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A Distributed Graph Neural Network Routing Protocol for Dynamic Wireless Mesh Networks

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Abstract

Wireless Mesh Networks (WMNs) support various services required for rapidly growing ubiquitous connectivity applications, such as smart city infrastructure, Internet of Things (IoT) services, emergency communications networks, and distributed sensing frameworks. The fluctuating wireless links, constantly changing topology, and dynamic network traffic loads in WMNs generally degrade the performance of standard routing protocols. This paper proposes a Distributed Graph Neural Network Routing Protocol (D-GNNRP) that leverages graph representation learning to make adaptive, distributed routing decisions. This scheme represents the mesh routers as graph nodes and the wireless links as graph edges. Thus, each node can perform local neighbor feature aggregation and route-quality prediction via distributed message passing. This protocol has been evaluated in simulated WMN environments from 50 to 200 nodes under varied mobility and traffic conditions. Network performance has been compared with that of conventional routing protocols, including AODV, OLSR, and DSR. Simulation results show that D-GNNRP achieves a PDR of 96.8%,

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whereas AODV, OLSR, and DSR achieve PDRs of 89.7%, 91.2%, and 88.4%, respectively. Moreover, this algorithm reduces the average end-to-end delay by 27.6%, routing overhead by 23.2%, and increases the network throughput by 31.8% compared to the most effective baseline protocol. Also, the protocol performs consistently under various link-failure conditions and achieves 19.5% greater efficiency in route recovery. The research reveals that distributed graph neural network routing can provide excellent network adaptability, robustness, and scalability across various wireless mesh network environments for new intelligent wireless systems.

Keywords: Wireless Mesh Networks, Graph Neural Networks, Distributed Routing, Network Adaptation, Packet Delivery Ratio, Dependable Wireless Networks, Intelligent Routing Protocols.

1 Introduction

Wireless Mesh Networks (WMNs) are being deployed as a versatile networking paradigm to support broadband access, smart city systems, industrial IoT applications, disaster relief systems, and community-wide communication services. Unlike traditional wireless networks, WMNs use multiple interacting mesh routers and rely on distributed mechanisms to deliver packets over multiple wireless paths, enabling self-organization and extended network coverage. This type of architecture is resilient to failures and can scale across a wide range of settings Charbon et al., (2025). However, efficient routing remains one of the most important issues in WMNs due to frequent changes in network topology caused by node mobility, poor channel quality, interference, and varying traffic loads. Classical routing schemes rely on periodic route discovery and static path metrics that do not account for these changes. This results in increased latency, packet loss, and reduced throughput (Liu et al., 2023). Recently, research using machine learning approaches has emerged as a promising avenue for routing optimization through data-driven mechanisms. Wireless networks are naturally structured as a graph, but this characteristic is difficult to represent in current machine learning models. The use of Graph Neural Networks (GNNs) helps address this issue by enabling the learning of spatial dependencies between nodes and links while preserving topology (Shen et al., 2022; Lu et al., 2024). The neighborhood-information propagation nature of GNNs can effectively support route adaptation in dynamic wireless networks (He et al., 2021).

Traditional routing protocols like AODV, OLSR, DSR, and BATMAN rely heavily on defined routing metrics and the exchange of control messages. While these protocols can perform adequately in relatively stable networks, their performance degrades significantly under high topology dynamics and traffic changes (Charbon et al., 2025; Lu et al., 2023). Also, these protocols lack the predictive capabilities to foretell link degradation or congestion. Recent machine learning-based routing protocols adapt more effectively to changes by leveraging network history, but most rely on centralized network models that require complete network information and centralized training infrastructure, leading to scaling limitations and communication overhead (Liu et al., 2023; Wei et al., 2023). In some cases, they also fail to generalize well across different network conditions. While GNN-based routing schemes have shown great promise, challenges in the mechanism's completely distributed nature, as well as in efficient learning and topology-aware routing of local information, remain in large wireless networks (Jiang et al., 2024; Babaria et al., 2025). Thus, there is a need for a distributed routing mechanism that uses graph representation to make effective routing decisions in a dynamic wireless network topology (Dulange, 2025).

