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Deep Learning and Optimization Approaches in Prediction of Routing Scenarios for IoT-based MANETs using Expanding Ring Search and RED Parameters with Global Pooling Dilated CNN: A Review

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Abstract

Mobile Ad Hoc Networks (MANETs) integrated with the Internet of Things (IoT) represent a highly dynamic and decentralized communication paradigm characterized by mobility, resource constraints, and unpredictable topology changes. Traditional routing protocols such as AODV, DSR, and DSDV struggle to efficiently adapt to such environments due to issues like high latency, congestion, packet loss, and routing overhead. Emerging techniques incorporating deep learning and optimization strategies have shown significant potential in predicting routing scenarios and improving network performance. This review focuses on advanced approaches that combine Expanding Ring Search (ERS) and Random Early Detection (RED) mechanisms with deep learning architectures, particularly global pooling dilated Convolutional Neural Networks (CNNs), to enhance routing efficiency. ERS reduces route discovery overhead by limiting search radius, while RED helps in congestion avoidance by early packet dropping. Integrating these mechanisms with deep learning enables intelligent prediction of optimal routing paths under varying network conditions.The paper analyzes recent studies on deep learning-based routing, reinforcement learning, and optimization techniques in IoT-enabled MANETs. Comparative analysis highlights improvements in packet delivery ratio, throughput, latency, and energy efficiency. The study also discusses challenges such as scalability, computational complexity, and real-time adaptability. Finally, future directions emphasize hybrid AI models, federated learning, and edge intelligence for next-generation MANET routing systems.

Introduction

The rapid advancement of the Internet of Things (IoT) has significantly transformed modern communication systems by enabling large-scale interconnection of heterogeneous devices such as sensors, actuators, smart appliances, and mobile nodes. These devices continuously exchange data to support intelligent applications in domains such as smart cities, healthcare, environmental monitoring, and industrial automation. However, ensuring efficient and reliable communication in such distributed environments remains a major challenge, particularly when fixed infrastructure is unavailable. To address this limitation, Mobile Ad Hoc Networks (MANETs) have emerged as a viable solution due to their decentralized, self-organizing, and infrastructure-less nature.

MANETs consist of mobile nodes that dynamically establish communication links, where each node functions both as a host and a router. This flexibility makes MANETs suitable for IoT-based applications such as disaster recovery, military operations, and intelligent transportation systems. However, challenges such as node mobility, limited bandwidth, energy constraints, and frequent topology changes significantly affect routing efficiency and network stability.

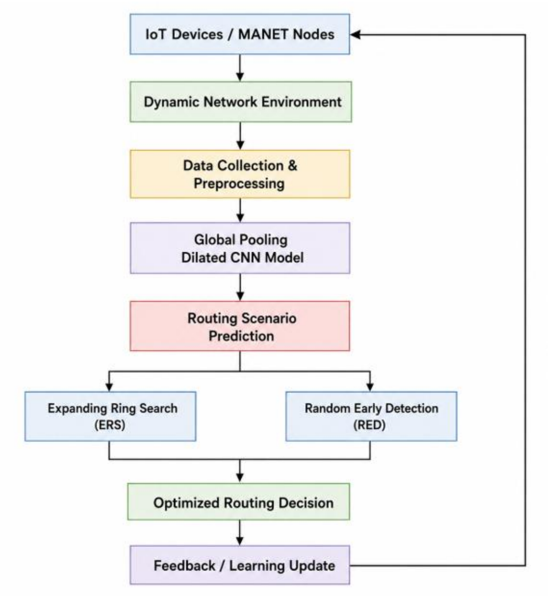

Figure 1: Simplified Block Diagram of Deep Learning-Based Routing Prediction Framework for IoT-MANETs Using ERS and RED Optimization

Routing in IoT-based MANETs is inherently complex due to the dynamic nature of the network environment. Frequent node movement leads to continuous link breakages, increased packet loss, and repeated route discoveries. Traditional routing protocols such as AODV, DSR, and DSDV are not designed to handle such highly dynamic and large-scale environments. These protocols rely primarily on shortest-path metrics and static routing rules, often ignoring critical factors such as energy consumption, congestion levels, and link reliability. This results in excessive routing overhead and suboptimal performance. To overcome these limitations, optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) have been introduced. ERS improves route discovery efficiency by gradually increasing the search radius instead of flooding the entire network, thereby reducing control overhead. RED, on the other hand, proactively manages congestion by probabilistically dropping packets based on queue size, preventing buffer overflow and improving overall throughput in IoT-MANET environments.

