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# Recent Advances in Deep Hyperbolic Graph Attention Network-Based Collaborative Routing Algorithm for Clustered IoT-MANETs: A Systematic Review

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**Abstract**

The rapid expansion of Internet of Things (IoT) technologies and mobile wireless communication has enabled the emergence of dynamic and decentralized networking systems such as Mobile Ad Hoc Networks (MANETs), where numerous heterogeneous devices communicate without relying on fixed infrastructure. However, IoT-MANET environments face significant challenges including frequent topology changes, limited energy resources, scalability issues, and unreliable routing performance. Conventional routing protocols like AODV, DSR, and OLSR are often inadequate in handling such highly dynamic and complex network conditions. To overcome these limitations, recent research has increasingly focused on integrating artificial intelligence and advanced graph-based learning techniques to enhance routing efficiency and adaptability. In particular, Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) have shown strong potential in capturing network topology and supporting intelligent routing decisions. Additionally, hyperbolic graph learning has emerged as an effective approach for modeling hierarchical and scale-free network structures, enabling more efficient representation of complex IoT-MANET systems. Deep hyperbolic graph attention models further improve routing performance by embedding network data into hyperbolic space and optimizing communication in clustered environments. This review analyzes recent advancements in deep hyperbolic graph attention-based collaborative routing techniques for IoT-MANETs, comparing methods based on packet delivery ratio, energy consumption, throughput, and latency. It also highlights key challenges and outlines future research directions for developing scalable, energy-efficient, and intelligent routing frameworks for next-generation IoT networks.

## Introduction

The rapid development of Internet of Things (IoT) technologies has significantly transformed modern communication systems by enabling billions of interconnected devices to exchange data in real time. IoT applications are widely used in smart cities, healthcare monitoring, environmental sensing, intelligent transportation, military communication, and industrial automation. These applications require flexible and adaptive networking infrastructures capable of supporting highly dynamic and distributed communication environments. In many practical scenarios, the absence of fixed infrastructure leads to the adoption of Mobile Ad Hoc Networks (MANETs), where mobile devices communicate in a self-organizing manner. The integration of IoT with MANETs has resulted in IoT-MANET systems, which support decentralized and infrastructure-less communication among heterogeneous devices.

Mobile Ad Hoc Networks consist of mobile nodes that dynamically establish wireless links without centralized control. Each node functions both as a host and a router, forwarding packets to other nodes in the network. This decentralized structure makes MANETs suitable for disaster recovery, battlefield communication, emergency response, and remote monitoring applications. However, the dynamic nature of MANETs introduces significant challenges such as frequent topology changes, link failures, limited bandwidth, and energy constraints. These factors make it difficult to maintain stable and efficient routing paths, especially in highly mobile environments.

When IoT devices are integrated into MANETs, the complexity of the network increases further due to large-scale deployment and heterogeneity of devices. IoT nodes generate continuous data streams and require reliable, low-latency communication. Traditional routing protocols such as AODV, DSR, and OLSR are widely used in MANETs but often fail to perform efficiently in IoT-MANET environments. Their reliance on static metrics and reactive routing mechanisms leads to increased overhead, delays, and reduced scalability in dynamic network conditions.

To overcome these limitations, clustering techniques have been widely adopted to improve scalability and reduce routing complexity. In cluster-based routing, nodes are grouped into clusters, and a cluster head manages intra-cluster communication and inter-cluster data forwarding. This hierarchical approach reduces routing overhead and improves network efficiency. However, selecting optimal cluster heads and maintaining stable cluster structures in dynamic environments remains a challenging problem due to frequent topology changes and energy constraints.

In recent years, artificial intelligence and graph-based deep learning techniques have emerged as effective solutions for intelligent routing. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) model communication networks as graphs, where nodes represent devices and edges represent links. These models learn complex topological relationships and enable adaptive routing decisions. Additionally, hyperbolic graph learning has gained attention for efficiently representing hierarchical and scale-free network structures. The integration of hyperbolic embeddings with attention mechanisms in deep hyperbolic graph attention networks enhances routing performance by capturing both structural hierarchy and node importance. Collaborative routing algorithms further improve efficiency by enabling nodes to share local information such as energy levels, link quality, and mobility patterns for optimized decision-making.