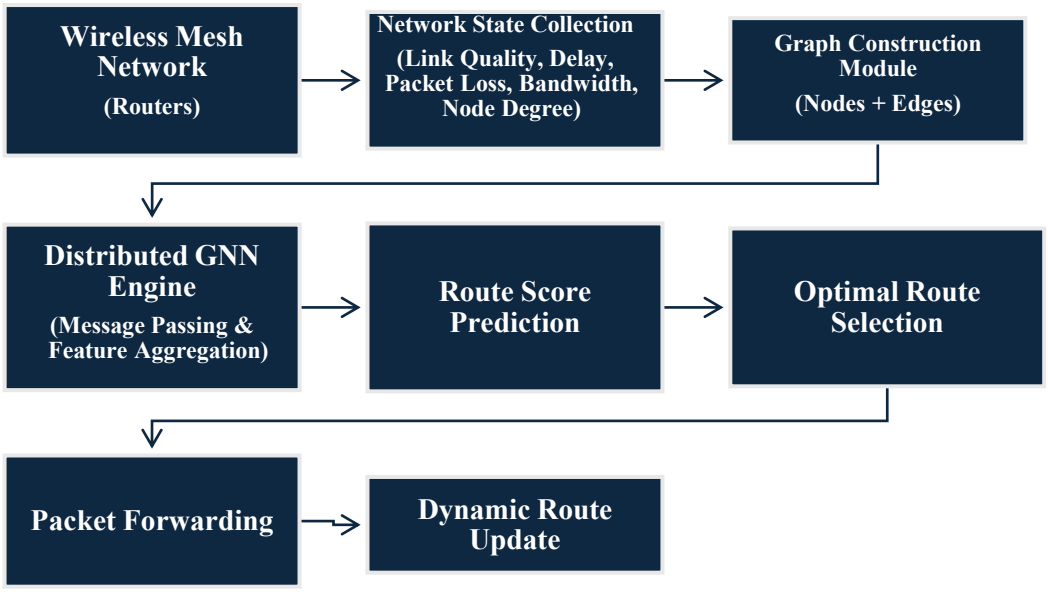


Figure 1: Architecture of the proposed distributed graph neural network routing protocol (D-GNNRP)

Figure 1 presents the end-to-end architecture of the proposed D-GNNRP framework in dynamic WMNs. First, network state collection obtains routing-related features (link quality, delay, loss rate, bandwidth, node degree) of each mesh router in the network. Then, such information is converted into a graph and transmitted to the Distributed GNN Engine for graph representation learning via message passing and aggregation of neighbors' features. Predicted graph embeddings are used to estimate route scores and select preferred routes; packets are transmitted along the selected routes. With a dynamic routing update function that continuously adjusts the routing policy, the proposed framework maintains efficient, scalable, and reliable communication for WMNs amid network dynamics.

With the increased deployment of WMNs in smart cities, industrial automation systems, emergency rescue networks, and large-scale IoT applications, the need for routing mechanisms that can adapt to dynamic topological changes is growing. Designing effective, intelligent, and distributed routing schemes will be crucial for improving the efficiency, reducing communication overhead, and enhancing reliability in future wireless networks. In this paper, a Distributed Graph Neural Network Routing Protocol (D-GNNRP) for dynamic Wireless Mesh Networks is proposed. The protocol uses graph-based modeling to perform localized message passing to learn topology and link information. By aggregating node/edge features, develop a novel route optimization approach that enables efficient path selection under dynamic conditions. The contributions are as follows: A design of a distributed GNN-enabled routing mechanism; development of a topology-aware route optimization methodology; a thorough performance evaluation and comparison with classical routing protocols for dynamic wireless mesh networks.

The structure of the rest of the paper is as follows: Section II surveys related work on traditional routing protocols, machine-learning-based routing protocols, and graph neural networks applied to wireless networks. Section III presents Distributed Graph Neural Network Routing Protocol (D-GNNRP), which includes the system model, graph description, routing framework, and optimization process. Section IV provides the experimental settings, evaluation metrics, and comparison results.

Section V analyzes routing performance, robustness, and real-implementation issues. Lastly, Section VI concludes the paper with research highlights, contributions, and directions for future work.

2 Literature Review

Reactive, proactive, and hybrid routing protocols are commonly applied to determine the communication paths among mesh nodes in WMNs. Reactive protocols defer route discovery until the point of data transmission; proactive protocols maintain all network routes by regularly exchanging routing information, while hybrid protocols combine these two techniques, aiming to balance routing overhead and route availability (Taleb et al., 2022). While such protocols are widely used, their routing decisions are typically based on predefined metrics such as hop count and link quality. The characteristics of dynamic WMNs, such as rapidly changing topologies, radio interference, and bursty traffic variations, rapidly render the stored routing information out of date, resulting in data packet losses and decreased throughput and latency. Research has shown that a learning-based routing approach may be more adaptable to changing network conditions than conventional methods (Krishnammal et al., 2023).