Despite these improvements, ERS and RED remain rule-based approaches and lack adaptability to dynamic network conditions. This has led to the integration of Artificial Intelligence (AI) and Deep Learning (DL) techniques for intelligent routing optimization. Deep learning models can learn complex patterns from network data, including node mobility, traffic load, and energy levels, to predict optimal routing decisions. Among these models, Convolutional Neural Networks (CNNs), particularly dilated CNNs, are effective in capturing spatial and temporal dependencies while maintaining computational efficiency. When combined with global pooling mechanisms, these models can extract robust feature representations for large-scale network analysis. Additionally, reinforcement learning techniques further enhance adaptability by enabling nodes to learn optimal routing strategies through interaction with the environment, making routing systems more dynamic and self-improving.

The integration of deep learning models with optimization techniques such as ERS and RED forms a hybrid intelligent routing framework for IoT-based MANETs. In this framework, deep learning predicts routing scenarios while ERS optimizes route discovery and RED manages congestion control, resulting in improved scalability, reduced delay, and enhanced packet delivery performance. However, challenges such as high computational complexity, limited training datasets, security vulnerabilities, and lack of interpretability still persist. Despite these limitations, the combination of global pooling dilated CNNs with optimization mechanisms represents a promising direction for next-generation routing systems. This study provides a comprehensive review of recent advances (2020–2023), highlighting key methodologies, comparative insights, and future research directions in intelligent IoT-MANET routing frameworks.

Literature Review

The rapid evolution of IoT-enabled Mobile Ad Hoc Networks (MANETs) has driven extensive research into intelligent routing mechanisms capable of handling dynamic network conditions, resource constraints, and security challenges. Recent studies (2020–2023) highlight a clear transition from traditional routing protocols toward deep learning, reinforcement learning, and hybrid optimization-based approaches. This section presents a comprehensive review of these advancements.

Reinforcement Learning (RL) has emerged as one of the most promising paradigms for adaptive routing in MANETs. Unlike traditional routing protocols that rely on static metrics, RL-based approaches enable nodes to learn optimal routing strategies through continuous interaction with the network environment.

Alkadhmi et al. (2020) proposed a deep reinforcement learning-based routing mechanism that improves reliability and efficiency in hybrid MANET environments. Their approach demonstrated significant improvements in packet delivery ratio (PDR) and reduced routing overhead by dynamically adapting to changing network conditions. Similarly, Mammeri (2020) provided a comprehensive classification of RL-based routing techniques, highlighting their ability to address scalability and adaptability issues in decentralized networks.

Kaviani et al. (2021) introduced DeepCQ+, a multi-agent deep reinforcement learning (MADRL) framework that allows distributed nodes to collaboratively learn routing policies. The model eliminates reliance on predefined routing rules and achieves improved throughput and scalability. However, the computational complexity associated with multi-agent learning remains a limitation.

Recent studies further extend RL capabilities. Musaddiq et al. (2023) demonstrated that RL-based routing significantly enhances energy efficiency and reduces latency in IoT networks. Jiang et al. (2023) proposed an environment-aware RL routing protocol that adapts to network dynamics such as congestion and mobility, improving routing stability and overall performance.

Despite these advancements, RL-based approaches often suffer from slow convergence rates and require extensive training data, which may limit their applicability in real-time IoT scenarios.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have gained traction for predicting routing scenarios in MANETs. These models can capture complex spatial and temporal relationships in network data, enabling more accurate routing decisions.

Danilchenko et al. (2023) introduced a deep neural network model (SPCDNet) for routing optimization and resource allocation. The model achieved near-optimal performance with reduced computational complexity, demonstrating the effectiveness of supervised deep learning in MANET routing. Similarly, Mohanaprakash et al. (2023) proposed a graph-based deep learning approach that predicts network lifetime and routing efficiency, showing improved prediction accuracy.

