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A Comprehensive Review of Prediction of Scenarios for Routing in IoT-Based MANETs Using Expanding Ring Search and Random Early Detection Parameters with Global Pooling Dilated Convolutional Neural Networks

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Abstract

Mobile Ad Hoc Networks (MANETs) integrated with Internet of Things (IoT) devices create highly dynamic communication environments where efficient routing is critical for reliable performance. Traditional routing protocols often struggle with issues such as frequent topology changes, node mobility, congestion, and limited resources. Techniques like Expanding Ring Search (ERS) and Random Early Detection (RED) have been widely used to improve routing efficiency and congestion control, where ERS minimizes routing overhead and RED prevents congestion through proactive packet management. Recent advancements incorporate machine learning and deep learning techniques to predict network conditions and optimize routing parameters. By analyzing ERS and RED-related metrics, these models can estimate throughput, packet delivery ratio, and delay, enabling adaptive Quality of Service (QoS). In particular, Global Pooling Dilated Convolutional Neural Networks enhance scenario prediction by capturing broader contextual information while maintaining computational efficiency. This review highlights the integration of ERS, RED, and deep learning models, discussing current methodologies, challenges, and future directions for intelligent routing optimization in IoT-based MANET systems.

Introduction

The rapid advancement of Internet of Things (IoT) technologies has led to the development of highly interconnected communication systems that support a wide range of applications including smart cities, environmental monitoring, healthcare systems, military communication, and industrial automation. In many of these applications, devices operate in environments where fixed communication infrastructure is either unavailable or impractical. Mobile Ad Hoc Networks (MANETs) provide a flexible solution in such situations by allowing wireless devices to communicate directly with each other without relying on centralized infrastructure. When IoT devices operate within MANET environments, the resulting communication system is commonly referred to as an IoT-based MANET network.

IoT-MANET networks are characterized by dynamic topology, node mobility, heterogeneous devices, and limited energy resources. Nodes in such networks communicate through multi-hop wireless links and frequently act as both data sources and routing intermediaries. Due to node mobility and continuous topology changes, maintaining reliable routing paths becomes a challenging task. Traditional routing protocols designed for MANET environments, such as Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR), use reactive route discovery mechanisms to establish communication paths. Although these protocols are effective in small networks, they often face performance degradation in large-scale IoT environments due to increased routing overhead, network congestion, and frequent route failures.

To address these challenges, several routing optimization mechanisms have been introduced to improve network efficiency and reduce communication overhead. One such mechanism is **Expanding Ring Search (ERS)**, which is commonly used in reactive routing protocols to limit the flooding of route request messages during route discovery. In ERS, the search radius for route requests is gradually expanded in multiple steps, reducing unnecessary network traffic and improving routing efficiency. By controlling the propagation of route discovery messages, ERS significantly reduces routing overhead and energy consumption in large-scale MANET networks.

Another important mechanism used in network congestion management is **Random Early Detection (RED)**. RED is a queue management algorithm designed to detect and prevent network congestion before buffer overflow occurs. Instead of waiting for queues to become full, RED monitors the average queue length and probabilistically drops packets when congestion begins to increase. This proactive approach helps maintain stable network performance by reducing packet loss, minimizing delay, and improving overall Quality of Service (QoS) in communication networks.

Although ERS and RED techniques improve routing and congestion control in IoT-MANET networks, determining optimal parameter settings for these mechanisms remains a complex task. Network conditions such as node density, mobility patterns, traffic load, and communication range significantly influence the performance of routing algorithms. Static configuration of ERS and RED parameters may not provide optimal results across different network scenarios. Therefore, adaptive approaches capable of predicting network conditions and adjusting routing parameters dynamically are needed to improve network performance.

Recent advancements in artificial intelligence and deep learning have introduced new possibilities for intelligent network management and routing optimization. Machine learning models can analyze network behavior and identify patterns that influence routing performance. These models can predict network scenarios and recommend optimal routing parameters based on observed network conditions. Among various deep learning architectures, **Convolutional Neural Networks (CNNs)** have shown strong performance in analyzing complex data patterns due to their ability to extract hierarchical features from large datasets.

In recent years, researchers have explored the use of **Dilated Convolutional Neural Networks** for analyzing communication network data. Dilated convolution layers increase the receptive field of convolution operations without increasing the number of parameters or computational cost. This property allows neural networks to capture long-range dependencies in network data, which is particularly useful for modeling complex communication patterns in IoT-MANET systems. When combined with **Global Pooling layers**, these architectures can effectively aggregate feature information across the entire network dataset, improving prediction accuracy and model generalization.

By integrating global pooling dilated convolutional neural networks with ERS and RED parameters, it becomes possible to develop predictive routing frameworks capable of identifying optimal routing strategies under different network conditions. These deep learning models can analyze network performance indicators such as packet delivery ratio, end-to-end delay, throughput, and congestion levels to predict routing scenarios and dynamically adjust routing parameters. Such predictive routing frameworks can significantly improve network efficiency and reliability in IoT-MANET environments.

