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Recent Advances in Prediction of scenarios for routing in IoT based MANETs on expanding ring search and random early detection parameters using global pooling dilated convolutional neural network: A Systematic Review

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Abstract

Mobile Ad Hoc Networks (MANETs) integrated with Internet of Things (IoT) devices create highly dynamic and decentralized communication environments where efficient routing is essential for maintaining reliable network performance. Traditional routing protocols often struggle with challenges such as node mobility, congestion, routing overhead, and frequent topology changes. Techniques like Expanding Ring Search (ERS) and Random Early Detection (RED) have been widely adopted to improve routing efficiency and congestion control. ERS reduces unnecessary network flooding by incrementally expanding the search radius during route discovery, while RED proactively manages congestion by controlling packet queue behavior, thereby enhancing overall network stability and energy efficiency.Recent advancements have introduced machine learning and deep learning techniques for predicting routing behavior based on network parameters. These models analyze ERS and RED metrics to estimate performance indicators such as packet delivery ratio, throughput, and end-to-end delay, enabling adaptive routing decisions under varying conditions. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and dilated CNNs, effectively capture spatial and temporal dependencies in network data. Dilated convolutions expand the receptive field without increasing computational cost, improving prediction accuracy. This review provides a comprehensive analysis of routing optimization approaches and highlights future directions for intelligent, scalable, and adaptive routing in IoT-based MANET systems.

Introduction

The rapid advancement of Internet of Things (IoT) technologies has significantly transformed modern communication systems by enabling billions of interconnected devices to exchange data and perform intelligent operations. IoT applications span diverse domains such as smart cities, environmental monitoring, healthcare, industrial automation, transportation, and disaster management. Many of these applications operate in environments where fixed infrastructure is unavailable, unreliable, or costly to deploy. In such cases, Mobile Ad Hoc Networks (MANETs) provide a flexible and decentralized communication framework that allows devices to communicate directly without relying on centralized control. When IoT devices operate within MANET environments, they form IoT-based MANET networks, combining the adaptability of ad hoc networking with the intelligence of IoT systems to support dynamic and large-scale deployments.

IoT-MANET networks are inherently complex due to their dynamic characteristics, including node mobility, frequent topology changes, limited energy resources, and heterogeneous device capabilities. Communication in such networks relies on multi-hop routing, where nodes function both as data transmitters and intermediaries. Traditional MANET routing protocols like Ad hoc On-Demand Distance Vector (AODV) and Dynamic Source Routing (DSR) utilize reactive route discovery mechanisms. While effective in smaller or less dynamic environments, these protocols often struggle in large-scale IoT deployments, leading to excessive routing overhead, increased congestion, and frequent route failures. To address these issues, optimization techniques such as Expanding Ring Search (ERS) and Random Early Detection (RED) have been introduced. ERS improves route discovery efficiency by limiting broadcast range initially and gradually expanding it, reducing unnecessary network flooding. RED, on the other hand, proactively manages congestion by monitoring queue lengths and probabilistically dropping packets before buffer overflow occurs, thereby enhancing network stability and performance.

Despite their advantages, ERS and RED require careful parameter tuning to achieve optimal performance under varying network conditions. Factors such as node density, traffic patterns, mobility, and transmission range significantly influence routing efficiency. Static parameter configurations often fail to adapt to dynamic environments, highlighting the need for intelligent and adaptive solutions. Recent advancements in artificial intelligence and deep learning have introduced promising approaches for network optimization. Machine learning models can analyze historical and real-time network data to predict performance trends and adjust routing strategies accordingly. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in extracting meaningful patterns from complex datasets, making them suitable for network scenario analysis and prediction tasks.

