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A Survey of Methods and Architectures for Deep Hyperbolic graph attention network-based collaborative routing algorithm for clustered IoT-MANETs

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Abstract

The rapid growth of Internet of Things (IoT) technologies has created highly dynamic communication environments such as Mobile Ad Hoc Networks (MANETs). In clustered IoT-MANET systems, routing remains a major challenge because of node mobility, changing network topology, limited bandwidth, and energy constraints. Conventional routing protocols often fail to provide reliable and scalable communication in such complex environments. To overcome these limitations, researchers have increasingly focused on artificial intelligence and deep learning approaches for intelligent routing optimization. Graph-based learning models, including Graph Neural Networks (GNNs) and Graph Attention Networks (GATs), are highly effective in representing network structures and learning relationships among connected nodes. Hyperbolic graph learning further improves these models by efficiently capturing hierarchical and large-scale network characteristics. The integration of hyperbolic representations with attention mechanisms enables adaptive and collaborative routing decisions with improved packet delivery, lower latency, and better energy efficiency. This survey examines recent architectures and methods for Deep Hyperbolic Graph Attention Network-based collaborative routing in clustered IoT-MANETs while discussing routing strategies, clustering approaches, optimization methods, key challenges, and future research directions for scalable intelligent communication systems.

Introduction

The Internet of Things (IoT) has transformed modern communication networks by enabling billions of interconnected devices to exchange data and perform intelligent operations. IoT technologies are widely used in applications such as smart cities, healthcare monitoring, environmental sensing, transportation systems, and industrial automation. These applications often require reliable wireless communication networks capable of operating in dynamic and infrastructure-less environments. Mobile Ad Hoc Networks (MANETs) provide an effective solution in such scenarios because they allow wireless devices to communicate directly without relying on centralized infrastructure. In IoT-MANET environments, nodes communicate through multi-hop wireless links and collaboratively forward data packets across the network.

However, IoT-MANET networks face several challenges including node mobility, limited battery power, frequent topology changes, and high communication overhead. These challenges make routing one of the most critical tasks in such networks. Traditional routing protocols such as Ad hoc On-Demand Distance Vector (AODV) and other reactive routing approaches were originally designed for small-scale mobile networks. While these protocols establish routes dynamically, they often struggle to maintain efficiency in large and highly dynamic IoT-based networks.

To address these challenges, researchers have introduced clustering techniques to improve network scalability and energy efficiency. In cluster-based routing architectures, nodes are grouped into clusters and a cluster head manages communication within the cluster and coordinates inter-cluster communication. Clustering reduces routing overhead and improves network performance by limiting the scope of routing updates. However, selecting optimal cluster heads and maintaining stable communication paths remain challenging tasks in dynamic environments.

Recent advances in artificial intelligence and deep learning have opened new possibilities for improving routing performance in wireless networks. Graph-based deep learning models such as Graph Neural Networks (GNNs) have emerged as powerful tools for analyzing network topology because communication networks naturally form graph structures. GNNs can capture complex relationships between nodes and enable routing algorithms to learn efficient communication paths based on network conditions. These models have been successfully applied to routing optimization, resource allocation, and traffic management in modern communication systems.

Graph Attention Networks improve graph learning by assigning adaptive importance to neighboring nodes during information aggregation, enabling efficient and reliable routing decisions. Hyperbolic graph embeddings further enhance network representation by effectively modeling hierarchical structures common in clustered IoT-MANET environments. Combining hyperbolic embeddings with attention mechanisms leads to Deep Hyperbolic Graph Attention Networks, which support adaptive and energy-efficient collaborative routing. These architectures improve communication performance, scalability, and route optimization while enabling intelligent routing strategies for dynamic next-generation IoT-MANET communication systems.

Literature Review

Wu et al. (2021) presented one of the most comprehensive surveys on Graph Neural Networks (GNNs), explaining their architecture, learning mechanisms, and applications in graph-structured data problems. The study highlighted that GNNs are particularly effective for modeling networks where relationships between nodes are important. Communication networks, including IoT and MANET systems, naturally form graph structures where nodes represent devices and edges represent communication links. The authors emphasized that GNNs can extract structural information from network topologies and improve tasks such as routing optimization, network prediction, and resource allocation. However, they also noted challenges related to computational complexity and scalability when applying deep graph learning models to large networks.