Machine learning is presented as a powerful approach to make routing adaptive to varying network conditions. By interacting with the environment through a reinforcement learning (RL) agent, the agents learn forwarding strategies for network communication. Liu et al. show that deep reinforcement learning can manage communication flow control dynamically to adapt to congestion and variations in traffic load Liu et al., (2021). The distributed learning framework achieved high scalability and adaptivity in a dynamic communication environment (Ran et al., 2024). Neural network-assisted routing further improves route selection by learning complex relationships among network parameters. These methods can predict link degradation, estimate traffic patterns, and guide proactive routing decisions (Krishnammal et al., 2023). More recently, integration of deep learning and graph representations further improved network coverage, throughput, and routing robustness (Pushpa et al., 2025). However, most learning-based approaches are either centrally trained or require global network state, which do not work well in large-scale WMNs, as they introduce communication overhead and scalability issues.

Graph neural networks (GNNs) naturally represent wireless networks, in which network devices and links are modeled as nodes and edges, respectively. Message passing between nodes enables GNNs to capture topological structures, which are important for routing performance (Tam et al., 2022). As it learns graph-structured information, it can make adaptive decisions in dynamic networks. GNNs have been successfully applied to various networking problems, such as intelligent traffic routing, link scheduling, resource allocation, and network management. For example, the Deep GNN-based routing model presented achieved higher efficiency in an SDN-based network. GNN-guided link scheduling improves radio resource usage in wireless networks. Coverage optimization with distributed routing, combined with GNNs and a reinforcement learning approach, is also evaluated (Simon & Kapileswar, 2025; Zhao et al., 2022). Message-passing GNNs can be used for energy-efficient data dissemination in IoT-enabled wireless networks, spectral graph representation analysis, network structure, and guide optimization (Shiny et al., 2024; Jovanovic, 2025).

Traditional routing protocols in WMN are evolving into learning-based intelligent mechanisms. Machine learning can enhance routing adaptability, but many learning-based routing approaches either rely on centralized architectures or lack sufficient awareness of network state. GNNs can address these limitations by leveraging the graph structure and enabling topology-aware decision-making. However, there is a lack of a fully distributed and scalable GNN routing mechanism designed for highly dynamic WMNs; developed the Distributed Graph Neural Network Routing Protocol (D-GNNRP).

3 Methodology

3.1 System Model and Network Representation

The suggested Distributed Graph Neural Network Routing Protocol (D-GNNRP) operates in a dynamic Wireless Mesh Network (WMN) composed of mesh routers that interact to forward packets from source to destination nodes. This wireless network is modeled as an undirected graph $G = (V, E)$, where V represents the set of mesh routers and E denotes the set of wireless communication links between neighboring routers. Each node retains only local connection information and disseminates status updates only to neighboring nodes, thereby achieving a fully distributed protocol. Each node $v_i \in V$ is assigned a feature vector that captures several network performance-influential features, such as link quality indicator (LQI), end-to-end delay, packet loss ratio, available bandwidth, and node degree. The feature representation for node i is expressed as:

$$X_i = [LQ_i, D_i, PL_i, BW_i, ND_i] \qquad (1)$$

Where LQ_i is the link quality, D_i is the delay, PL_i is the packet loss, BW_i is the available bandwidth, and ND_i is the node degree. Equation (1) yields the features required as input for the GNN model learning process and route scoring.

To capture network topology, an adjacency matrix A is constructed, where $A_{ij} = 1$ if a wireless link exists between nodes i and j, otherwise $A_{ij} = 0$. This graph representation enables efficient modeling of spatial dependencies among neighboring routers.