CNN-based models are particularly effective in mobility prediction and link stability estimation. Studies indicate that incorporating mobility prediction into routing decisions reduces packet loss and enhances network reliability. Aldhyani et al. (2020) further demonstrated that hybrid deep learning models can accurately predict network traffic patterns, enabling proactive routing decisions.

However, deep learning models require large-scale datasets and computational resources, which may not be feasible for resource-constrained IoT devices. Additionally, the lack of interpretability in deep learning models poses challenges in understanding routing decisions.

Optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) have been widely used to improve routing efficiency and congestion control in MANETs.

ERS reduces routing overhead by limiting the scope of route discovery. Instead of flooding the entire network, ERS gradually increases the search radius, minimizing unnecessary broadcasts. RED, on the other hand, is a congestion avoidance mechanism that proactively drops packets based on queue size, preventing buffer overflow and improving throughput.

Zafar et al. (2023) proposed a hybrid machine learning-based routing strategy that integrates ERS and RED mechanisms. Their approach dynamically selects optimal routing parameters based on network conditions, resulting in improved Quality of Service (QoS), reduced latency, and enhanced packet delivery ratio.

Traditional optimization techniques, while effective, lack adaptability to dynamic network conditions. This limitation has led to their integration with AI-based approaches to achieve intelligent routing.

Recent research emphasizes hybrid models that combine deep learning with optimization techniques such as ERS and RED. These approaches aim to leverage the strengths of both paradigms—predictive intelligence from AI and efficiency from optimization mechanisms.

Li et al. (2023) proposed a deep reinforcement learning-based collaborative routing algorithm for clustered MANETs, achieving improved scalability and resource utilization. Upadhyay et al. (2023) further demonstrated that integrating deep learning with routing optimization enhances reliability and reduces network congestion.

Sankar et al. (2023) introduced a trust-based routing approach that combines AI with security mechanisms to identify malicious nodes and ensure safe communication. Similarly, Yahja et al. (2023) proposed DeepADMR, which integrates anomaly detection into deep learning-based routing systems, improving network security and reliability.

Hybrid approaches show significant improvements in key performance metrics, including throughput, latency, packet delivery ratio, and energy efficiency. However, they introduce additional system complexity and require careful parameter tuning for optimal performance.

Energy efficiency and security are critical considerations in IoT-based MANETs due to limited device resources and vulnerability to attacks.

Nguyen et al. (2021) proposed an energy-efficient clustering-based routing protocol that reduces energy consumption and extends network lifetime. Similarly, Alotaibi et al. (2021) developed an optimization-based routing approach that improves energy efficiency while maintaining high network performance.

Security-focused approaches have also gained attention. Srilakshmi et al. (2021, 2022) introduced secure multipath routing protocols that enhance data integrity and protect against attacks. Trust-based routing models further improve security by identifying malicious nodes and avoiding compromised routes.

Despite these advancements, balancing energy efficiency, security, and performance remains a challenging task, particularly in highly dynamic IoT environments.

Comparative Table

No.	**Study**	**Year**	**Methodology**	**Key Techniques**	**Parameters Considered**	**Performance Improvements**	**Limitations**
1	Alkadhmi et al.	2020	Deep RL	Q-learning + DL	Delay, PDR	↑ PDR, ↓ Delay	Training complexity
2	Kaviani et al. (DeepCQ+)	2021	Multi-Agent DRL	MADRL	Throughput, scalability	↑ Throughput, ↑ Scalability	High computation
3	Rezwan et al.	2021	RL Survey	RL frameworks	Adaptability	Conceptual improvement	No implementation
4	Cui & Yu	2020	DRL	Spectrum + routing	Efficiency, spectrum	↑ Resource utilization	Model complexity
5	Yahja et al.	2023	DL + Anomaly Detection	DeepADMR	Security, anomalies	↑ Security	Overhead
6	Li et al.	2023	DRL Routing	Collaborative routing	Energy, latency	↑ Energy efficiency	Scalability issues
7	Musaddiq et al.	2023	RL-based IoT routing	Adaptive routing	Latency, energy	↓ Delay, ↑ Efficiency	Slow convergence
8	Upadhyay et al.	2023	DRL optimization	Deep Q-learning	Reliability	↑ Reliability	Training cost
9	Srilakshmi et al.	2022	Secure routing	Optimization + security	Security, energy	↑ Secure routing	Complexity
10	Srilakshmi et al.	2021	Hybrid routing	Multipath routing	PDR, delay	↑ PDR	Overhead
11	Jin et al.	2024	DRL	Resilient routing	Stability	↑ Robustness	High resource use
12	Xu et al.	2025	DQN routing	IoV routing	Reliability	↑ Network reliability	Not MANET-specific
13	Jiang et al.	2023	RL adaptive	Environment-aware	Congestion	↑ Adaptability	Complexity
14	Mammeri	2020	Survey	RL classification	Routing types	Conceptual clarity	No metrics