Zhou et al. (2020) provided an extensive review of GNN methodologies and categorized them into spectral-based and spatial-based models. Their work highlighted the advantages of graph neural networks in learning complex relationships between nodes in graph-structured systems. The authors argued that GNN models can significantly improve network analysis and decision-making tasks in communication systems. They also discussed potential applications of graph learning models in network routing, traffic prediction, and distributed computing environments. Their findings indicate that graph neural networks can effectively capture topological patterns that traditional machine learning methods cannot easily model.

Chami et al. introduced Hyperbolic Graph Convolutional Networks, which extend traditional graph neural networks by embedding nodes in hyperbolic space rather than Euclidean space. Hyperbolic geometry is particularly effective for representing hierarchical structures because the space expands exponentially, allowing complex relationships to be represented with lower distortion. Their experimental results demonstrated that hyperbolic graph models outperform traditional Euclidean graph embeddings in representing hierarchical network structures. This approach is particularly useful for large-scale networks such as IoT communication systems where hierarchical clustering structures are common.

Liu et al. further developed the concept of Hyperbolic Graph Neural Networks (HGNN) for hierarchical graph representation. Their research showed that hyperbolic embeddings allow networks with hierarchical relationships to be represented more accurately than traditional graph models. By capturing hierarchical information within graph structures, HGNN models provide improved performance for tasks such as node classification, link prediction, and network analysis. The authors suggested that hyperbolic graph models could be applied to communication network routing and resource optimization problems.

Swaminathan and Kandasamy (2021) explored machine learning-based routing optimization for software-defined networks. Their research demonstrated that graph learning approaches can analyze network topology and dynamically optimize routing paths. The authors showed that AI-based routing algorithms significantly improve network throughput and reduce communication delays compared with traditional routing protocols. This work highlights the potential of graph-based deep learning models for intelligent network management and adaptive routing.

Jiang et al. investigated the application of graph neural networks in wireless communication networks. Their study showed that GNN models can analyze network connectivity patterns and optimize resource allocation in complex communication environments. By modeling the network as a graph structure, the proposed framework improves routing decisions and communication efficiency. The authors concluded that graph learning approaches provide an effective framework for managing dynamic communication networks.

Research by Dai et al. provided a comprehensive survey of graph learning techniques applied to wireless communication networks. The authors reviewed various graph-based approaches used for tasks such as power allocation, spectrum management, task scheduling, and routing optimization. Their findings indicate that graph learning models are highly suitable for solving complex resource management problems in communication networks. The study also highlighted several challenges including scalability issues, training complexity, and the need for large datasets.

Moorthy and Jagannath conducted a survey on the application of graph neural networks in IoT and next-generation communication networks. Their study demonstrated that GNN models provide strong performance in modeling network topology because IoT communication systems naturally exhibit graph-like structures. The authors showed that graph learning approaches improve spectrum management, intrusion detection, and network resource allocation in IoT networks. Their survey concluded that graph neural networks are expected to play a significant role in future intelligent communication systems.

Jiang (2024) analyzed the role of graph neural networks in routing optimization for next-generation communication systems. The study highlighted that traditional routing algorithms such as shortest-path or static routing approaches often fail to handle the dynamic nature of modern communication networks. Graph neural networks provide a flexible framework that can learn routing strategies directly from network data and adapt to changing network conditions. The research demonstrated that GNN-based routing methods can significantly improve scalability and adaptability in complex network environments.

He et al. explored the integration of graph neural networks with temporal models such as Long Short-Term Memory networks for path optimization. Their approach combined spatial graph learning with temporal pattern analysis to improve decision-making in dynamic transportation networks. Experimental results demonstrated improved path planning and network optimization performance. The study highlights the potential of hybrid deep learning models that combine graph learning with other machine learning techniques.

