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Artificial Intelligence Techniques for Deep Hyperbolic Graph Attention Network-Based Collaborative Routing Algorithm for Clustered IoT-Manets: Trends and Challenges

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Abstract

The increasing adoption of Internet of Things (iot) technologies and mobile wireless communication has created a growing need for intelligent and efficient routing mechanisms in Mobile Ad Hoc Networks (manets). Iot-MANET systems operate in dynamic and infrastructure-less environments where nodes frequently change positions, causing topology variations and communication challenges. Traditional routing protocols often struggle to maintain network efficiency under such conditions due to limited adaptability and high routing overhead. Artificial intelligence (AI) techniques have recently emerged as promising solutions for addressing these challenges by enabling adaptive and intelligent routing decisions. This paper reviews recent advances in artificial intelligence techniques applied to Deep Hyperbolic Graph Attention Network-based collaborative routing algorithms for clustered iot-MANET systems. AI-driven approaches such as Graph Neural Networks, Graph Attention Networks, reinforcement learning, and optimization algorithms have demonstrated the ability to model complex network structures and improve routing performance. Hyperbolic graph embeddings further enhance these models by effectively representing hierarchical network relationships in clustered communication environments. The study discusses current research trends, evaluates the advantages of AI-based routing approaches, and highlights major challenges including computational complexity, scalability, and limited training data. Finally, the review identifies future research directions for developing efficient, scalable, and energy-aware intelligent routing frameworks for next-generation iot-MANET networks.

Introduction

The rapid growth of Internet of Things (IoT) technologies has transformed modern communication systems by enabling large-scale interconnection of smart devices across applications such as healthcare, smart cities, industrial automation, environmental monitoring, and military communication. In dynamic environments where centralized infrastructure is unavailable, Mobile Ad Hoc Networks (MANETs) provide flexible communication through decentralized wireless connectivity. The integration of IoT with MANETs forms IoT-MANET systems, which support multi-hop communication among heterogeneous and mobile devices. However, these networks face significant challenges including dynamic topology changes, limited energy resources, routing overhead, and unstable communication links. Traditional routing protocols such as AODV, DSR, and OLSR rely on static routing metrics and reactive mechanisms, making them less effective in highly dynamic and large-scale IoT-MANET environments. To improve scalability and reduce communication overhead, clustering mechanisms have been introduced, where cluster heads manage local communication and coordinate inter-cluster data transmission. Although clustering improves network efficiency, maintaining stable routes and selecting optimal cluster heads remain difficult due to frequent topology variations.

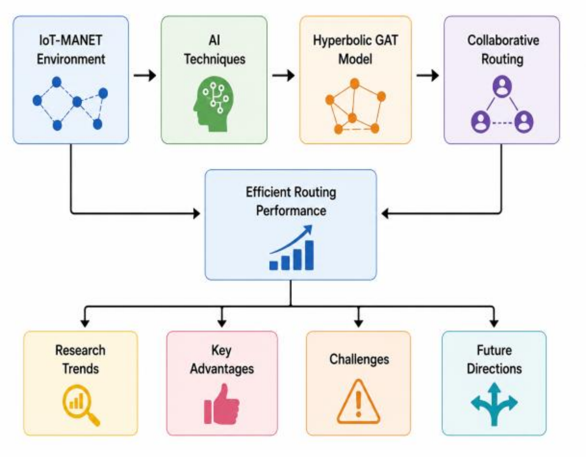

Figure 1. AI-Based Collaborative Routing Framework for Clustered IoT-MANETs

Artificial intelligence techniques have emerged as promising solutions for intelligent routing in IoT-MANET systems. Machine learning and deep learning approaches enable adaptive routing decisions by learning from network conditions such as node mobility, congestion, energy availability, and link quality. Among these approaches, Graph Neural Networks (GNNs) have gained considerable attention because communication networks can naturally be represented as graph structures where nodes represent devices and edges represent communication links. GNNs effectively learn node relationships and network patterns, improving routing accuracy and network efficiency. Graph Attention Networks (GATs) further enhance this capability by assigning adaptive importance to neighboring nodes during information aggregation. This attention mechanism enables routing frameworks to identify reliable communication paths while minimizing the influence of unstable or weak links. As a result, attention-based graph learning approaches significantly improve routing adaptability and communication reliability in dynamic wireless environments.