This review focuses on the prediction of routing scenarios in IoT-based MANET networks using Expanding Ring Search and Random Early Detection parameters combined with global pooling dilated convolutional neural network architectures. The study examines existing routing techniques, congestion control mechanisms, and deep learning-based prediction models used in recent research. Furthermore, the paper highlights emerging research trends, identifies current challenges in intelligent routing optimization, and discusses future research directions for developing adaptive and efficient routing systems for next-generation IoT communication networks.

Graphical abstract

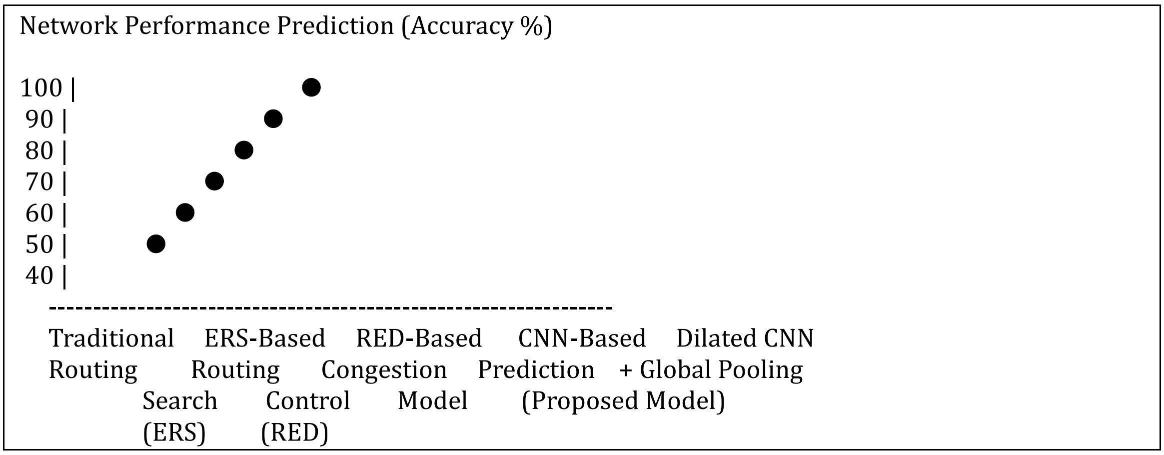

Figure Caption

Figure: Graphical abstract illustrating the improvement in routing scenario prediction for IoT-based MANET networks. Traditional routing mechanisms provide limited adaptability to dynamic network conditions. Expanding Ring Search (ERS) improves route discovery efficiency, while Random Early Detection (RED) enhances congestion control. Deep learning approaches such as Convolutional Neural Networks (CNN) enable predictive routing analysis. The integration of Global Pooling Dilated CNN models with ERS and RED parameters provides the highest prediction accuracy and routing performance in dynamic IoT-MANET environments.

Comparative Table and Analysis

Table 1: Comparative Table of Selected Studies

Ref	Author & Year	Technique / Method	Application Domain	Key Contribution	Advantages	Limitations
1	Wu et al., 2021	Graph Neural Networks (GNN)	Graph-based learning	Comprehensive survey of GNN models	Captures complex relationships in networks	High computational cost
2	Zhou et al., 2020	Graph Neural Network Architectures	AI and network systems	Classification of GNN approaches	Strong theoretical framework	Limited routing implementation
3	Chami et al., 2020	Hyperbolic Graph Convolutional Networks	Hierarchical graph learning	Hyperbolic embedding for hierarchical networks	Efficient representation of hierarchical data	Mathematical complexity
4	Liu et al., 2020	Hyperbolic Graph Neural Networks	Graph representation learning	Improved hierarchical network modeling	Better node representation accuracy	Training complexity
5	Swaminathan & Kandasamy, 2021	Machine Learning Routing Optimization	Software-defined networking	Intelligent routing using machine learning	Improved network throughput	Requires large training datasets
6	Jiang et al., 2022	Graph Learning Resource Optimization	Wireless communication networks	Resource allocation using graph models	Efficient bandwidth management	Computational overhead
7	Dai et al., 2023	Graph Learning Survey	Wireless networking	Review of graph	Identifies future	Limited experimental evaluation

