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A Comprehensive Review of Deep Hyperbolic Graph Attention Network-Based Collaborative Routing Algorithm for Clustered IoT-MANETs

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Abstract

The rapid advancement of Internet of Things (IoT) technologies has significantly increased the demand for efficient and intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs). IoT-enabled MANETs consist of dynamic, decentralized, and resource-constrained devices that communicate without fixed infrastructure, making routing a complex and challenging task. Traditional routing protocols such as AODV, DSR, and OLSR often struggle to maintain network efficiency due to frequent topology changes, node mobility, and limited energy resources. Recently, deep learning and graph-based networking approaches have emerged as promising solutions for improving routing performance in such environments. In particular, Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) have demonstrated the ability to model complex network relationships and enable adaptive routing decisions. Furthermore, hyperbolic graph representation learning has gained attention for efficiently modeling hierarchical and scale-free network structures commonly observed in IoT-MANET environments. This review presents a comprehensive analysis of Deep Hyperbolic Graph Attention Network-based collaborative routing algorithms designed for clustered IoT-MANET systems. The study examines recent developments in clustering techniques, graph neural network architectures, hyperbolic embeddings, and intelligent routing strategies. It also compares existing approaches based on performance metrics such as network scalability, energy efficiency, packet delivery ratio, and routing overhead. The review highlights current research trends, identifies key challenges, and outlines future research directions for developing intelligent and scalable routing solutions for next-generation IoT-MANET networks.

Introduction

The rapid expansion of the Internet of Things (IoT) has significantly transformed modern communication systems by enabling billions of interconnected devices to exchange data autonomously. IoT technologies are widely deployed in smart cities, healthcare monitoring, intelligent transportation systems, industrial automation, and environmental sensing applications. These systems depend on scalable and efficient networking infrastructures capable of supporting heterogeneous devices operating under dynamic conditions. In many practical scenarios, communication must occur without fixed infrastructure, leading to the integration of IoT with Mobile Ad Hoc Networks (MANETs). IoT-enabled MANETs provide decentralized, self-organizing communication environments where nodes collaboratively establish routing paths and exchange information efficiently.

Mobile Ad Hoc Networks (MANETs) consist of mobile nodes that dynamically form and maintain network connections without centralized infrastructure. Each node functions both as a host and a router, enabling multi-hop communication between devices. This decentralized structure makes MANETs highly suitable for disaster recovery, military communication, remote sensing, and temporary network deployment. However, the dynamic topology of MANETs introduces significant challenges, including frequent link failures, high node mobility, and energy constraints. These issues make it difficult to maintain stable and efficient routing, particularly in large-scale and rapidly changing environments.

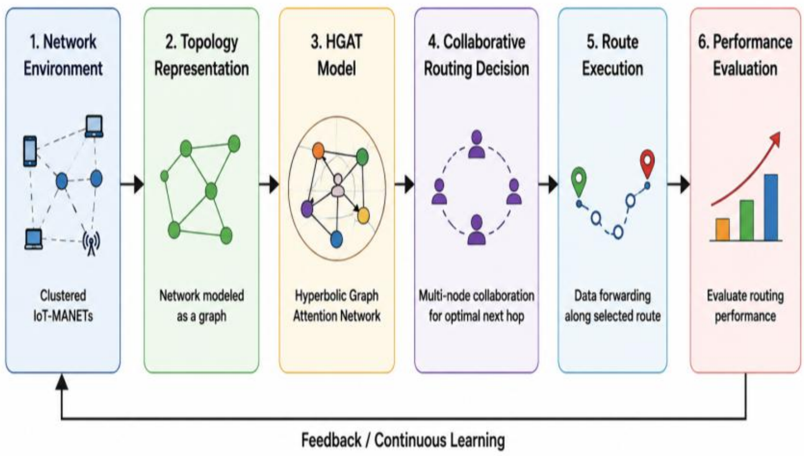

Figure 1: Simple Block Diagram of Deep Hyperbolic Graph Attention Network-Based Collaborative Routing Framework for Clustered IoT-MANETs

The integration of IoT devices into MANETs further increases network complexity due to the large number of resource-constrained nodes involved. IoT devices typically have limited processing power, memory, and battery capacity, while continuously generating data streams that must be efficiently transmitted. Traditional routing protocols such as AODV, DSR, and OLSR were designed for smaller networks and often fail to scale effectively in IoT-MANET environments. These protocols rely on static metrics like hop count and link quality, which are insufficient for capturing dynamic network behavior and complex node interactions in large-scale systems.