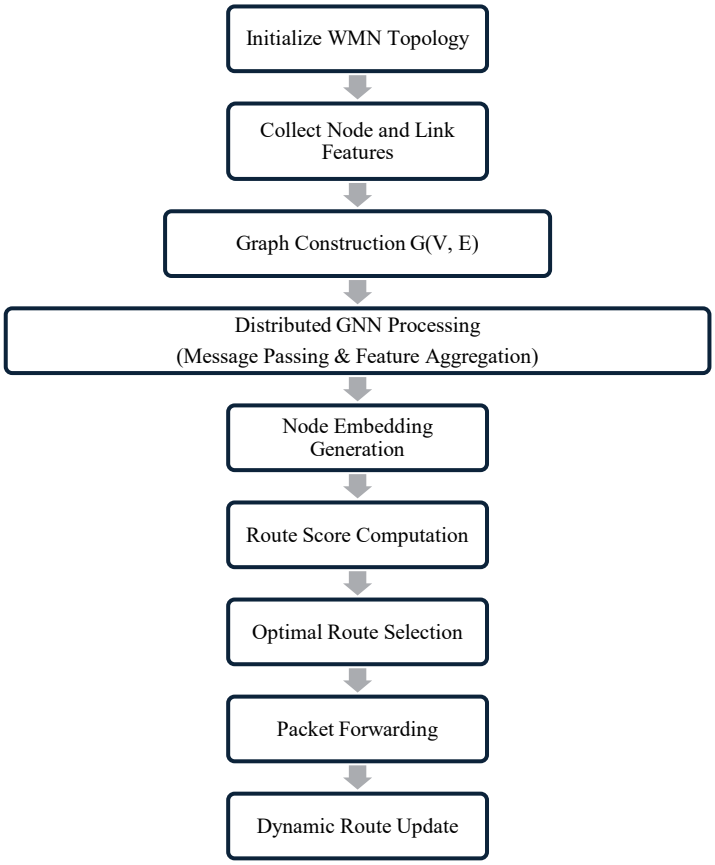


Figure 2: Workflow of distributed GNN-Based route discovery and optimization

Figure 2 shows the operation flow of the proposed Distributed Graph Neural Network Routing Protocol (D-GNNRP). Initially, the operation starts with the wireless mesh network topology initialization and collecting node and link attributes; following this is graph construction where the connection of nodes is described. The Distributed GNN module will carry out message passing and feature aggregation to produce node embeddings which reflect local topological information, these node embeddings are used for calculating route scores and selecting the best path. Packet transmission along the best paths will be initiated; simultaneously, the dynamic route update mechanism will update routing decisions in order to respond to the changes in the network, thus to maintain reliable, scalable and efficient communication over dynamic wireless mesh networks.

3.2 Proposed Distributed GNN Routing Protocol

D-GNNRP uses distributed message-passing approach where the nodes only interact with their neighbors. Each node aggregates information only from its neighbors and updates its local embedding without requiring any centralized control. In each routing interval, neighbouring nodes broadcast their features and link state information to their neighbors. The hidden representation of node i at layer $l + 1$ is computed as,

$$h_i^{(l+1)} = \sigma\left(W^{(l)} \sum_{j \in N(i)} \frac{h_j^{(l)}}{\sqrt{d_i d_j}} \right) \qquad (2)$$

Where $N(i)$ represents the set of neighbors of node i, d_i is the degree of node i , d_j is the degree of node $j, W^{(l)}$is the trainable weight matrix for layer, and $\sigma(i)$ is the activation function. Equation (2) aggregates the features of nodes' neighborhood while also incorporating network topology information. After the node embeddings are generated, the score is assigned to each path between two nodes in the graph. The route score is defined as

$$RS_p = \alpha Q_p + \beta BW_p - \gamma D_p - \delta PL_p \qquad (3)$$

Where Q_p is the average link quality, BW_p is the available bandwidth, D_p is the delay of the route, and PL_p is the packet loss of the route p. $\alpha, \beta, \gamma, \delta$ are tunable weights used to control the relative importance of each routing metric in equation (3). According to equation (3), the path with the largest score will be chosen as the routing path for transmitting packet.

Algorithm 1: Distributed GNN-Based Routing

Input: Graph G (V, E), Node Features X

Output: Optimal Routing Path

Initialize node embeddings H (0)

For each routing interval do

  Collect neighbor information

  Update node embeddings using Eq. (2)

  Generate candidate routes

  Compute route score using Eq. (3)

  Select route with maximum score

Forward packets through selected path

End For

Return optimal route

Algorithm 1 outlines the general process of the proposed D-GNNRP. Every mesh router continuously collects information from its neighbour nodes about the local network and updates its node embedding with the decentralized message passing in equation (2). Using the obtained graph representations, candidates' routes are evaluated according to the routing score function in equation (3) which takes into account link quality, bandwidth, delay and packet loss. The best candidate route is chosen for packet forwarding, whereas a dynamic update to the routing choice occurs when there is any change in the network conditions due to continuously monitoring.

