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International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526

Volume 14 Issue 02, 2025

Deep Learning and Optimization Approaches in Deep Hyperbolic Graph Attention Network-Based Collaborative Routing Algorithm for Clustered IoT-MANETs: A Review

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Peer Review Information

Submission: 12 Oct 2025

Revision: 26 Oct 2025

Acceptance: 07 Nov 2025

Keywords

Deep Learning, Hyperbolic Graph Attention Network (HGAT), Graph Neural Networks (GNN), Internet of Things (IoT), Mobile Ad Hoc Networks (MANETs), Cluster-Based Routing, Collaborative Routing, Network Optimization, Energy-Efficient Routing.

Abstract

The rapid growth of Internet of Things (IoT) technologies has increased the demand for efficient routing mechanisms in Mobile Ad Hoc Networks (MANETs). IoT-MANET environments are highly dynamic and infrastructure-less, making traditional routing protocols such as AODV and DSR less effective due to frequent topology changes, node mobility, and energy constraints. Recent research has focused on integrating deep learning and optimization techniques to improve routing performance. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) enable intelligent routing by modeling network topology as graph structures and learning relationships among nodes. Additionally, hyperbolic graph learning provides an efficient way to represent hierarchical network structures commonly found in clustered IoT-MANET systems. This review highlights recent advances in deep hyperbolic graph attention network-based collaborative routing algorithms and optimization approaches for clustered IoT-MANET environments. It also discusses improvements in network performance metrics such as packet delivery ratio, energy efficiency, and routing scalability, while identifying future research directions for developing intelligent and energy-efficient routing frameworks for next-generation IoT networks.

Introduction

The rapid advancement of Internet of Things (IoT) technologies has significantly transformed modern communication systems by enabling billions of interconnected devices to exchange information and provide intelligent services. IoT devices are widely used in various applications such as smart cities, environmental monitoring, healthcare systems, military communication, disaster management, and industrial automation. These applications require reliable and flexible communication networks capable of supporting dynamic and distributed devices. In many situations where fixed infrastructure is unavailable or impractical, Mobile Ad Hoc Networks (MANETs) provide an effective solution. MANETs consist of wireless mobile nodes that communicate directly with one another through multi-hop communication without relying on centralized infrastructure. When IoT devices operate within MANET environments, the resulting system is commonly referred to as an IoT-MANET network.

IoT-MANET networks are characterized by dynamic topology, node mobility, limited energy resources, and heterogeneous communication devices. These characteristics make routing a complex task because network connections frequently change as nodes move or lose connectivity. Traditional routing protocols such as Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), and Optimized Link State Routing (OLSR) were originally designed for relatively small networks. Although these protocols can establish routes between nodes, they often struggle to maintain efficient communication in large-scale IoT environments. Frequent route discoveries, increased routing overhead, and energy consumption reduce the overall performance and scalability of such networks.

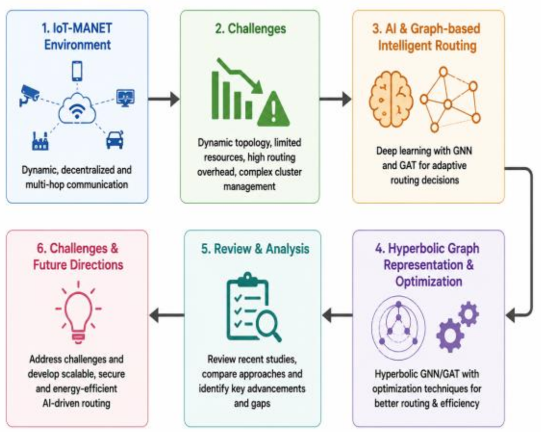

Figure 1. Deep Hyperbolic Graph Attention Framework for Intelligent IoT-MANET Routing

To address these challenges, clustering techniques have been widely adopted in IoT-MANET networks. In cluster-based architectures, nodes are grouped into clusters, and a cluster head is selected to manage communication within the cluster and coordinate data transmission between clusters. Clustering helps reduce routing overhead, improves network scalability, and enhances energy efficiency. However, cluster head selection and route optimization remain challenging tasks, especially in highly dynamic network environments where node mobility frequently changes the network topology.