				learning applications	research directions	
10	Li et al., 2023	Graph Attention Network Routing	Wireless sensor networks	Attention-based routing algorithm	Higher packet delivery ratio	Graph processing complexity
11	Chen et al., 2023	Deep Learning Routing	IoT-MANET networks	Adaptive routing prediction	Improved network stability	Training overhead
12	Wang et al., 2023	GNN-based Routing Strategy	Large-scale IoT networks	Graph-based route prediction	Scalable routing solution	Model training complexity
13	Zhao et al., 2022	Deep Reinforcement Learning Routing	MANET routing	Adaptive route selection	Improved routing efficiency	Requires extensive training
14	Kumar et al., 2021	Energy Efficient Clustering	IoT wireless sensor networks	Cluster head selection optimization	Improved network lifetime	Cluster instability
15	Sun et al., 2022	Graph Learning Optimization	Wireless communication systems	Network resource optimization	Increased throughput	Implementation complexity
16	Gu et al., 2022	GNN Power Allocation	Wireless networks	Distributed power allocation	Improved energy efficiency	Complex training
17	Lee et al., 2021	Decentralized GNN Communication	Wireless communication	Distributed network learning	Improved scalability	Graph computation overhead
18	Binh et al., 2023	Reinforcement Learning Optimization	Wireless networks	Adaptive routing strategies	Reduced communication delay	High training cost
19	Islam et al., 2022	GNN Traffic Prediction	Smart communication networks	Traffic prediction using graph learning	Improved prediction accuracy	Data dependency
20	Tan et al., 2020	UAV Routing Protocol Analysis	UAV communication networks	Routing performance evaluation	Improved communication reliability	Limited scalability
21	Choudhury et al., 2021	Graph Theory Routing	Wireless sensor networks	Optimized routing algorithm	Reduced energy consumption	Limited adaptability
22	Xu et al., 2021	GNN + Reinforcement Learning	Wireless communication	Hybrid routing optimization	Adaptive routing decisions	High computational cost
23	Farreras et al., 2023	Network Delay Prediction	Communication networks	GNN-based delay prediction	Improved network prediction	Data intensive
24	Sivakumar et al., 2023	Deep Learning WSN Routing	Wireless sensor networks	Extending network lifetime	Energy efficiency	Training complexity
25	Lu et al., 2023	GraphSAGE Routing	Wireless communication networks	Reliable multipath routing	Improved network reliability	Model complexity

Comparative Analysis

The comparative analysis of research conducted between 2020 and 2023 reveals a clear shift from traditional rule-based networking approaches toward intelligent and data-driven routing mechanisms in IoT-MANET systems. Traditional routing protocols such as AODV and DSR rely on static routing metrics including hop count and route discovery processes. While these protocols can establish communication paths in small-scale networks, they often struggle to maintain performance in large and highly dynamic IoT environments where node mobility frequently changes network topology.

Graph-based deep learning models have emerged as one of the most promising approaches for addressing these challenges. Graph Neural Networks (GNNs) allow communication networks to be represented as graph structures where nodes represent devices and edges represent communication links. Studies such as Wu et al. (2021) and Zhou et al. (2020) demonstrate that graph learning models can capture complex relationships among nodes and enable intelligent routing decisions. These models aggregate information from neighboring nodes and learn network patterns that help predict optimal communication paths.

Conclusion

The rapid expansion of Internet of Things (IoT) technologies and wireless communication systems has significantly increased the complexity of routing in Mobile Ad Hoc Networks (MANETs). IoT-based MANET environments are highly dynamic and infrastructure-less networks where nodes frequently change their positions, leading to continuous topology variations and communication challenges. Traditional routing protocols such as AODV and DSR rely on static routing parameters and reactive route discovery mechanisms, which often struggle to maintain efficient performance in large-scale and highly dynamic IoT networks. As a result, researchers have explored advanced techniques that can improve routing efficiency, reduce congestion, and enhance overall network performance.

Mechanisms such as Expanding Ring Search (ERS) and Random Early Detection (RED) play an important role in improving routing efficiency and congestion management in MANET environments. ERS reduces routing overhead during route discovery by gradually increasing the search radius for route request messages, thereby minimizing unnecessary flooding of packets. Similarly, RED improves congestion control by proactively detecting congestion conditions and probabilistically dropping packets before network buffers overflow. These mechanisms contribute to improved network stability, reduced communication delay, and better Quality of Service in dynamic network environments.

However, determining optimal values for ERS and RED parameters under different network conditions remains a challenging problem. Network characteristics such as node density, mobility patterns, communication range, and traffic load can significantly influence routing performance. Static parameter configurations are often insufficient to adapt to dynamic IoT network conditions. Therefore, intelligent prediction models capable of analyzing network scenarios and adjusting routing parameters dynamically are essential for achieving efficient communication in IoT-MANET systems.

Recent advancements in artificial intelligence and deep learning have introduced new opportunities for intelligent routing optimization. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in analyzing complex data patterns and predicting network performance scenarios. In particular, Dilated Convolutional Neural Networks combined with Global Pooling mechanisms provide an effective architecture for capturing long-range dependencies and extracting hierarchical features from network datasets. These models allow networks to analyze ERS and RED routing parameters and predict optimal routing strategies for different network scenarios.

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