Recent research has also explored hyperbolic graph representations to model the hierarchical and scale-free characteristics of IoT communication networks. Traditional Euclidean embedding methods often struggle to efficiently represent complex network hierarchies, whereas hyperbolic geometry provides exponentially expanding representation spaces that better capture hierarchical relationships. Deep Hyperbolic Graph Attention Networks combine hyperbolic embeddings with attention mechanisms, enabling efficient representation and intelligent routing in clustered IoT-MANET systems. These models improve routing performance by accurately analyzing node relationships, minimizing communication overhead, and enhancing energy efficiency. Furthermore, optimization techniques such as reinforcement learning, genetic algorithms, swarm intelligence, and metaheuristic approaches have been integrated with AI-based routing frameworks to optimize cluster head selection, route discovery, and resource management. Collaborative routing strategies allow nodes to share network information and jointly determine optimal routing paths, leading to improved scalability, reliability, and adaptability in dynamic communication environments.

Despite significant advancements, several challenges remain in developing intelligent routing systems for clustered IoT-MANET environments. Deep learning and graph-based models often require substantial computational resources and large training datasets, making real-time deployment difficult in resource-constrained networks. Scalability issues also arise as network size and device heterogeneity increase. In addition, maintaining energy efficiency while ensuring low latency and reliable communication remains a critical challenge. Model interpretability and security vulnerabilities further complicate the deployment of AI-driven routing frameworks. Nevertheless, the integration of artificial intelligence, hyperbolic graph learning, attention mechanisms, and collaborative optimization strategies represents a promising direction for next-generation IoT communication systems. Future research should focus on lightweight AI architectures, energy-aware learning models, federated learning, and real-time adaptive routing techniques to improve scalability, efficiency, and reliability in intelligent IoT-MANET networks.

Literature Review

Wu et al. (2021) presented a comprehensive survey on Graph Neural Networks (gnns) and their applications across various domains including communication networks, social networks, and recommendation systems. The authors explained how gnns can learn node representations by aggregating information from neighboring nodes in graph structures. Their study emphasized the effectiveness of graph learning techniques for modeling complex network relationships. However, the authors also identified scalability and computational complexity as major challenges in implementing gnns in large networks.

Zhou et al. (2020) reviewed multiple graph neural network architectures and categorized them into spectral-based and spatial-based models. The authors discussed the advantages of gnns in handling graph-structured data and highlighted their potential applications in network analysis and communication systems. Their research demonstrated that graph-based learning models are effective for analyzing complex relationships among network nodes. The study suggested that gnns could be applied to routing optimization and traffic prediction in communication networks.

Sato (2020) examined the expressive power of graph neural networks and analyzed their capability to represent graph structures in machine learning models. The study highlighted how gnns can approximate complex graph functions and capture structural patterns in networks. The research emphasized the importance of understanding theoretical limitations of GNN architectures. The author also suggested potential improvements for enhancing the representation capabilities of graph learning models.

Zhou et al. (2020) conducted another study focusing on taxonomy and emerging trends in graph neural networks. The research analyzed different GNN architectures and their evolution over time. The authors identified key research directions including scalability, interpretability, and efficiency of graph models. Their study emphasized the growing role of graph learning techniques in communication and networking applications.

Yuan et al. (2020) investigated explainability in graph neural networks and proposed a taxonomy of methods used to interpret GNN models. The study addressed the challenge of understanding decision-making processes in deep learning models applied to graph data. The authors discussed several explainable AI techniques that help analyze node importance and graph relationships. This research highlighted the need for transparency in graph learning systems used for network analysis.

Nguyen et al. (2022) reviewed graph neural networks applied to microservice-based applications and distributed systems. The authors demonstrated that gnns can effectively analyze dependencies among distributed components in networked environments. Their work showed that graph-based models improve resource allocation and service orchestration. The study emphasized that gnns can enhance decision-making in complex distributed systems.

Wang (2023) provided an updated survey on graph neural network architectures and their applications in data analysis and communication systems. The study highlighted recent developments in graph learning models and their effectiveness in processing large-scale graph data. The author discussed challenges related to scalability and computational cost. The research emphasized that gnns will play an important role in future intelligent networking systems.