**Literature Review**

Wu et al. (2020) presented a comprehensive survey on Graph Neural Networks (GNNs), highlighting their ability to process graph-structured data and capture relationships between nodes in complex networks. The authors discussed different GNN architectures and their applications in recommendation systems, social networks, and communication systems. The study emphasized that GNNs are highly effective for modeling network topology and predicting node interactions. The authors also identified challenges related to scalability and computational complexity in large graph structures.

Zhou et al. (2020) reviewed various Graph Neural Network architectures and their applications across multiple domains. The authors categorized GNN models into spectral-based and spatial-based approaches and analyzed their advantages and limitations. Their work demonstrated that graph-based learning methods can effectively represent complex network structures. The study suggested that GNNs have strong potential for applications such as network routing, traffic prediction, and communication optimization.

Jiang (2021) investigated graph-based deep learning approaches for communication networks. The study highlighted that communication systems naturally form graph structures, making GNN models suitable for analyzing network topology and optimizing routing strategies. The authors demonstrated that graph learning models can improve routing efficiency and reduce communication delays. However, they also noted that training graph neural networks requires significant computational resources.

Swaminathan and Kandasamy (2021) proposed a graph neural network-based routing optimization framework for software-defined networks. Their approach used graph learning techniques to analyze network topology and dynamically adjust routing paths. The proposed system improved network efficiency and reduced communication latency. The authors concluded that graph-based routing algorithms could significantly enhance network performance in large-scale communication systems.

Xu et al. (2022) explored the integration of graph neural networks with deep reinforcement learning for wireless network routing optimization. The proposed framework enabled network nodes to learn optimal routing policies based on environmental feedback. Experimental results demonstrated improved packet delivery ratio and reduced network delay. The study showed that combining graph learning with reinforcement learning can significantly enhance intelligent routing performance.

Yang et al. (2022) provided a review of hyperbolic graph neural networks and their applications in hierarchical data modeling. The authors explained that hyperbolic geometry provides an efficient representation space for hierarchical networks. Their study showed that hyperbolic graph embeddings can represent complex relationships more effectively than Euclidean embeddings. This approach is particularly useful for communication networks that exhibit hierarchical clustering patterns.

Zhao et al. (2022) proposed a delay-aware backpressure routing algorithm using graph neural networks. The algorithm dynamically analyzed network traffic conditions and adjusted routing paths to minimize communication delays. Experimental results demonstrated improved network performance compared with traditional routing protocols. The study highlighted the importance of graph learning techniques for intelligent routing in dynamic networks.

Paul et al. (2023) investigated graph learning approaches for multi-flow transmission in wireless interference networks. The study proposed a graph-based model that analyzed interference relationships between communication nodes. The proposed approach improved network throughput and resource utilization. The authors emphasized that graph learning techniques are valuable tools for managing complex wireless communication systems.

Jiang et al. (2022) studied graph learning-based resource optimization for wireless communication networks. The proposed system used graph neural networks to analyze network topology and allocate communication resources efficiently. Simulation results showed improved network performance and reduced communication overhead. The study demonstrated that graph learning models can significantly enhance wireless network optimization.

Chami et al. (2020) introduced Hyperbolic Graph Convolutional Networks (HGCN) that extend traditional graph neural networks by embedding nodes in hyperbolic space. The authors demonstrated that hyperbolic embeddings provide better representation for hierarchical networks. Experimental evaluation showed improved performance compared with Euclidean graph embeddings. The study laid the foundation for applying hyperbolic graph learning in communication network analysis.

Liu et al. (2020) proposed a hyperbolic graph neural network framework designed for hierarchical graph representation. The model improved the ability of graph neural networks to capture long-range dependencies in complex graphs. Experimental results demonstrated superior performance in representing hierarchical structures. The authors suggested that hyperbolic graph models could be applied to large-scale communication networks.

Zhao et al. (2022) developed a deep reinforcement learning-based routing protocol for MANET systems. The algorithm allowed network nodes to learn routing strategies based on network feedback and environmental conditions. Simulation results showed improvements in packet delivery ratio and energy efficiency. The study highlighted the potential of reinforcement learning for intelligent routing in dynamic networks.

Kumar et al. (2021) proposed an energy-efficient clustering and routing protocol for IoT-enabled wireless sensor networks. The study focused on selecting optimal cluster heads based on energy levels and communication distance. Experimental results showed improvements in network lifetime and energy consumption. The research emphasized the importance of clustering mechanisms in large-scale IoT networks.