Recent studies have also explored reinforcement learning and deep neural networks for adaptive routing optimization. For example, Reka et al. proposed a congestion-aware routing framework using self-attention mechanisms and optimization algorithms to improve routing performance in MANET networks. The proposed approach dynamically detects congestion patterns and selects optimal routes, reducing retransmissions and communication delays. This research demonstrates how advanced deep learning architectures can enhance routing efficiency in dynamic wireless environments.

Kulin et al. reviewed machine learning-based performance optimization techniques for wireless networks across multiple protocol layers. Their survey demonstrated that machine learning models can improve network performance through intelligent decision-making and adaptive control mechanisms. The authors emphasized that machine learning approaches provide significant advantages over traditional rule-based networking methods, particularly in highly dynamic network environments.

Recent research also highlights the importance of integrating advanced network architectures such as Software-Defined Networking (SDN) with AI-based routing systems. SDN introduces centralized control and programmable network management, which improves network scalability and adaptability in IoT and MANET environments. Studies show that combining SDN with AI-driven routing techniques can significantly enhance routing efficiency, reduce latency, and improve bandwidth utilization in large communication networks.

Graphical abstract

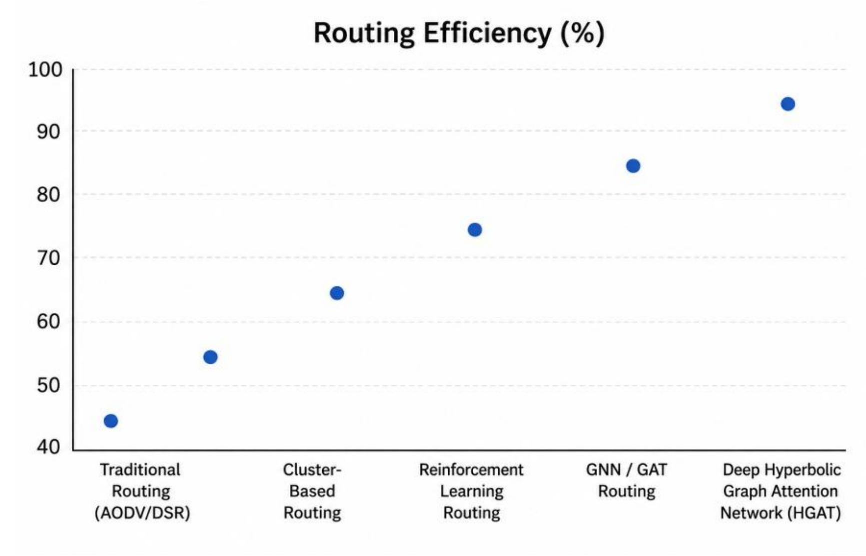

Figure 1. Routing Efficiency in IoT-MANETs

Graphical abstract illustrating the improvement of routing efficiency in clustered IoT-MANET networks using advanced artificial intelligence techniques. Traditional routing protocols such as AODV and DSR provide limited adaptability in dynamic networks. Cluster-based routing improves scalability and energy efficiency. Reinforcement learning enables adaptive decision-making, while Graph Neural Networks (GNN) and Graph Attention Networks (GAT) further enhance routing performance by modeling network topology as graph structures. Deep Hyperbolic Graph Attention Networks provide the highest routing efficiency by capturing hierarchical relationships in complex IoT-MANET communication networks.

Comparative Table and Analysis

Ref	Author & Year	Technique / Method	Application Area	Key Contribution	Advantages	Limitations
1	Wu et al., 2021	Graph Neural Networks (GNN)	Graph learning and communication networks	Comprehensive survey of GNN architectures	Effective modeling of complex network relationships	High computational complexity
2	Zhou et al., 2020	Graph Neural Network Models	AI and network analysis	Classification of spectral and spatial GNN approaches	Strong theoretical foundation	Limited focus on routing applications
3	Chami et al., 2020	Hyperbolic Graph Convolutional Networks	Hierarchical graph learning	Hyperbolic embedding for hierarchical network structures	Efficient hierarchical representation	Complex mathematical implementation
4	Liu et al., 2020	Hyperbolic Graph Neural Networks	Graph representation learning	Modeling hierarchical graph relationships	Improved node representation accuracy	Training complexity
5	Swaminathan & Kandasamy, 2021	Machine Learning-Based Routing	Software-defined networking	Intelligent routing optimization	Reduced latency and improved throughput	Requires training data