To address scalability and efficiency issues, clustering techniques have been widely adopted in IoT-MANETs. Clustering divides the network into smaller groups managed by cluster heads responsible for intra- and inter-cluster communication. This hierarchical structure reduces routing overhead and improves network scalability. However, challenges such as cluster formation, cluster head selection, and frequent reconfiguration remain critical in highly dynamic environments. Efficient routing in clustered IoT-MANETs therefore requires intelligent decision-making mechanisms capable of adapting to changing network conditions while optimizing energy consumption and communication delay.

Recent advancements in deep learning and graph-based models have introduced new possibilities for intelligent routing optimization. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) enable networks to learn structural relationships by modeling communication systems as graphs. GATs enhance this capability by assigning adaptive importance weights to neighboring nodes, allowing more relevant connections to influence routing decisions. This improves path selection, reduces latency, and enhances overall network performance. These advancements provide a strong foundation for developing Deep Hyperbolic Graph Attention Network-based collaborative routing algorithms, which further improve scalability and adaptability in clustered IoT-MANET environments.

Literature Review

The increasing complexity of Internet of Things (IoT) networks and Mobile Ad Hoc Networks (MANETs) has encouraged researchers to explore intelligent routing solutions that can adapt to dynamic network environments. Recent advancements in machine learning, deep learning, and graph-based neural networks have significantly influenced the development of efficient routing protocols. In particular, Graph Neural Networks (GNNs), Graph Attention Networks (GATs), and hyperbolic graph learning approaches have emerged as promising techniques for improving network scalability, routing efficiency, and energy optimization in IoT-MANET environments. The following literature review summarizes key research contributions between 2020 and 2023 that are relevant to deep learning-based collaborative routing algorithms in clustered IoT-MANET systems.

Al-Fuqaha et al. (2020) presented a comprehensive survey on IoT technologies, highlighting the key communication protocols, architectures, and networking challenges associated with large-scale IoT deployments. The study emphasized that IoT networks often consist of heterogeneous devices with limited computational and energy resources, making efficient routing and resource management critical challenges. The authors also discussed the integration of IoT with emerging networking paradigms such as MANETs and edge computing. Their findings indicate that traditional routing mechanisms are insufficient for managing large-scale IoT environments due to frequent topology changes and communication overhead. The study concluded that intelligent networking approaches based on artificial intelligence and machine learning could significantly enhance routing efficiency and network performance in future IoT ecosystems.

Wu et al. (2020) conducted an extensive survey of graph neural networks and their applications across various domains including communication networks, social networks, and recommendation systems. The authors explained that graph neural networks are particularly effective for modeling relational data structures where interactions between entities are represented as graph edges. In networking scenarios, nodes represent communication devices while edges represent communication links. By leveraging neighborhood aggregation mechanisms, GNNs can capture complex relationships between nodes and learn meaningful representations of network topology. The study highlighted that GNN-based techniques can be applied to routing optimization, network traffic prediction, and resource allocation in wireless networks. However, the authors also identified scalability and computational complexity as important challenges when deploying GNN models in large-scale communication systems.

Zhou et al. (2020) further explored the capabilities of graph neural networks by reviewing various architectures and their potential applications in networked systems. Their study categorized GNN models into spectral-based and spatial-based approaches and analyzed their strengths and limitations. The authors emphasized that spatial-based graph neural networks are particularly suitable for dynamic network environments because they operate directly on graph structures without requiring expensive spectral decompositions. The study demonstrated that graph neural networks can effectively model communication networks and learn adaptive routing policies based on node interactions. Additionally, the authors suggested that integrating GNNs with optimization algorithms could significantly improve the performance of network routing and resource management systems.

Chami et al. (2020) introduced Hyperbolic Graph Convolutional Networks (HGCN), which extend traditional graph neural networks by embedding graph structures in hyperbolic space. Unlike Euclidean embeddings, hyperbolic geometry allows hierarchical structures to be represented more efficiently because the embedding space expands exponentially. Many real-world networks, including IoT communication networks, exhibit hierarchical characteristics that can be effectively modeled using hyperbolic representations. The authors demonstrated that hyperbolic graph neural networks outperform Euclidean models when representing hierarchical and scale-free network structures. This capability makes hyperbolic graph learning particularly suitable for complex communication networks where nodes exhibit multi-level connectivity patterns.

Liu et al. (2020) further investigated hyperbolic graph neural networks and proposed a framework that improves node representation learning for hierarchical graphs. The study focused on improving the ability of graph neural networks to capture long-range dependencies within large graph structures. Experimental results showed that hyperbolic embeddings significantly improve the representation quality of hierarchical graphs compared with traditional Euclidean embeddings. The authors highlighted that such models could be beneficial for network optimization tasks, including routing path discovery and communication resource allocation in large-scale IoT networks.