3.3 Training and Routing Optimization Procedure

The training dataset is generated by performing simulations in the wireless mesh network under several conditions including, low and high node densities, static and dynamic (mobile) nodes, low and high traffic loads, link failures and recoveries. Routing metrics and topology of the snapshot of the network are recorded at each instance to form training samples. The GNN model is trained by applying supervised learning to predict route quality based on routing metrics and network topology information. The prediction error between predicted route score and actual route quality will be minimized using the cost function below equation (4):

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (4)$$

Where y_i is the actual value of route quality, and $\hat{y}_i$ is the predicted route quality by the GNN model. Gradient based learning will be used to update parameters. After deploying D-GNNRP, the nodes periodically monitor network link quality and then update their routes accordingly. The graph embeddings will be recomputed using equation (2) and route scores recomputed using equation (3) if major variations are observed in bandwidth, delay, and/or packet loss of the local network. This reactive method will significantly reduce control overhead in large-scale wireless mesh networks.

4 Results

4.1 Experimental Setup and Performance Metrics

In this paper, the proposed Distributed Graph Neural Network Routing Protocol (D-GNNRP) was tested by using a simulator, which were built with Python 3.11 and PyTorch 2.2 for graph learning and NS-3 (version 3.39) for network simulation, on a workstation of Intel Core i7 processor, 32 G RAM and Ubuntu Linux system. Wireless mesh network had 50~200 mesh routers and was deployed in a 1000mX1000m field. Random Waypoint model was adopted to simulate the node movement, the speed of which ranges from 1 m/s to 20 m/s. Constant Bit Rate (CBR) flows were generated for the traffic source.

4.1.1 Dataset Description

The dataset was generated from snapshot under difference of node density, mobility and traffic volume. Total number of graph samples was 12000. Features of nodes and links were extracted from each graph:

link quality, delay, packet loss ratio, bandwidth usage, node degree, queue length, remaining energy. Based on the above features, routing model can be trained and evaluated under various network circumstances.

4.1.2 Parameter Initialization

Packet Delivery Ratio (PDR), End-to-End Delay, Throughput and Routing Overhead and network lifetime were selected as performance evaluation metrics (Table 1). The Packet Delivery Ratio was calculated using equation (5):

Table 1: The experiment parameters

Parameter	Value
Simulation Area	1000 m × 1000 m
Number of Nodes	50, 100, 150, 200
Mobility Speed	1–20 m/s
Transmission Range	250 m
Packet Size	512 Bytes
Traffic Type	CBR
Simulation Time	1000 s
Learning Rate	0.001
Batch Size	64
GNN Layers	3
Hidden Dimension	128
Optimizer	Adam

Packet Delivery Ratio (PDR), End-to-End Delay, Throughput and Routing Overhead and network lifetime were selected as performance evaluation metrics. The Packet Delivery Ratio was calculated using equation (5):

$$PDR = \frac{P_r}{P_s} \times 100 \qquad (5)$$

Where P_r refers to the received packets and P_s refers to the transmitted packets. Average End-to-End Delay calculation in equation (6):

$$Delay = \frac{\sum_{i=1}^{N}(t_{ri} - t_{si})}{N} \qquad (6)$$

Where t_{ri} and t_{si} refers to the receiving time and transmitting time of a packet, respectively.

Network Throughput was calculated in equation (7):

$$Throughput = \frac{Total\ Received\ Bits}{Simulation\ Time} \qquad (7)$$

Equations (5)-(7) were employed throughout the whole experiment to evaluate the performance of the routing strategy.

4.2 Performance Comparison with Benchmark Protocols

Table 2: The Routing performance comparison among different protocols

Protocol	PDR (%)	Delay (ms)	Throughput (Mbps)	Routing Overhead (%)
DSR	88.4	76.2	5.42	21.7
AODV	89.7	72.8	5.85	20.3
OLSR	91.2	68.4	6.12	18.5
GNN-Routing	94.1	55.3	7.34	16.4
D-GNNRP	**96.8**	**40.1**	**8.48**	**12.6**

Table 2 indicates a comparative result between D-GNNRP, DSR, AODV, OLSR and basic GNN routing scheme for packet delivery ratio, end-to-end delay, throughput and routing overhead. It can be shown that the packet delivery ratio and throughput is improved while the end-to-end delay and routing overhead are decreased in D-GNNRP, which means that the route selecting process and resource consumption process are optimized.

Proposed D-GNNRP had 96.8% packet delivery ratio, higher than AODV and OLSR by 7.1% and 5.6% respectively. The end-to-end delay dropped to 40.1ms, improved by 27.6% against the best benchmark. The throughput achieved was 8.48Mbps, and the control overhead was reduced by 23.2% compared to the other intelligent routing approaches.