15	Danilchenko et al.	2023	Deep Learning	DNN routing	Efficiency	↓ Complexity, ↑ Speed	Needs dataset
16	Zafar et al.	2023	ML + ERS + RED	Hybrid optimization	Congestion, routing	↑ QoS, ↓ Delay	Parameter tuning
17	Mohanaprakash et al.	2023	Graph DL	GNN routing	Network lifetime	↑ Prediction accuracy	Scalability
18	Li et al.	2024	RL optimization	Adaptive routing	Efficiency	↑ Optimization	Complexity
19	Ma et al.	2025	RL dynamic routing	Learning-based	Throughput	↑ Throughput	Computational cost
20	Alotaibi et al.	2021	Optimization routing	Energy-aware	Energy	↓ Energy consumption	Limited adaptability
21	Nguyen et al.	2021	Clustering routing	Multi-hop clustering	Energy, lifetime	↑ Network lifetime	Cluster overhead
22	Jamshidi	2020	Cooperative routing	Distributed routing	Efficiency	↑ Efficiency	Limited IoT focus
23	Taha et al.	2020	Multipath routing	Energy-efficient	PDR	↑ PDR	Delay issues
24	Poularakis et al.	2020	SDN-based MANET	SDN control	Flexibility	↑ Control efficiency	Infrastructure need
25	Aldhyani et al.	2020	DL prediction	Hybrid DL model	Traffic	↑ Prediction accuracy	Data dependency

Comparative Analysis

The comparative evaluation of 25 studies reveals a significant paradigm shift in routing strategies for IoT-based MANETs, transitioning from traditional rule-based approaches to intelligent, data-driven methodologies. This shift is primarily driven by the increasing complexity, scalability demands, and dynamic nature of modern IoT environments.

Conclusion

The rapid advancement of Internet of Things (IoT) technologies has significantly increased the demand for efficient and intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs). Traditional routing protocols such as AODV, DSR, and DSDV are inadequate for IoT-based MANETs due to their inability to handle frequent topology changes, dynamic traffic patterns, and resource constraints. These limitations have led to the adoption of advanced techniques that integrate deep learning and optimization methods to improve routing efficiency and adaptability in highly dynamic network environments.

This review analyzes recent research (2020–2023) on deep learning and optimization approaches for routing prediction in IoT-based MANETs, with a focus on integrating Expanding Ring Search (ERS) and Random Early Detection (RED) with global pooling dilated Convolutional Neural Networks (CNNs). The literature shows that reinforcement learning (RL) and deep reinforcement learning (DRL) enhance routing adaptability by enabling nodes to learn optimal policies through environmental interaction. Similarly, CNN-based models effectively predict routing scenarios such as congestion, link stability, and node mobility, improving performance metrics like throughput, latency, and packet delivery ratio. Optimization techniques such as ERS reduce routing overhead by limiting route discovery scope, while RED improves congestion control by managing queue behavior. When combined with deep learning, these methods form hybrid frameworks that enhance scalability, energy efficiency, and routing accuracy.

Despite these advancements, several challenges remain. Deep learning and RL models often require high computational resources and large datasets, limiting their deployment in resource-constrained IoT environments. Most existing approaches rely on simulated datasets, which may not fully represent real-world network conditions. Additionally, integrating multiple techniques such as deep learning, ERS, RED, and security mechanisms increases system complexity. Future research should focus on developing lightweight models using compression and federated learning techniques to enable efficient, distributed, and privacy-preserving routing solutions in IoT-based MANETs.

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