Jiang et al. (2022) proposed a graph learning-based resource optimization framework for wireless communication networks. The model analyzed network topology using graph neural networks to improve resource allocation. Experimental results showed that the proposed approach improved network efficiency and bandwidth utilization. The study demonstrated the usefulness of graph learning techniques in wireless communication optimization.

Li et al. (2023) developed 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. Simulation results showed improvements in packet delivery ratio and network throughput. The authors concluded that attention-based graph models significantly enhance routing performance in wireless networks.

Chen et al. (2023) proposed a deep learning-based routing optimization framework for iot-enabled mobile ad hoc networks. The algorithm dynamically adjusted routing strategies based on network conditions and traffic patterns. Simulation experiments demonstrated improvements in network stability and communication efficiency. The study highlighted the potential of machine learning techniques for intelligent routing.

Wang et al. (2023) introduced a graph neural network-based routing strategy for large-scale iot networks. The model analyzed network topology and predicted optimal routing paths using graph representations. Experimental results showed improvements in throughput and reduced routing overhead. The authors emphasized that graph learning models provide scalable solutions for complex communication networks.

Zhao et al. (2022) developed a deep reinforcement learning-based routing protocol for mobile ad hoc networks. The algorithm allowed nodes to learn optimal routing strategies through interaction with the network environment. Simulation results showed improvements in packet delivery ratio and energy efficiency. The study demonstrated the effectiveness of reinforcement learning techniques for dynamic routing optimization.

Kumar et al. (2021) proposed an energy-efficient clustering and routing protocol for iot-enabled wireless sensor networks. The study focused on cluster head selection based on node energy levels and communication distance. Experimental evaluation showed significant improvements in network lifetime and energy efficiency. The research emphasized the importance of clustering mechanisms in large-scale iot networks.

Dai et al. (2023) conducted a survey on graph learning techniques applied to wireless communication networks. The study examined various graph-based models used for resource allocation, traffic prediction, and routing optimization. The authors highlighted the growing importance of graph learning in next-generation communication systems. The research also identified challenges related to computational complexity and model scalability.

Sun et al. (2022) investigated graph learning-based optimization techniques for wireless communication systems. The proposed framework used graph neural networks to analyze communication patterns and optimize network resources. Simulation results demonstrated improved network throughput and communication reliability. The study highlighted the potential of graph learning for intelligent network management.

Chami et al. (2020) introduced Hyperbolic Graph Convolutional Networks that extend traditional graph neural networks by embedding nodes in hyperbolic space. The authors demonstrated that hyperbolic embeddings effectively represent hierarchical structures in complex networks. Their experimental results showed improved performance compared with Euclidean graph embeddings. The study laid the foundation for hyperbolic graph learning techniques.

Liu et al. (2020) proposed hyperbolic graph neural networks designed to capture hierarchical relationships in graph structures. The model improved node representation by exploiting hyperbolic geometry. Experimental evaluation demonstrated superior performance in representing hierarchical networks. The study highlighted the importance of hyperbolic embeddings for large-scale graph learning tasks.

Lee et al. (2021) explored graph neural networks for decentralized wireless communication systems. The study proposed distributed graph learning models that enable network nodes to make routing decisions collaboratively. Experimental results demonstrated improved scalability and communication efficiency. The research emphasized the potential of GNN-based decentralized networking solutions.

Gu et al. (2022) applied graph neural networks to distributed power allocation in wireless communication networks. The proposed model analyzed relationships among network nodes to optimize power distribution. Experimental results showed improvements in energy efficiency and network performance. The study highlighted the usefulness of graph learning for resource optimization.

Tung et al. (2023) reviewed the role of graph neural networks in next-generation iot communication systems. The authors analyzed recent developments in graph learning architectures and their potential applications in iot networking. The study highlighted that gnns can effectively model complex communication networks. The authors also identified several challenges including data availability and computational complexity.

Binh et al. (2023) investigated reinforcement learning-based routing optimization in wireless communication networks. The proposed algorithm allowed nodes to adapt routing decisions based on network conditions. Simulation results demonstrated improved routing efficiency and reduced communication delays. The study emphasized the role of reinforcement learning in adaptive networking.