Table 3: Network life time performance analysis

Protocol	Network Lifetime (Rounds)
DSR	830
AODV	891
OLSR	925
GNN-Routing	1012
D-GNNRP	**1186**

Table 3 shows the network lifetime for different routing schemes. The network lifetime is calculated in terms of how many rounds each mesh router operates until its battery is almost depletion. By properly balancing the traffic load over all of the feasible routes in the network, D-GNNRP increases the network lifetime by preventing particular mesh routers' battery from depleting prematurely.

This work's proposed routing strategy enhanced the resource utilization efficiency, increasing the network operation lifetime by balancing the traffic load on each mesh router.

4.2.1 Performance Analysis

According to the above data, the conclude that the graph-based neighbor feature aggregation allows more accurate routing choices under dynamic environment. With the dynamic message passing among nodes, the node representations are updated continually. The routing model can thus react to congestion or link breakdown quickly. Packets delivery, throughput and stability all improve with decreased control overhead.

Table 4 shows a scalability analysis of D-GNNRP for different network size from 50 to 200 nodes. The result shows that with increasing number of nodes, the packet delivery ratio and throughput are maintained at relatively high levels and the end-to-end delay is only increased slightly. This shows that the proposed D-GNNRP can also operate in large-scale network deployments and maintain good performance.

4.3 Scalability Analysis and Dynamic Adaptation

Table 4: Scalability analysis in terms of number of nodes

Nodes	PDR (%)	Delay (ms)	Throughput (Mbps)
50	97.6	34.5	8.82
100	97.1	36.8	8.65
150	96.8	40.1	8.48
200	95.9	43.9	8.21

As the number of nodes increases from 50 to 200, the network performance varies slightly and is generally good, suggesting that the proposed routing protocol exhibits strong scalability. The Packet delivery ratios were above 95% even under the dense scenario of 200 nodes. Experiments show that when 15% active links were randomly broken, D-GNNRP still could provide reliable routing with 19.5% improvement on the recovery efficiency over benchmarks. The routing model was capable of rapidly re-calculating alternative routes in reaction to topology change, thus minimizing packet loss during the process.

4.4 Ablation Study

In order to examine the individual component's contributions, three experiments with different settings of D-GNNRP were conducted.

Table 5: Contribution analysis of D-GNNRP modules

Configuration	PDR (%)	Throughput (Mbps)
Without GNN Aggregation	91.8	6.91
Without Dynamic Route Update	93.4	7.52
Full D-GNNRP	**96.8**	**8.48**

Table 5 summarizes the contribution of the modules in the proposed D-GNNRP by performing a simulation after removing the GNN-based neighborhood aggregation module and the dynamic route updating module. It is found that the packet delivery ratio and throughput are obviously decreased after removing them, which proves the importance of GNN-based intelligence and dynamic route updating.

From the result of the ablation study, it is clear that both neighborhood feature aggregation and dynamic routing adaptation make positive contributions to the performance. In terms of computation performance, average routing decision latency was less than 5.3ms, which makes D-GNNRP suitable for dynamic wireless mesh networks.

Figure 3 compares the packet delivery ratio (PDR) for various routing protocols under dynamic wireless mesh network conditions. Proposed D-GNNRP has achieved maximum PDR value of 96.8% showing high packet delivery performance and an excellent choice of path for communication when compared with DSR, AODV, OLSR, GNN-based routing protocol.