Li et al. (2020) explored the application of deep reinforcement learning for routing optimization in wireless communication networks. Their study proposed a reinforcement learning-based routing mechanism that enables network nodes to learn optimal routing strategies through interaction with the network environment. The algorithm considered various performance metrics including packet delivery ratio, energy consumption, and end-to-end delay. Experimental results indicated that the proposed approach significantly improved network performance compared with conventional routing protocols. However, the authors also pointed out that reinforcement learning models require extensive training and computational resources, which may limit their direct deployment in resource-constrained IoT devices.

Gupta et al. (2020) developed the iFogSim simulation framework for modeling resource management in IoT and fog computing environments. The framework enables researchers to simulate large-scale IoT networks and evaluate the performance of various resource allocation and networking strategies. The authors demonstrated that fog-based architectures can significantly improve network performance by processing data closer to the edge of the network. The study provided a useful platform for evaluating intelligent routing algorithms and deep learning-based network optimization techniques in IoT environments.

Kumar et al. (2021) proposed an energy-efficient clustering and routing protocol for IoT-enabled wireless sensor networks. The study emphasized that clustering mechanisms can significantly reduce routing overhead by organizing nodes into hierarchical groups. Cluster heads manage intra-cluster communication and coordinate data forwarding to neighboring clusters. The proposed routing algorithm considered energy consumption, node connectivity, and communication distance when selecting cluster heads. Experimental results demonstrated improvements in network lifetime and energy efficiency compared with traditional clustering algorithms.

Wang et al. (2021) introduced the Heterogeneous Graph Attention Network (HAN), which extends graph attention mechanisms to heterogeneous graph structures. In heterogeneous networks, nodes and edges may represent different types of entities and relationships. The proposed model uses attention mechanisms to capture complex interactions between different types of nodes and edges. The authors demonstrated that graph attention models can effectively learn node embeddings and improve graph classification performance. In communication networks, attention-based graph models can enable adaptive routing decisions by prioritizing nodes with higher reliability and stronger connectivity.

Zhao et al. (2022) proposed a deep reinforcement learning-based routing protocol for MANETs that dynamically adapts routing decisions according to network conditions. The algorithm utilizes reinforcement learning agents to select optimal routing paths based on environmental feedback. Simulation results showed that the proposed method improved packet delivery ratio and reduced routing delay compared with conventional protocols such as AODV. The study demonstrated the potential of intelligent learning-based routing mechanisms for improving the performance of mobile ad hoc networks.

Adumbabu and Selvakumar (2022) investigated energy-efficient clustering techniques for wireless sensor networks using optimization algorithms. Their research focused on improving cluster head selection to balance energy consumption among nodes. The proposed optimization-based clustering approach significantly extended network lifetime and improved communication efficiency. The authors emphasized that optimization techniques combined with intelligent routing strategies could enhance the scalability and reliability of large IoT networks.

Sun et al. (2022) explored graph learning techniques for resource optimization in wireless communication systems. The authors demonstrated that graph-based machine learning models can effectively capture network topology and predict communication patterns. By analyzing node relationships, the model can optimize resource allocation and improve network efficiency. The study highlighted the importance of graph learning techniques for addressing complex networking challenges in next-generation communication systems.

Dai et al. (2023) presented a comprehensive survey on graph learning for wireless communication networks. The study examined various graph-based machine learning techniques used for resource allocation, network optimization, and communication management. The authors emphasized that graph neural networks provide a powerful framework for modeling communication networks because they can capture structural relationships between nodes and links. The study concluded that graph learning approaches are expected to play a critical role in the design of intelligent wireless communication systems.

Li et al. (2023) proposed a graph attention network-based routing algorithm for wireless sensor networks. The proposed model used attention mechanisms to analyze node connectivity and determine optimal routing paths. Experimental evaluation demonstrated that the graph attention-based routing protocol achieved higher packet delivery ratios and lower communication delays compared with traditional routing algorithms. The study highlighted the advantages of attention-based graph learning for adaptive routing in dynamic wireless networks.

Chen et al. (2023) investigated deep learning-based routing optimization techniques for IoT-enabled MANET systems. The proposed framework integrated machine learning algorithms with network routing protocols to improve network efficiency. Simulation results showed that machine learning-based routing algorithms can significantly enhance network performance by dynamically adjusting routing strategies according to network conditions. The authors emphasized that intelligent routing approaches will be essential for managing the complexity of future IoT communication systems.