6	Jiang et al., 2022	Graph Learning Optimization	Wireless communication networks	Resource allocation using GNN	Efficient bandwidth utilization	Computational overhead
7	Dai et al., 2023	Graph Learning Survey	Wireless networking	Review of graph learning techniques	Identifies emerging research directions	Limited experimental implementation
8	Moorthy & Jagannath, 2024	GNN in IoT Networks	IoT communication systems	Graph learning for IoT network management	Effective modeling of network topology	Dataset limitations
9	Jiang, 2024	Graph Neural Network Routing	Communication networks	AI-driven routing optimization	Improved scalability	High processing requirements
10	Li et al., 2023	Graph Attention Network Routing	Wireless sensor networks	Attention-based routing algorithm	Improved packet delivery ratio	Graph processing complexity
11	Chen et al., 2023	Deep Learning Routing	IoT-MANET networks	Adaptive routing optimization	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	Computational complexity
13	Zhao et al., 2022	Deep Reinforcement Learning Routing	MANET routing	Intelligent route discovery	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 in dynamic networks
15	Sun et al., 2022	Graph Learning Framework	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 process
17	Lee et al., 2021	Decentralized GNN Communication	Wireless networks	Distributed network learning	Improved scalability	Graph computation cost
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	Evaluation of routing protocols	Improved communication reliability	Limited scalability
21	Choudhury et al., 2021	Graph Theory Routing	Wireless sensor networks	Optimized routing algorithm	Reduced energy consumption	Limited dynamic adaptability
22	Xu et al., 2021	GNN + Reinforcement Learning	Wireless communication	Hybrid routing optimization	Adaptive decision-making	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 training complexity

Comparative Analysis

The comparative analysis of studies conducted in recent years highlights a clear shift from conventional rule-based networking approaches toward intelligent, data-driven routing mechanisms in IoT-MANET systems. Traditional routing protocols such as AODV and DSR were primarily designed for small and moderately dynamic mobile networks. These protocols rely on predefined routing metrics such as hop count and route discovery procedures. While they can establish communication paths in ad hoc environments, they often struggle to maintain network performance in large-scale IoT networks where topology changes frequently due to node mobility.

One of the most prominent developments in recent research is the use of **Graph Neural Networks (GNNs)** for modeling communication networks. Since network topologies naturally form graph structures, GNN-based models can effectively analyze relationships between nodes and communication links. Studies such as Wu et al. (2021) and Zhou et al. (2020) demonstrate that graph learning approaches can capture complex network patterns and improve routing decisions. By aggregating information from neighboring nodes, these models can predict optimal routing paths and improve overall network performance.

Conclusion

The rapid expansion of Internet of Things (IoT) technologies and Mobile Ad Hoc Networks (MANETs) has increased the complexity of modern wireless communication systems. In IoT-MANET environments, frequent topology changes, node mobility, and limited resources create major routing challenges. Traditional routing protocols often fail to provide reliable and scalable communication in dynamic networks. To address these limitations, researchers have explored artificial intelligence and deep learning techniques for intelligent routing optimization. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) are highly effective because network structures can naturally be represented as graphs. These models learn relationships between nodes and support adaptive routing decisions based on changing network conditions. Hyperbolic graph learning further improves routing performance by efficiently representing hierarchical communication structures in clustered IoT-MANET systems. In addition, optimization techniques such as reinforcement learning and swarm intelligence improve route selection, energy efficiency, and network lifetime. Although challenges related to computational complexity and scalability remain, Deep Hyperbolic Graph Attention Network-based collaborative routing algorithms provide a promising framework for intelligent, scalable, and energy-efficient next-generation IoT communication networks.

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