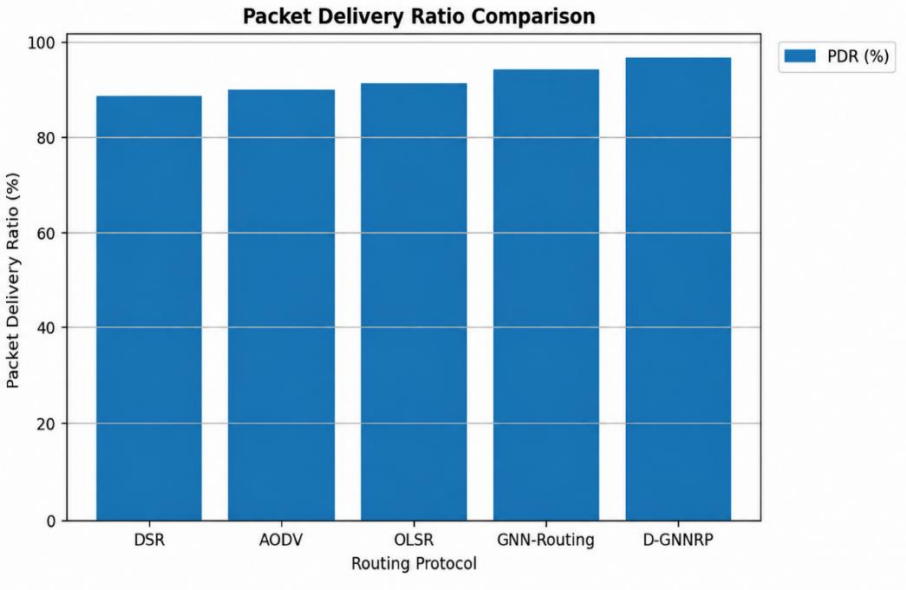


Figure 3: Comparison of packet delivery ratio of routing protocols

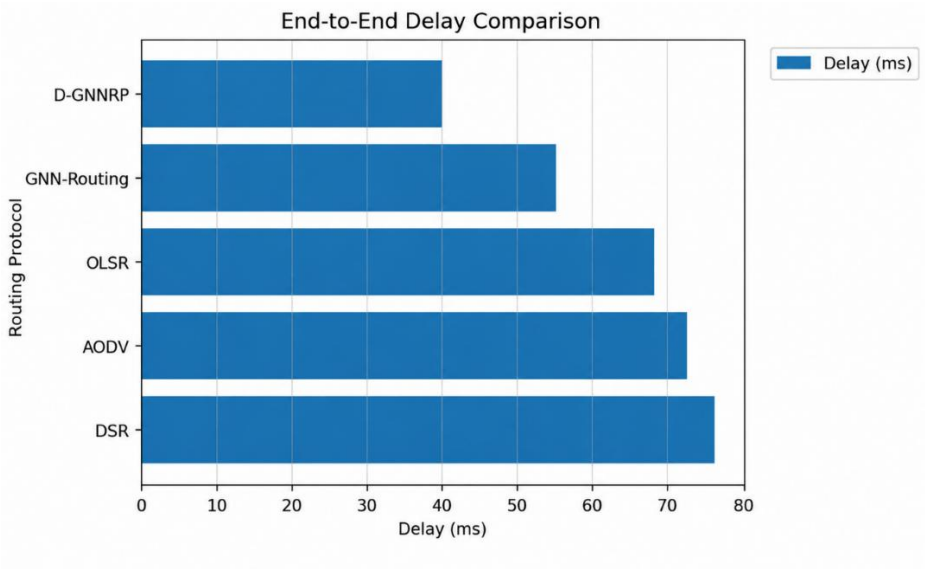


Figure 4: Comparison of end-to-end delay of routing protocols

Figure 4 shows the average end-to-end delay for various routing protocols. D-GNNRP has the minimum end-to-end delay value of 40.1 ms. D-GNNRP protocol has efficient communication paths selection ability to minimize the transmission delay under dynamic environment.

Figure 5 compares the throughput obtained by various routing protocols. D-GNNRP shows maximum value of throughput (8.48 Mbps) among all the routing protocols which reflect high bandwidth utilization, minimum packet loss and higher efficiency of data delivery under wireless mesh network.