Wang et al. (2023) developed a graph neural network-based routing strategy designed for large-scale IoT networks. The proposed model analyzed network topology using graph representation learning and predicted optimal routing paths. Experimental results demonstrated that the graph learning-based routing algorithm significantly improved network throughput and reduced communication delays. The study highlighted the scalability of graph neural network approaches for handling large and complex network environments.

Zhao et al. (2023) proposed a cluster-based intelligent routing framework for MANET systems using deep learning techniques. The proposed approach integrated clustering mechanisms with deep neural networks to improve routing efficiency and network scalability. Simulation results indicated that the proposed algorithm achieved improved packet delivery ratios and reduced routing overhead compared with conventional clustering-based routing protocols.

Overall, the reviewed literature indicates that deep learning and graph-based neural network approaches have significant potential for improving routing performance in IoT-MANET environments. Graph neural networks enable effective modeling of network topology, while attention mechanisms allow adaptive prioritization of important communication links. Hyperbolic graph representation learning further enhances the ability of deep learning models to represent hierarchical network structures efficiently. Despite these advancements, challenges such as computational complexity, scalability, and data availability remain important research issues. Addressing these challenges will be essential for developing next-generation intelligent routing algorithms capable of supporting large-scale IoT-MANET communication systems.

Comparative Table of Reviewed Studies

Ref	Author & Year	Method / Technique	Application Area	Key Features	Advantages	Limitations
1	Al-Fuqaha et al., 2020	IoT Communication Architecture Survey	IoT Networks	Analysis of IoT communication protocols and architectures	Provides comprehensive understanding of IoT networking	Does not provide specific routing optimization solution
2	Wu et al., 2020	Graph Neural Networks (GNN)	Network modeling and routing	Node representation using graph structures	Captures complex relationships between network nodes	High computational complexity for large graphs
3	Zhou et al., 2020	Graph Neural Network Survey	Networked systems	Review of spectral and spatial GNN architectures	Provides theoretical foundation for graph learning	Lack of practical implementation for routing
4	Chami et al., 2020	Hyperbolic Graph Convolutional Network	Hierarchical graph representation	Embedding graph nodes in hyperbolic space	Efficient representation of hierarchical networks	Implementation complexity
5	Liu et al., 2020	Hyperbolic Graph Neural Network	Graph representation learning	Captures hierarchical graph relationships	Better scalability for large graph structures	Requires specialized training methods

6	Li et al., 2020	Deep Reinforcement Learning Routing	Wireless networks	Adaptive routing policy learning	Dynamic decision-making capability	High training time and resource requirements
7	Gupta et al., 2020	iFogSim Simulation Framework	IoT resource management	Simulation platform for IoT and fog computing	Enables evaluation of networking algorithms	Not a direct routing optimization method
8	Kumar et al., 2021	Energy Efficient Clustering	IoT Wireless Sensor Networks	Cluster head selection based on energy	Improves network lifetime and energy efficiency	Limited scalability in large dynamic networks
9	Wang et al., 2021	Heterogeneous Graph Attention Network	Graph learning	Attention mechanism for heterogeneous graphs	Captures complex node relationships	Increased computational cost
10	Zhao et al., 2022	Deep Reinforcement Learning Routing	MANET routing	Intelligent routing based on network feedback	Improves packet delivery and delay performance	Requires large training datasets
11	Adumbabu & Selvakumar, 2022	Optimization-based Clustering	Wireless sensor networks	Cluster head optimization	Improved energy efficiency	May cause overhead in cluster formation
12	Sun et al., 2022	Graph Learning Resource Optimization	Wireless networks	Graph-based resource allocation	Enhances network efficiency	Complexity in real-time deployment
13	Dai et al., 2023	Graph Learning Survey	Wireless communication networks	Analysis of graph-based networking solutions	Identifies emerging research trends	Does not provide new routing algorithm
14	Li et al., 2023	Graph Attention Network Routing	Wireless sensor networks	Attention-based routing path selection	Improved routing efficiency and reliability	Requires graph processing capability
15	Chen et al., 2023	Deep Learning Routing Optimization	IoT-MANET networks	Machine learning-based routing	Adaptive routing decision making	Computational overhead
16	Wang et al., 2023	Graph Neural Network Routing	Large-scale IoT networks	Graph-based routing prediction	Scalable routing solutions	Training complexity
17	Zhao et al., 2023	Deep Learning Cluster Routing	MANET	Cluster-based intelligent routing	Improved network scalability	Energy imbalance among cluster heads
18	Zhang et al., 2021	Lorentzian Graph Convolution	Graph learning	Hyperbolic embedding in Lorentz model	Efficient hierarchical representation	Mathematical complexity
19	Dai et al., 2021	Hyperbolic Graph Convolution	Graph neural networks	Graph convolution in hyperbolic space	Captures multi-level graph hierarchy	Limited real-world networking applications