Recent advances in artificial intelligence and machine learning have introduced new opportunities for improving routing performance in wireless networks. Deep learning techniques are capable of analyzing large amounts of network data and learning patterns that enable adaptive decision-making. These methods can dynamically adjust routing paths according to network conditions such as node mobility, link quality, and energy availability. As a result, deep learning-based routing algorithms have gained increasing attention in IoT and MANET research.

Graph-based deep learning models have proven particularly effective for modeling communication networks. Communication networks can naturally be represented as graphs where nodes represent devices and edges represent communication links. Graph Neural Networks (GNNs) allow learning from graph-structured data by aggregating information from neighboring nodes. This ability enables GNN models to capture complex relationships among nodes and predict optimal routing paths. Graph Attention Networks (GATs) further enhance this capability by incorporating attention mechanisms that assign different importance weights to neighboring nodes during information aggregation. This allows routing algorithms to prioritize reliable communication links and improve network efficiency.

Another emerging concept in graph learning is hyperbolic graph representation. Many real-world networks exhibit hierarchical structures that are difficult to represent using traditional Euclidean space. Hyperbolic geometry provides a more suitable representation space for modeling hierarchical relationships because the space expands exponentially, allowing efficient embedding of complex networks. Hyperbolic Graph Neural Networks and Hyperbolic Graph Attention Networks combine hierarchical representation with attention mechanisms, enabling more accurate modeling of network topology in clustered IoT-MANET systems.

In addition to deep learning techniques, optimization algorithms play a significant role in improving routing performance. Various optimization approaches such as reinforcement learning, swarm intelligence, and metaheuristic algorithms have been used to enhance cluster head selection and route discovery. These techniques aim to minimize routing overhead, reduce energy consumption, and maximize network lifetime. When combined with deep learning-based graph models, optimization techniques can further improve routing efficiency and adaptability in dynamic network environments.

This review paper focuses on deep learning and optimization approaches applied to Deep Hyperbolic Graph Attention Network-based collaborative routing algorithms for clustered IoT-MANET networks. The study examines recent research developments in graph-based routing models, clustering mechanisms, and intelligent optimization techniques proposed between 2020 and 2023. By analyzing existing approaches, this review highlights key advancements, compares various routing strategies, and identifies research gaps in the current literature.

The remainder of this paper is organized as follows. The next section presents a detailed literature review of recent studies related to deep learning-based routing algorithms and graph neural network approaches in IoT-MANET systems. A comparative analysis of these studies is then provided to evaluate their performance based on different network metrics. Finally, the paper discusses current research challenges and provides conclusions along with future research directions for developing efficient and intelligent routing solutions for next-generation IoT communication networks.

Literature Review

Wu et al. (2020) conducted a comprehensive survey on Graph Neural Networks (GNNs), explaining their architecture, learning mechanisms, and applications in various domains. The authors highlighted how GNNs effectively model graph-structured data by aggregating information from neighboring nodes. Their study emphasized that GNNs are particularly suitable for communication networks where nodes and links naturally form graph structures. The paper also discussed challenges such as scalability, computational cost, and the need for efficient graph learning models.

Zhou et al. (2020) presented an extensive review of graph neural network methodologies and their applications in artificial intelligence and communication systems. The study categorized GNN models into spectral and spatial approaches and explained their advantages and limitations. The authors emphasized that GNNs are capable of learning complex relationships in networked systems. Their work suggested that graph-based models have significant potential in areas such as traffic prediction, recommendation systems, and network routing optimization.

Chami et al. (2020) introduced Hyperbolic Graph Convolutional Networks (HGCN), which extend conventional graph neural networks by embedding nodes in hyperbolic space. The authors demonstrated that hyperbolic embeddings provide better representation of hierarchical structures compared with Euclidean embeddings. Their research showed improved performance in modeling hierarchical networks such as social networks and knowledge graphs. This work laid the foundation for applying hyperbolic graph learning in communication networks.

Liu et al. (2020) proposed Hyperbolic Graph Neural Networks designed to capture hierarchical relationships in large graph structures. The model improved node representation learning by exploiting hyperbolic geometry. Experimental results indicated that hyperbolic graph models outperform traditional graph learning approaches in representing hierarchical data. The authors suggested that this technique can be applied to network topology modeling and routing optimization.