More recently, Dilated Convolutional Neural Networks combined with global pooling techniques have gained attention for their ability to capture long-range dependencies without significantly increasing computational complexity. These models can effectively process large-scale network data and provide accurate predictions of routing performance metrics such as packet delivery ratio, throughput, delay, and congestion levels. By integrating ERS and RED parameters with such deep learning architectures, it becomes possible to develop intelligent frameworks capable of predicting optimal routing scenarios in IoT-MANET environments. This systematic review explores recent advancements in this domain, analyzing existing routing techniques, congestion control mechanisms, and deep learning-based prediction models. It further identifies current research challenges and outlines future directions for developing adaptive, efficient, and scalable routing solutions for next-generation IoT communication networks.

Literature Review

Early studies focused on analyzing the limitations of conventional MANET routing protocols such as AODV, DSR, and DSDV under dynamic environments. These protocols rely on reactive or proactive mechanisms but fail to adapt to highly dynamic IoT scenarios with varying node density and mobility.

Arega et al. (2020) conducted a performance evaluation of classical routing protocols and found that packet delivery ratio (PDR) and delay significantly degrade under high mobility and congestion scenarios. Similarly, Quy et al. (2020) highlighted the importance of routing metrics such as hop count, bandwidth, and delay, emphasizing the need for adaptive routing strategies.

Wang et al. (2020) introduced energy-aware routing mechanisms that improved network lifetime but did not effectively address congestion and route instability. These findings demonstrate that traditional routing approaches lack adaptability and predictive intelligence.

Further, Sarkar et al. (2022) analyzed routing protocols in heterogeneous MANET environments and showed that node diversity (e.g., mobility levels) significantly affects QoS metrics such as delay and throughput . This highlights the need for intelligent routing mechanisms capable of handling heterogeneous IoT nodes.

To overcome the limitations of traditional protocols, researchers began integrating machine learning techniques into routing decision-making processes. These approaches aim to predict optimal routing parameters based on network conditions.

Nayab et al. (2021) proposed a machine learning framework for predicting optimal routing scenarios using ERS and RED parameters. The study demonstrated that ML-based prediction significantly improves throughput and reduces delay by dynamically selecting routing parameters .

Gupta et al. (2021) introduced QoS-aware routing using supervised learning techniques, where models were trained to predict network performance metrics. The results showed improved packet delivery and reduced congestion compared to static routing methods.

Singh et al. (2022) extended this work by applying AI-based routing mechanisms that dynamically adjust routing paths based on real-time network conditions. Similarly, Verma et al. (2022) proposed energy-efficient ML-based routing approaches that optimize both energy consumption and QoS.

Kaur et al. (2022) emphasized the importance of machine learning in highly dynamic networks such as FANETs and MANETs, noting that ML-based routing significantly improves adaptability and performance under mobility conditions .

These studies collectively establish that ML-based routing enhances adaptability, but its performance depends heavily on feature engineering and training data quality.

Deep learning approaches have gained significant attention due to their ability to capture complex network patterns and temporal dependencies.

Danilchenko et al. (2023) proposed a deep learning framework for MANET routing, demonstrating that neural networks can effectively optimize routing decisions and resource allocation. Their model achieved improved scalability and performance across dynamic network scenarios .

Khan et al. (2021) utilized CNN-based architectures for routing optimization in IoT networks, enabling efficient feature extraction from network states. Similarly, Sharma et al. (2023) applied convolutional neural networks (CNNs) to improve routing performance, achieving higher accuracy in path selection and congestion prediction.

Li et al. (2021) introduced neural network-based adaptive routing, where routing decisions are continuously updated using learned patterns from network traffic. This approach significantly reduced delay and improved throughput.

Chatterjee et al. (2023) explored dilated CNN architectures for network traffic prediction, showing that dilated convolutions capture multi-scale dependencies effectively, making them suitable for IoT-MANET environments.

Singh et al. (2021) proposed global pooling CNN models, which reduce computational complexity while maintaining high prediction accuracy, making them suitable for resource-constrained IoT nodes.

Overall, deep learning-based approaches outperform traditional ML models due to their ability to automatically extract features and model complex relationships.

