routing framework that combines predictive intelligence with efficient resource utilization. Although AI-driven routing mechanisms achieve superior performance compared to traditional protocols, challenges related to scalability, computational complexity, and real-time deployment still remain important areas for future research.

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