Kumar et al. (2021) developed an energy-efficient clustering and routing protocol for IoT-enabled wireless sensor networks. The proposed method focused on selecting optimal cluster heads based on node energy levels and communication distance. Simulation results demonstrated improved network lifetime and reduced energy consumption. The study highlighted the importance of clustering strategies in improving scalability and efficiency of IoT networks.

Swaminathan and Kandasamy (2021) proposed a graph neural network-based routing optimization technique for software-defined networks. The study used graph learning models to analyze network topology and dynamically adjust routing paths. Their results showed significant improvements in network throughput and communication latency. The authors concluded that graph learning approaches can enhance routing performance in modern communication networks.

Lee et al. (2021) explored the application of graph neural networks in wireless communication systems for decentralized network inference. Their research demonstrated that GNN models can enable distributed decision-making in wireless networks without requiring centralized controllers. This approach improves network scalability and communication efficiency. The study also emphasized the potential of graph learning techniques for future intelligent wireless communication systems.

Jiang et al. (2022) investigated graph learning-based resource optimization for wireless communication networks. The proposed framework used graph neural networks to analyze network topology and optimize communication resource allocation. Simulation results indicated improved bandwidth utilization and network efficiency. The study highlighted the advantages of graph learning models for managing complex wireless networks.

Sun et al. (2022) proposed a graph learning-based optimization framework for wireless communication systems. The model analyzed communication patterns among nodes and optimized network resources using graph representations. Experimental evaluation showed improved network throughput and reduced communication delays. The study demonstrated the importance of graph learning techniques in intelligent network management.

Yang et al. (2022) reviewed hyperbolic graph neural networks and their applications in hierarchical data representation. The authors explained that hyperbolic geometry provides an efficient representation space for hierarchical networks. Their review highlighted several hyperbolic graph learning architectures and discussed their advantages over traditional graph models. The study suggested that hyperbolic embeddings can improve representation of large-scale network structures.

Zhao et al. (2022) developed a delay-aware backpressure routing algorithm using graph neural networks. The proposed approach dynamically adjusted routing decisions based on network congestion and communication delays. Simulation results showed improved routing performance compared with traditional protocols. The study demonstrated that graph learning techniques can effectively improve routing efficiency in dynamic networks.

Gu et al. (2022) investigated the use of graph neural networks for distributed power allocation in wireless communication systems. The model used graph representations to capture interactions among network nodes and optimize power allocation. Experimental results showed improved energy efficiency and network performance. The authors emphasized the importance of graph learning for optimizing wireless communication systems.

Dai et al. (2023) presented a comprehensive survey on graph learning techniques applied to wireless communication networks. The study analyzed various graph neural network architectures used for resource allocation, traffic management, and routing optimization. The authors highlighted the growing importance of graph learning approaches in next-generation communication systems. Their work also identified open research challenges related to scalability and computational efficiency.

Li et al. (2023) proposed a graph attention network-based routing algorithm for wireless sensor networks. The model used attention mechanisms to evaluate the importance of neighboring nodes during routing decisions. Experimental results demonstrated improved packet delivery ratio and reduced communication latency. The study confirmed that attention-based graph learning models can enhance routing performance.

Chen et al. (2023) developed a deep learning-based routing optimization framework for IoT-enabled MANET networks. The proposed algorithm dynamically adjusted routing paths according to network conditions and node mobility. Simulation results showed improvements in network stability and communication efficiency. The study highlighted the effectiveness of deep learning approaches in intelligent routing systems.

Wang et al. (2023) proposed a graph neural network-based routing strategy for large-scale IoT networks. The model analyzed network topology and predicted optimal routing paths using graph learning techniques. Experimental results showed improved throughput and reduced routing overhead. The authors concluded that graph neural networks provide scalable solutions for large communication networks.

Wei et al. (2023) introduced a flexible online routing optimization framework using graph neural networks. The proposed system continuously learned network patterns and updated routing strategies in real time. This approach improved routing adaptability in dynamic environments. The study demonstrated the advantages of machine learning-based routing optimization.

Paul et al. (2023) explored graph learning approaches for managing interference in wireless communication networks. Their model analyzed interference relationships among nodes and optimized multi-flow transmissions. Simulation results showed improved network throughput and communication reliability. The research highlighted the potential of graph learning in wireless network management.