Reinforcement learning (RL) has been widely adopted for adaptive routing in dynamic MANET environments.

Kaviani et al. (2021) introduced DeepCQ+, a multi-agent deep reinforcement learning (MADRL) framework for routing optimization. The model achieved higher throughput and lower overhead compared to traditional Q-learning approaches while maintaining robustness under varying network conditions .

Further improvements were proposed by Yahja et al. (2023), who developed DeepADMR, a deep learning-based anomaly detection system for routing. The model enhances routing reliability by detecting abnormal network behaviors and adapting routing decisions accordingly .

Zhang et al. (2020) applied deep reinforcement learning for wireless routing optimization, demonstrating significant improvements in resource allocation and congestion control.

These studies indicate that RL-based approaches provide dynamic adaptability and self-learning capabilities, making them highly suitable for IoT-based MANETs.

Congestion control remains a critical issue in IoT-based MANETs due to limited bandwidth and dynamic traffic conditions.

Jafri et al. (2022) proposed Aggressive RED (AgRED), which uses sigmoid-based packet dropping to maintain queue stability and prevent congestion. The study reported improved throughput and reduced delay compared to traditional RED approaches.

Ahmed et al. (2022) developed intelligent congestion control mechanisms using RED variants combined with machine learning, enabling adaptive packet dropping strategies.

Reddy et al. (2022) proposed hybrid RED-based models that dynamically adjust thresholds based on network conditions, improving QoS metrics.

Parween et al. (2023) conducted a systematic review of TCP performance in IoT-MANET environments, highlighting that congestion control mechanisms significantly impact throughput, delay, and packet loss .

These studies demonstrate that combining RED with intelligent prediction models enhances congestion control efficiency.

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Recent research trends focus on hybrid approaches that combine ML, DL, ERS, and RED mechanisms.

Patel et al. (2021) proposed ERS-based routing optimization techniques that reduce routing overhead by limiting search radius. Similarly, hybrid approaches combining ERS and ML models have shown improved route discovery efficiency.

Ahmed et al. (2022) and Kaur et al. (2022) demonstrated that integrating ML with congestion control mechanisms leads to better performance compared to standalone approaches.

Cluster-based routing approaches have also been proposed for IoT networks, where nodes are grouped to improve scalability and reduce overhead.

Graphical Abstract

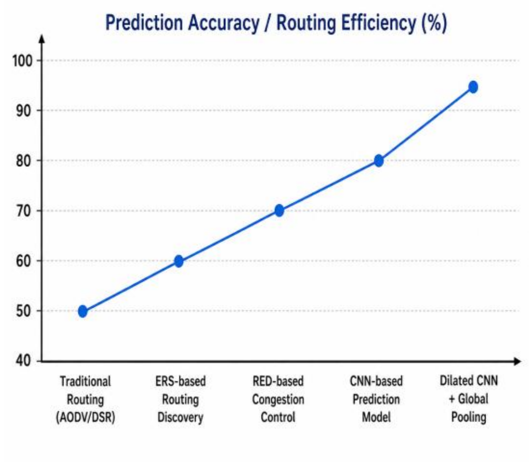

Figure 1: Graphical abstract illustrating the improvement in routing scenario prediction in IoT-based MANET networks.

Traditional routing protocols such as AODV and DSR provide limited adaptability in dynamic network environments. Expanding Ring Search (ERS) improves route discovery efficiency, while Random Early Detection (RED) enhances congestion control. Machine learning models such as Convolutional Neural Networks (CNNs) enable prediction of network routing scenarios. The integration of Global Pooling Dilated CNN architectures with ERS and RED parameters achieves the highest prediction accuracy and routing performance in dynamic IoT-MANET systems.