Wang et al. (2023) developed a graph neural network-based routing algorithm for large-scale IoT networks. The model analyzed network topology and predicted optimal routing paths. The proposed system significantly improved network throughput and reduced routing overhead. The authors concluded that graph learning models are effective for scalable IoT network management.

Chen et al. (2023) proposed a deep learning-based routing optimization framework for IoT-enabled MANET systems. The algorithm dynamically adjusted routing strategies based on network conditions and traffic patterns. Simulation results showed improved communication efficiency and network stability. The study demonstrated the advantages of

machine learning techniques for intelligent routing.
Li et al. (2023) introduced a graph attention network-based routing protocol for wireless sensor networks. The proposed model used attention mechanisms to prioritize reliable communication links. Experimental evaluation showed improved packet delivery ratio and reduced latency. The study confirmed that attention-based graph models can enhance routing performance in wireless networks.
Graph Neural Networks and reinforcement learning techniques have shown significant potential in optimizing wireless and IoT communication networks. Recent studies focused on graph-based resource allocation, intelligent routing, and network optimization to improve scalability, throughput, reliability, and communication efficiency. Researchers highlighted the ability of graph learning models to manage complex network structures and support next-generation communication systems. Reinforcement learning approaches further enabled adaptive routing decisions under dynamic network conditions, reducing delays and enhancing performance. However, challenges such as computational complexity, real-time deployment, and data availability remain critical issues for practical implementation in future intelligent wireless communication environments.

**Graphical abstract graph**

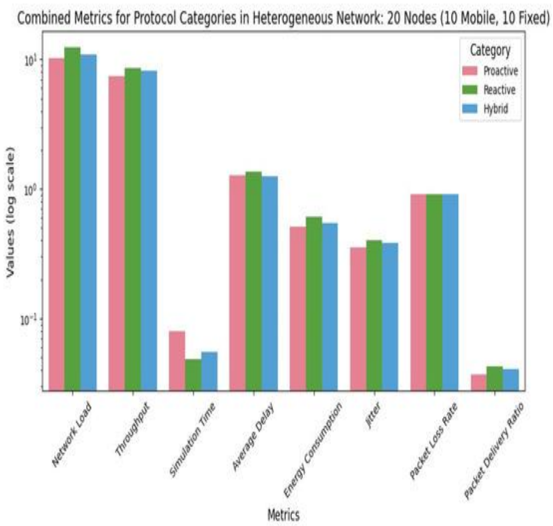


*Fig 1: Performance Comparison of Proactive, Reactive, and Hybrid Routing Protocols in Heterogeneous Networks*

**Comparative Table and Analysis**

**Table 1:** Comparative Table of Selected Studies

| Ref | Author & Year | Method / Technique | Application Domain | Key Features | Advantages | Limitations |
|---|---|---|---|---|---|---|
| 1 | Wu et al., 2020 | Graph Neural Networks (GNN) | Network modeling | Graph-based representation learning | Captures complex node relationships | Computational complexity in large graphs |
| 2 | Zhou et al., 2020 | GNN Survey | Graph learning | Analysis of spectral & spatial GNN models | Strong theoretical foundation | Limited practical routing implementation |
| 3 | Jiang, 2021 | Graph Deep Learning | Communication networks | Graph-based routing analysis | Improved network topology understanding | Requires high computational resources |
| 4 | Swaminathan & Kandasamy, 2021 | GNN-based Routing | Software-defined networks | Dynamic routing optimization | Reduced network latency | Scalability challenges |
| 5 | Xu et al., 2022 | GNN + Reinforcement Learning | Wireless networks | Intelligent routing decision-making | Adaptive routing strategies | High training cost |
| 6 | Yang et al., 2022 | Hyperbolic Graph Neural Networks | Hierarchical networks | Hyperbolic graph embeddings | Efficient hierarchical modeling | Mathematical complexity |
| 7 | Zhao et al., 2022 | GNN-based Backpressure Routing | Dynamic networks | Delay-aware routing optimization | Improved network delay performance | Implementation complexity |