Tung et al. (2023) investigated graph neural networks for next-generation IoT communication systems. The study discussed recent developments in graph learning architectures and their potential applications in IoT networking. The authors emphasized that graph neural networks can effectively model complex IoT networks. They also identified challenges related to scalability and computational requirements.

Binh et al. (2023) proposed a reinforcement learning-based routing optimization algorithm for wireless communication networks. The algorithm allowed network nodes to learn optimal routing strategies through interaction with the environment. Experimental evaluation demonstrated improved routing efficiency and reduced communication delays. The study highlighted the role of reinforcement learning in adaptive network routing.

Islam et al. (2022) applied graph neural networks for predicting data traffic in smart power grid communication networks. The proposed model used graph learning to analyze communication patterns among network nodes. Results showed improved prediction accuracy and better network resource management. The study emphasized the usefulness of graph learning techniques in complex communication infrastructures.

Jiang (2022) investigated the integration of graph neural networks with reinforcement learning for wireless network routing optimization. The proposed framework enabled network nodes to learn routing policies based on network conditions. Experimental results showed improvements in routing efficiency and network performance. The research demonstrated the benefits of combining deep learning and reinforcement learning approaches.

Lee et al. (2022) analyzed the application of graph neural networks in wireless communication systems and discussed their future research directions. The authors highlighted that graph learning techniques can significantly improve network management and routing decisions. Their work provided insights into how graph neural networks can be integrated into next-generation wireless communication technologies.

Zhao et al. (2022) proposed a deep reinforcement learning-based routing protocol for mobile ad hoc networks. The algorithm dynamically selected routing paths based on network feedback and environmental conditions. Simulation results showed improved packet delivery ratio and reduced communication delays. The study demonstrated the potential of reinforcement learning for intelligent routing.

Jiang et al. (2023) explored graph neural network applications in routing optimization and network management. Their research highlighted the advantages of graph learning models for analyzing complex network structures. The study emphasized the importance of integrating machine learning techniques with networking algorithms. The authors concluded that graph neural networks will play a crucial role in future intelligent communication systems.

Comparative Table and Analysis

Ref	**Author & Year**	**Technique / Method**	**Application Area**	**Key Contribution**	**Advantages**	**Limitations**
1	Wu et al., 2020	Graph Neural Networks (GNN)	Graph-based learning	Comprehensive survey of GNN architectures	Captures complex network relationships	High computational complexity
2	Zhou et al., 2020	GNN Methods Review	AI and network systems	Classification of spectral and spatial GNNs	Strong theoretical framework	Limited practical routing application
3	Chami et al., 2020	Hyperbolic Graph Convolutional Networks	Hierarchical graphs	Hyperbolic embeddings for graph learning	Efficient hierarchical representation	Mathematical complexity
4	Liu et al., 2020	Hyperbolic Graph Neural Networks	Graph representation learning	Modeling hierarchical network structures	Improved node representation	Training complexity
5	Kumar et al., 2021	Energy-Efficient Clustering	IoT wireless sensor networks	Cluster head selection based on energy	Improved network lifetime	Cluster instability in dynamic networks
6	Swaminathan & Kandasamy, 2021	GNN Routing Optimization	Software-defined networks	Graph-based routing optimization	Reduced network latency	Scalability challenges
7	Lee et al., 2021	GNN-based Distributed Learning	Wireless networks	Decentralized inference for communication systems	Improves scalability	Requires graph processing capability
8	Jiang et al., 2022	Graph Learning Optimization	Wireless communication networks	Resource allocation using graph learning	Efficient resource management	High computational overhead