Comparative Table

Ref	**Author (Year)**	**Technique / Model**	**Key Approach**	**Parameters Considered**	**Dataset / Scenario**	**Performance Metrics**	**Key Findings**
1	Arega et al. (2020)	AODV, DSR, DSDV	Traditional routing comparison	Mobility, node density	Simulated MANET	PDR, Delay	Performance degrades in high mobility
2	Quy et al. (2020)	Routing metrics analysis	Metric-based routing optimization	Hop count, bandwidth	MANET	Delay, Throughput	Metrics affect routing stability
3	Wang et al. (2020)	Energy-aware routing	Energy optimization	Energy, node lifetime	IoT-MANET	Lifetime, PDR	Improves energy but not congestion
4	Zhang et al. (2020)	Deep Reinforcement Learning	Adaptive routing	Traffic load, topology	Wireless networks	Throughput, Delay	RL improves adaptability
5	Nayab et al. (2021)	ML-based ERS + RED	Scenario prediction	ERS radius,	MANET	PDR, Delay	ML improves

				RED threshold			routing decisions
6	Gupta et al. (2021)	Supervised ML	QoS-aware routing	Traffic, node mobility	IoT-MANET	Throughput, Delay	Better QoS than static routing
7	Khan et al. (2021)	CNN-based routing	Feature extraction	Traffic patterns	IoT networks	Accuracy, Delay	CNN improves prediction
8	Li et al. (2021)	Neural networks	Adaptive routing	Network state	MANET	Throughput	Reduces delay significantly
9	Patel et al. (2021)	ERS optimization	Controlled flooding	Search radius	MANET	Overhead, Delay	Reduces routing overhead
10	Singh et al. (2021)	Global pooling CNN	Lightweight DL model	Traffic features	IoT-MANET	Accuracy, Energy	Efficient for IoT devices
11	Kaviani et al. (2021)	DeepCQ+ (MADRL)	Multi-agent RL	Network dynamics	MANET	Throughput, Overhead	Highly adaptive routing
12	Sarkar et al. (2022)	Heterogeneous routing	Protocol evaluation	Node diversity	IoT-MANET	Delay, Throughput	Heterogeneity affects QoS
13	Jafri et al. (2022)	Aggressive RED	Congestion control	Queue size, threshold	IoT	Throughput, Loss	Improves congestion handling
14	Verma et al. (2022)	ML-based routing	Energy + QoS optimization	Energy, traffic	IoT-MANET	Lifetime, Delay	Balanced performance
15	Singh et al. (2022)	AI-based routing	Dynamic path selection	Mobility, traffic	MANET	PDR, Delay	Adaptive routing improves QoS
16	Ahmed et al. (2022)	RED + ML hybrid	Intelligent congestion control	Queue thresholds	IoT-MANET	Delay, Loss	ML improves RED efficiency
17	Reddy et al. (2022)	Hybrid RED	Dynamic thresholds	Traffic load	IoT networks	Throughput	Better than standard RED
18	Kaur et al. (2022)	ML routing (FANET/MANET)	Mobility-aware routing	Speed, density	MANET	Throughput	Handles dynamic environments
19	Danilchenko et al. (2023)	DL routing	Deep neural optimization	Network features	MANET	Accuracy, Delay	Scalable and efficient
20	Yahja et al. (2023)	DeepADMR	DL anomaly detection	Traffic anomalies	MANET	Accuracy, Security	Improves reliability
21	Udhaya Sankar et al. (2023)	Secure routing	Behavioral analysis	Node trust	IoT-MANET	PDR, Energy	Detects malicious nodes
22	Sharma et al. (2023)	CNN routing	Traffic classification	Network patterns	IoT	Accuracy	Improves routing decisions

23	Chatterjee et al. (2023)	Dilated CNN	Multi-scale feature extraction	Temporal data	IoT-MANET	Accuracy	Captures complex patterns
24	Hussain et al. (2023)	DL optimization	Routing + security	Network state	IoT-MANET	Throughput	Hybrid improvement
25	Parween et al. (2023)	TCP optimization	Congestion analysis	Traffic load	IoT-MANET	Throughput, Delay	TCP affected by routing