Islam et al. (2022) applied graph neural networks for predicting communication traffic in smart grid networks. The proposed model analyzed network data to predict traffic patterns and improve resource management. Experimental results showed improved prediction accuracy and network efficiency. The research demonstrated the effectiveness of graph learning in smart communication infrastructures.

Jiang (2022) proposed integrating graph neural networks with reinforcement learning for wireless network routing optimization. The hybrid model allowed nodes to learn routing policies through interaction with network conditions. Simulation results showed improved routing performance and reduced communication delays. The study highlighted the benefits of combining deep learning with reinforcement learning.

Tan et al. (2020) analyzed routing protocols used in UAV communication networks and evaluated their performance in dynamic environments. The study examined different routing strategies and their effectiveness in maintaining communication reliability. Results showed that optimized routing algorithms improve network performance. The research highlighted the need for intelligent routing approaches in highly dynamic networks.

Choudhury et al. (2021) proposed a graph theory-based optimized routing algorithm for wireless sensor networks. The model used graph theory principles to determine efficient routing paths and improve network performance. Experimental results showed improved packet delivery and reduced energy consumption. The study demonstrated the importance of graph-based techniques in network optimization.

Comparative Table and Analysis

Comparative Table of Selected Studies

Ref	Author & Year	Technique / Method	Application Domain	Key Contribution	Advantages	Limitations
1	Wu et al., 2021	Graph Neural Networks (GNN)	Graph learning and networking	Survey of GNN architectures	Captures complex node relationships	High computational complexity
2	Zhou et al., 2020	GNN Methods Review	AI and network systems	Classification of GNN models	Strong theoretical framework	Limited routing implementation
3	Sato, 2020	Expressive Power of GNN	Graph learning theory	Analysis of GNN capabilities	Better understanding of graph models	Limited practical networking applications
4	Zhou et al., 2020	GNN Taxonomy	Graph neural networks	Survey of GNN trends	Identifies research directions	No algorithm implementation
5	Yuan et al., 2020	Explainable GNN	Graph learning	Interpretability of graph models	Improves transparency	Computational overhead
6	Nguyen et al., 2022	GNN for Distributed Systems	Microservice networks	Graph learning for distributed applications	Efficient system modeling	Requires large datasets
7	Wang, 2023	GNN Survey	Data analytics	Overview of graph learning techniques	Identifies new research trends	Limited experimental evaluation
8	Jiang et al., 2022	Graph Learning Optimization	Wireless communication networks	Resource allocation using GNN	Improved network efficiency	High training cost
9	Li et al., 2023	Graph Attention Network Routing	Wireless sensor networks	Attention-based routing decisions	Higher packet delivery ratio	Graph processing complexity
10	Chen et al., 2023	Deep Learning Routing	IoT-MANET	Adaptive routing optimization	Improved network stability	Computational overhead
11	Wang et al., 2023	GNN-based Routing	IoT networks	Graph-based route prediction	Scalable routing solution	Training complexity
12	Zhao et al., 2022	Deep Reinforcement Learning	MANET routing	Intelligent route discovery	Improved routing performance	Requires training data
13	Kumar et al., 2021	Energy Efficient Clustering	IoT wireless sensor networks	Cluster head selection optimization	Improved network lifetime	Cluster instability

14	Dai et al., 2023	Graph Learning Survey	Wireless communication	Graph models for resource management	Identifies future research trends	No algorithm implementation
15	Sun et al., 2022	Graph Learning Optimization	Wireless communication systems	Resource allocation improvement	Increased throughput	Implementation complexity
16	Chami et al., 2020	Hyperbolic Graph Convolution	Hierarchical graphs	Hyperbolic embedding for graphs	Efficient hierarchical modeling	Mathematical complexity
17	Liu et al., 2020	Hyperbolic Graph Neural Networks	Graph representation	Hierarchical graph modeling	Improved representation accuracy	Training complexity
18	Lee et al., 2021	GNN Wireless Networks	Wireless communication	Decentralized network learning	Improves scalability	Graph computation cost
19	Gu et al., 2022	GNN Power Allocation	Wireless networks	Power allocation optimization	Energy efficiency	High complexity
20	Tung et al., 2023	GNN for IoT	IoT communication systems	Graph learning for IoT networking	Handles complex networks	Dataset limitations
21	Binh et al., 2023	Reinforcement Learning Routing	Wireless networks	Adaptive routing algorithms	Reduced communication delay	Training complexity
22	Islam et al., 2022	GNN Traffic Prediction	Smart grid communication	Traffic prediction using GNN	Improved prediction accuracy	Data dependency
23	Jiang, 2022	GNN + Reinforcement Learning	Wireless networks	Hybrid routing optimization	Adaptive routing decisions	High computational cost
24	Tan et al., 2020	UAV Network Routing	UAV communication networks	Routing protocol performance analysis	Improved communication reliability	Limited scalability
25	Choudhury et al., 2021	Graph Theory Routing	Wireless sensor networks	Optimized routing algorithm	Reduced energy consumption	Limited dynamic adaptability