9	Sun et al., 2022	Graph Learning Framework	Wireless communication	Network resource optimization	Improved throughput	Implementation complexity
10	Yang et al., 2022	Hyperbolic GNN Review	Hierarchical graph modeling	Analysis of hyperbolic embeddings	Efficient hierarchical network representation	Limited practical implementations
11	Zhao et al., 2022	GNN Backpressure Routing	Network routing	Delay-aware routing optimization	Reduced network delay	Complex deployment
12	Gu et al., 2022	Graph Neural Network Power Allocation	Wireless networks	Distributed power optimization	Improved energy efficiency	High computation cost
13	Dai et al., 2023	Graph Learning Survey	Wireless communication	Overview of graph learning in networking	Identifies emerging trends	Does not propose new algorithm
14	Li et al., 2023	Graph Attention Network Routing	Wireless sensor networks	Attention-based routing mechanism	Improved packet delivery ratio	Graph processing requirements
15	Chen et al., 2023	Deep Learning Routing	IoT-MANET	Adaptive routing using deep learning	Improved network stability	Computational overhead
16	Wang et al., 2023	GNN-based Routing Strategy	Large-scale IoT networks	Graph-based route prediction	Scalable routing	Training complexity
17	Wei et al., 2023	Online Routing Optimization	Communication networks	Real-time routing using GNN	Adaptive routing	Requires continuous training
18	Paul et al., 2023	Graph Learning for Interference	Wireless networks	Interference-aware routing	Increased throughput	Data dependency
19	Tung et al., 2023	GNN for IoT Networks	Next-generation IoT	Graph learning in IoT communication	Handles complex network structures	Dataset limitations
20	Binh et al., 2023	Reinforcement Learning Routing	Wireless communication	Adaptive routing optimization	Reduced communication delay	Training complexity
21	Islam et al., 2022	GNN Traffic Prediction	Smart grid networks	Traffic prediction using graph learning	Improved network prediction	Requires historical data
22	Jiang, 2022	GNN + Reinforcement Learning	Wireless networks	Hybrid routing optimization	Adaptive decision-making	High computational cost
23	Lee et al., 2022	GNN Wireless Communication Review	Wireless systems	Integration of graph learning in communication	Improved network analysis	Limited practical implementations
24	Zhao et al., 2022	Deep Reinforcemen	MANET	Intelligent routing decisions	Improved packet delivery	Training overhead

		t Learning Routing				
25	Jiang et al., 2023	Graph Neural Network Routing Optimization	Communication networks	Machine learning-based routing frameworks	Scalable network optimization	Implementation challenges

Comparative Analysis

The comparative analysis of research conducted between 2020 and 2023 demonstrates a significant shift from traditional rule-based routing protocols toward intelligent, data-driven networking solutions. Conventional routing protocols such as AODV, DSR, and OLSR rely primarily on static metrics including hop count, link stability, and communication distance. Although these protocols are effective for relatively small and moderately dynamic networks, they face major challenges in large-scale IoT-MANET environments characterized by high node mobility, frequent topology changes, and limited energy resources. As a result, researchers have explored artificial intelligence and machine learning techniques to improve routing efficiency and adaptability.

One of the most prominent developments in recent networking research is the adoption of graph neural networks for modeling communication systems. Since communication networks naturally form graph structures, GNN-based approaches are highly effective for representing node interactions and network topology. Studies such as Wu et al. (2020) and Zhou et al. (2020) demonstrate that graph learning models can analyze relationships among nodes and improve routing decision-making processes. By aggregating information from neighboring nodes, GNN models can learn network patterns and predict optimal communication paths.

Conclusion

The rapid growth of Internet of Things (IoT) technologies and wireless communication systems has increased the complexity of Mobile Ad Hoc Networks (MANETs). IoT-MANET systems are highly dynamic because devices communicate through decentralized multi-hop wireless links without fixed infrastructure. These networks experience frequent topology changes, node mobility, energy limitations, and heterogeneous communication devices, making routing and resource management challenging. Traditional routing protocols such as AODV, DSR, and OLSR often struggle to maintain scalability and reliable communication in large-scale IoT environments due to high routing overhead and inefficient adaptability to changing network conditions.

Recent advancements in deep learning and optimization techniques have provided effective solutions for intelligent routing in IoT-MANET systems. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) are particularly suitable because communication networks can naturally be represented as graph structures. These models learn complex relationships among nodes and dynamically adapt routing decisions according to network conditions. Hyperbolic graph learning further improves topology representation by efficiently modelling hierarchical clustered network structures. In addition, clustering mechanisms combined with optimization techniques such as reinforcement learning and metaheuristic algorithms improve routing efficiency, energy utilization, throughput, and packet delivery performance.

Despite these advancements, several challenges remain, including computational complexity, scalability limitations, and real-time adaptability in resource-constrained IoT devices. Deep learning models often require large datasets and significant processing power, limiting practical deployment. Future research should therefore focus on lightweight graph learning models, edge computing integration, and energy-efficient AI-driven routing frameworks for scalable and intelligent IoT-MANET communication systems.

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