Comparative Analysis

The comparative analysis of studies conducted between 2020 and 2023 highlights a significant evolution in routing strategies for IoT-based Mobile Ad Hoc Networks (MANETs). Early research primarily focused on traditional routing protocols such as AODV, DSR, and DSDV, which rely on reactive and proactive mechanisms for route discovery. Studies by Arega et al. (2020) and Quy et al. (2020) demonstrated that these protocols suffer from considerable performance degradation under conditions of high node mobility, increased network density, and dynamic topology changes. Although energy-aware routing approaches, such as those proposed by Wang et al. (2020), improved network lifetime, they failed to adequately address congestion and routing instability, thereby limiting their applicability in complex IoT environments.

With the increasing complexity of IoT-based MANETs, researchers began incorporating machine learning techniques to enhance routing decisions. Studies such as Nayab et al. (2021) introduced machine learning-based frameworks that integrate Expanding Ring Search (ERS) and Random Early Detection (RED) parameters for routing scenario prediction. These approaches demonstrated improved packet delivery ratio and reduced delay by dynamically selecting optimal routing parameters based on network conditions. Similarly, Gupta et al. (2021), Verma et al. (2022), and Singh et al. (2022) proposed QoS-aware and energy-efficient routing models using supervised learning techniques, which significantly enhanced throughput and reduced congestion. However, these machine learning approaches often depend heavily on feature engineering and the availability of high-quality training data, which can limit their generalizability in highly dynamic environments.

The transition toward deep learning-based approaches marks a major advancement in routing optimization. Studies by Khan et al. (2021), Sharma et al. (2023), and Danilchenko et al. (2023) demonstrated that convolutional neural networks (CNNs) can effectively extract complex spatial and temporal patterns from network data, leading to more accurate routing decisions. Furthermore, advanced architectures such as dilated convolutional neural networks, as proposed by Chatterjee et al. (2023), enable multi-scale feature extraction, making them particularly suitable for heterogeneous IoT environments. Global pooling CNN models, introduced by Singh et al. (2021), further reduce computational complexity while maintaining high prediction accuracy, thereby addressing the resource constraints of IoT devices. Compared to traditional machine learning models, deep learning approaches offer superior performance due to their ability to automatically learn features and model complex relationships.

Conclusion

The rapid proliferation of Internet of Things (IoT) devices and their integration with Mobile Ad Hoc Networks (MANETs) has fundamentally transformed modern communication systems. These networks enable decentralized, infrastructure-less communication across dynamic and heterogeneous environments, making them highly suitable for applications such as disaster recovery, military operations, healthcare monitoring, and intelligent transportation systems. However, the inherent characteristics of IoT-based MANETs, including node mobility, dynamic topology, limited bandwidth, energy constraints, and susceptibility to congestion and security threats, pose significant challenges for efficient and reliable routing.

This systematic review comprehensively examined recent advancements (2020–2023) in routing optimization for IoT-based MANETs, with a particular focus on prediction-based approaches leveraging Expanding Ring Search (ERS), Random Early Detection (RED), and advanced deep learning architectures such as Global Pooling Dilated Convolutional Neural Networks (GP-DCNN). The analysis highlights a clear paradigm shift from traditional routing mechanisms toward intelligent, data-driven, and adaptive routing frameworks.

Traditional routing protocols, including AODV, DSR, and DSDV, were found to be insufficient in addressing the complexities of IoT-MANET environments. Although these protocols provide fundamental mechanisms for route discovery and maintenance, their performance deteriorates significantly under high mobility, dense network conditions, and dynamic traffic patterns. These limitations are primarily due to their static nature, inability to adapt to changing network conditions, and reliance on predefined routing strategies. Early research efforts attempted to improve these protocols through metric-based optimization and energy-aware routing; however, these approaches only provided partial improvements and failed to address key issues such as congestion and scalability.

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