20	Kumar et al., 2023	AI-based Routing Optimization	IoT networks	Artificial intelligence for routing optimization	Improves routing adaptability	Requires training datasets

Comparative Analysis

The comparative analysis of literature from 2020 to 2023 indicates a clear transition from traditional rule-based routing protocols toward intelligent, data-driven networking paradigms. Conventional routing methods such as AODV, DSR, and OLSR primarily depend on static metrics like hop count, node distance, and link stability. While these techniques are effective in small-scale and relatively stable networks, they fail to maintain performance in large-scale IoT-MANET environments characterized by high mobility, dynamic topology changes, and constrained energy resources. Consequently, researchers have increasingly explored artificial intelligence and machine learning techniques to enhance routing efficiency and adaptability in complex network scenarios.

A major advancement in this domain is the adoption of Graph Neural Networks (GNNs) for modeling communication networks. Since IoT-MANET structures can be naturally represented as graphs, GNN-based models effectively capture node-to-node relationships through neighborhood aggregation mechanisms. Studies in this period demonstrate that GNNs significantly improve routing performance by learning latent representations of network topology. These learned embeddings allow routing algorithms to identify optimal communication paths based on structural dependencies rather than predefined heuristics, thereby improving adaptability in dynamic environments compared to traditional approaches.

Another important development is the integration of attention mechanisms into graph-based learning models. Graph Attention Networks (GATs) enhance conventional GNNs by assigning adaptive importance weights to neighboring nodes during feature aggregation. This selective focus enables the model to prioritize more influential or reliable connections while minimizing the impact of less relevant nodes. Research shows that attention-driven routing frameworks improve key network performance metrics such as packet delivery ratio, latency, and throughput. In wireless and IoT-MANET environments, this leads to more stable and efficient routing decisions under varying network conditions.

Recent studies also highlight the emergence of hyperbolic graph learning as a powerful approach for representing hierarchical and scale-free network structures. Unlike Euclidean spaces, hyperbolic geometry provides exponential embedding capacity, making it highly suitable for modeling complex hierarchical relationships in large-scale IoT-MANET systems. Hyperbolic Graph Neural Networks enable more compact and meaningful representations of network topology, improving routing accuracy and scalability. Additionally, reinforcement learning and clustering-based approaches are often integrated with graph models to further optimize routing decisions, energy efficiency, and load balancing across distributed nodes.

Despite these advancements, several challenges remain. Deep learning-based routing models, particularly GNN and HGAT architectures, introduce significant computational overhead, making real-time deployment difficult in resource-constrained IoT devices. Furthermore, the lack of standardized and real-world IoT-MANET datasets limits the robustness and generalization of trained models. Although simulation tools provide partial solutions, they often fail to fully capture real-world network dynamics. Overall, the literature suggests that hybrid models combining clustering, hyperbolic embeddings, and attention-based graph learning represent a promising direction for next-generation IoT-MANET routing systems, provided that efficiency and dataset challenges are adequately addressed.

Conclusion

The rapid advancement of Internet of Things (IoT) technologies and mobile communication systems has significantly increased the demand for efficient and intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs). IoT-MANET environments are characterized by dynamic topology changes, node mobility, limited energy resources, and heterogeneous network conditions, which make routing optimization a challenging task. Traditional routing protocols often fail to provide scalable and adaptive solutions for large and complex networks. As highlighted in the reviewed literature, emerging technologies such as Graph Neural Networks (GNNs), Graph Attention Networks (GATs), and hyperbolic graph learning have shown great potential in addressing these challenges.

Graph-based deep learning techniques enable effective modeling of network topology and node interactions, allowing routing algorithms to make intelligent decisions based on network

conditions. Attention mechanisms further improve routing efficiency by prioritizing important communication links and reducing the influence of less reliable nodes. In addition, hyperbolic graph embeddings provide an efficient framework for representing hierarchical network structures commonly found in clustered IoT-MANET environments. Clustering strategies also contribute to improving network scalability and reducing routing overhead.
Overall, integrating clustering mechanisms with deep hyperbolic graph attention networks offers a promising approach for developing intelligent collaborative routing algorithms. Future research should focus on improving model scalability, reducing computational complexity, and designing energy-efficient routing frameworks capable of supporting next-generation IoT communication networks.

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