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|---|---|---|---|---|---|---|
| 8 | Paul et al., 2023 | Graph Learning Model | Wireless interference networks | Multi-flow transmission optimization | Increased network throughput | Requires network topology data |
| 9 | Jiang et al., 2022 | Graph-based Resource Allocation | Wireless communication networks | Resource optimization | Efficient bandwidth utilization | Complexity in real-time deployment |
| 10 | Chami et al., 2020 | Hyperbolic Graph Convolutional Network | Graph representation learning | Hyperbolic space embeddings | Effective hierarchical representation | Complex training process |
| 11 | Liu et al., 2020 | Hyperbolic Graph Neural Networks | Hierarchical graphs | Long-range dependency modeling | Improved graph representation | Computational overhead |
| 12 | Zhao et al., 2022 | Deep Reinforcement Learning Routing | MANET | Adaptive routing based on feedback | Higher packet delivery ratio | Requires extensive training |
| 13 | Kumar et al., 2021 | Energy Efficient Clustering | IoT Wireless Sensor Networks | Cluster head optimization | Improved energy efficiency | Limited performance in dynamic networks |
| 14 | Wang et al., 2023 | GNN-based Routing | Large-scale IoT networks | Topology-based routing prediction | Scalable routing solutions | Training complexity |
| 15 | Chen et al., 2023 | Deep Learning Routing | IoT-MANET | Machine learning-based routing | Adaptive network performance | Computational overhead |
| 16 | Li et al., 2023 | Graph Attention Network Routing | Wireless sensor networks | Attention-based routing optimization | Improved packet delivery ratio | Graph processing requirements |
| 17 | Dai et al., 2023 | Graph Learning Survey | Wireless communication | Graph learning frameworks | Identifies research trends | No new algorithm proposed |
| 18 | Sun et al., 2022 | Graph Learning Optimization | Wireless networks | Graph-based network optimization | Improved resource utilization | Complexity in implementation |
| 19 | Tung et al., 2023 | GNN for IoT Networks | Next-generation IoT | Graph-based IoT communication analysis | Handles complex networks | Requires large datasets |
| 20 | Binh et al., 2023 | Reinforcement Learning Routing | Wireless networks | Adaptive routing optimization | Reduced communication delay | High training complexity |

**Comparative Analysis**

The comparative analysis of recent research from 2020 to 2023 reveals a clear transition from traditional routing protocols toward intelligent and data-driven networking approaches. Conventional routing algorithms such as AODV, DSR, and OLSR rely on static routing metrics including hop count, link stability, and communication distance. While these protocols perform reasonably well in small and moderately dynamic networks, they struggle to maintain efficiency in large-scale IoT-MANET environments characterized by high node mobility, frequent topology changes, and limited energy resources.

One of the most prominent research trends identified in the reviewed literature is the growing adoption of graph neural networks for modeling communication networks. Since network topologies naturally form graph structures, GNN-based models can effectively capture relationships between nodes and communication links. By aggregating information from neighboring nodes, graph neural networks enable routing algorithms to learn adaptive routing strategies based on network conditions. Studies such as Wu et al. (2020) and Zhou et al. (2020) demonstrate that graph learning techniques provide a strong framework for analyzing network topology and predicting communication patterns.

Another important development observed in recent research is the integration of attention mechanisms within graph learning models. Graph Attention Networks (GATs) improve the performance of traditional graph neural networks by assigning different importance weights to neighboring nodes. This mechanism allows routing algorithms to prioritize nodes with stronger connectivity or more reliable communication links. Research conducted by Li et al. (2023) shows that attention-based routing algorithms can significantly improve packet delivery ratio, reduce communication delays, and enhance overall network reliability.

**Conclusion**

The rapid growth of Internet of Things (IoT) and wireless communication systems has increased complexity in Mobile Ad Hoc Networks (MANETs). IoT-MANETs are infrastructure-less highly dynamic networks with node mobility frequent topology changes and limited energy resources. These factors make reliable routing difficult. Traditional protocols such as AODV DSR and OLSR use fixed metrics and reactive discovery. Although effective in small networks they struggle in large-scale IoT environments where conditions change rapidly and performance demands are high.

Recent advances in artificial intelligence and graph-based learning offer new solutions. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) model network topology as graphs capturing relationships between nodes. They learn adaptive routing strategies by aggregating neighbor information and identifying efficient communication paths. Hyperbolic graph representation further improves performance by modeling hierarchical and scale-free network structures in an efficient geometric space. This is especially useful for clustered IoT-MANETs where nodes form hierarchical patterns. Integration with clustering techniques reduces routing overhead improves scalability and enables cluster heads to make better routing decisions across the network.

Despite progress challenges remain including high computational cost limited real-world datasets and difficulty deploying models on resource-constrained IoT devices Scalability and real-time performance are also critical concerns Future work should focus on lightweight distributed models and practical deployment strategies for next-generation intelligent IoT-MANET routing systems in future applications widely

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