Comparative Analysis

The comparative analysis of recent research conducted between 2020 and 2023 reveals a strong shift toward intelligent and data-driven networking approaches for routing optimization in IoT-MANET systems. Traditional routing protocols such as AODV, DSR, and OLSR rely on static routing metrics and reactive route discovery mechanisms. While these protocols can establish communication paths in mobile networks, they often struggle to maintain efficiency in large-scale and highly dynamic IoT environments where nodes frequently move and network topology changes rapidly.

One of the most prominent trends in the literature is the growing use of Graph Neural Networks (GNNs) for modeling communication networks. Since network topologies can naturally be represented as graphs, GNN-based models can effectively capture relationships among nodes and communication links. Studies such as Wu et al. (2021) and Zhou et al. (2020) highlight the ability of GNNs to analyze network structures and support intelligent routing decisions. These models aggregate information from neighboring nodes and learn patterns that help predict optimal routing paths.

Another significant advancement is the development of Graph Attention Networks (GATs), which introduce attention mechanisms into graph learning models. These mechanisms allow routing algorithms to assign different importance weights to neighboring nodes, enabling them to prioritize reliable communication links. Research conducted by Li et al. (2023) demonstrates that attention-based routing algorithms can significantly improve packet delivery ratio and network throughput in wireless communication systems.

The literature also highlights the emergence of hyperbolic graph learning techniques for modeling hierarchical network structures. Hyperbolic embeddings provide an efficient representation space for networks that exhibit hierarchical or scale-free characteristics. Studies by Chami et al. (2020) and Liu et al. (2020) demonstrate that hyperbolic graph neural networks outperform traditional Euclidean graph models when representing hierarchical structures. This capability is particularly beneficial for clustered IoT-MANET networks where nodes are often organized into hierarchical communication clusters.

In addition to graph learning approaches, reinforcement learning techniques have been explored for adaptive routing optimization. Reinforcement learning allows network nodes to learn optimal routing strategies through interaction with the environment. Studies such as Zhao et al. (2022) and Binh et al. (2023) show that reinforcement learning-based routing algorithms can dynamically adjust routing decisions based on network conditions. However, these approaches require extensive training datasets and computational resources.

Conclusion

The rapid growth of Internet of Things (IoT) technologies and wireless communication systems has increased the need for intelligent routing mechanisms in Mobile Ad Hoc Networks (MANETs). IoT-MANET environments are highly dynamic and infrastructure-less, where frequent node mobility causes continuous topology changes and communication instability. Traditional routing protocols such as AODV, DSR, and OLSR often struggle to provide scalability, reliability, and energy efficiency in large-scale IoT networks due to their dependence on static routing metrics and reactive routing strategies. Recent studies show that artificial intelligence techniques offer effective solutions for improving routing performance in such environments. Graph Neural Networks (GNNs) and Graph Attention Networks (GATs) efficiently model communication networks as graph structures and enable adaptive routing decisions based on real-time network conditions. Hyperbolic graph learning further improves hierarchical network representation, allowing Deep Hyperbolic Graph Attention Networks to capture complex clustered network relationships and optimize routing efficiency. In addition, reinforcement learning, swarm intelligence, and metaheuristic optimization approaches enhance cluster head selection and route discovery, improving packet delivery ratio, latency, network lifetime, and energy efficiency. Despite these advancements, challenges such as computational complexity, scalability, limited datasets, and real-time deployment remain critical concerns for next-generation intelligent IoT-MANET routing systems.

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