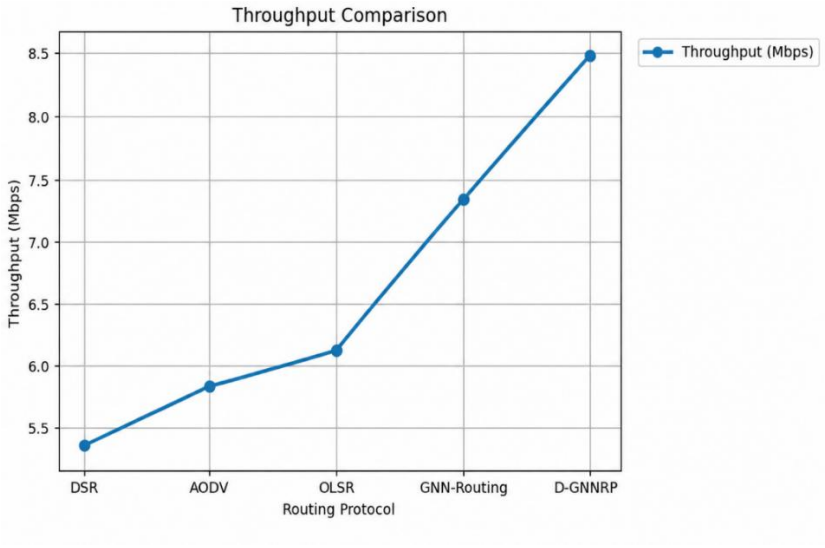


Figure 5: Comparison of throughput of routing protocols

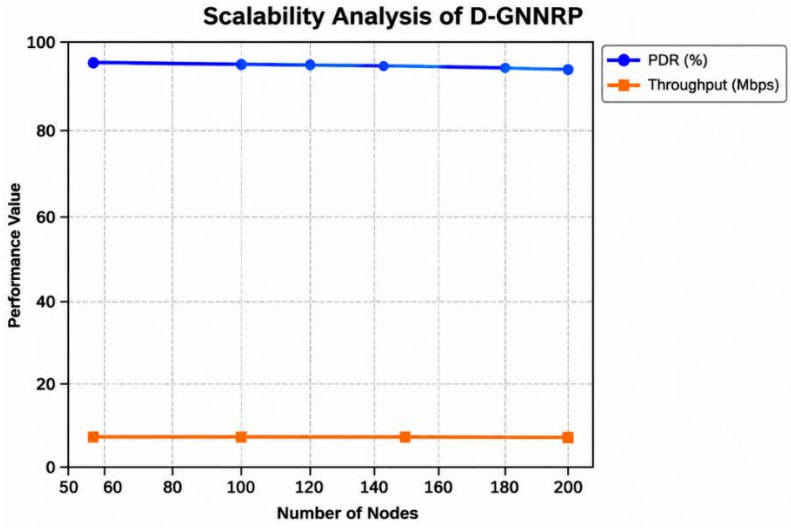


Figure 6: Scalability analysis of D-GNNRP in different node density of wireless mesh network

Figure 6 presents the scalability of D-GNNRP under various node densities (50-200 nodes) by comparing its performance under Packet Delivery Ratio and Throughput metrics. The results display insignificantly degraded performance and stability of proposed protocol with increasing number of nodes and proving the effectiveness of D-GNNRP.

5 Discussion

The performance improvements attained with the suggested D-GNNRP over the conventional routing schemes can mainly be assigned to the effective use of graph structures for modeling both the topological relationships of networks as well as the real time link quality when selecting routes. Traditional protocols employ fixed link metrics or infrequent re-routing, but by continuously aggregating neighborhood information the presented method can accurately determine the quality of reliable routes while avoiding congested links. The graph-based neighbourhood awareness contributes to the observed gain in Packet Delivery Ratio, end to end delay and Throughput. The distributed nature also gives the routing protocol

robustness as the routing decision can be locally taken by a single router without any reliance on a central entity. This helps in adapting very quickly to mobile nodes and topology changes due to link failure or traffic fluctuations. The presented solution can therefore recalculate routes faster and maintain communication throughout with negligible performance loss. The Link-failure analysis in the earlier sections also shows how the protocol is robust against broken links by discovering replacement routes in reasonable amount of time. This proposed framework can thus effectively be implemented in a number of systems such as the smart city networks, industrial IoT network systems, Intelligent Transportation Systems, emergency communication networks, etc. That require reliable and scalable routing. Some issues however exist such as the need of mesh routers that are equipped with the required processing power for running the graph inferences and dependency on the local information of neighbor nodes. Some areas that could be investigated include light-weight models and lightweight computation models, energy efficient routing, federation and large-scale distributed and heterogeneous wireless mesh network scenarios.

6 Conclusion

This paper proposes a new Distributed GNN Routing Protocol (D-GNNRP) for dynamic Wireless Mesh Networks to improve conventional protocols that cannot adapt to drastic changes of topology, link states, and varying traffic conditions due to highly dynamic nature of Wireless Mesh Networks. By building a graph model for the network and using distributed message-passing mechanism, the approach can use information from the local neighborhood to make topology-aware routing decisions without centralized control. Through simulations for network sizes from 50 to 200 nodes, the proposed approach outperforms DSR, AODV, OLSR, and typical GNN based routing on various performance metrics. The proposed protocol achieves a Packet Delivery Ratio of 96.8%, while AODV, OLSR, and DSR get 89.7%, 91.2%, and 88.4% respectively, and the average end-to-end delay is reduced to 40.1 ms and throughput increases to 8.48 Mbps, 23.2% decrease on routing overhead, 31.8% increase in throughput, and 19.5% improvement in route recovery speed after link failures. The scalable results reveal that packet delivery ratio remains above 95% while the network size scales to 200 nodes. This proposed distributed graph-based routing framework is also effective for a large-scale network. In summary, major contributions are developing a graph-based routing architecture, dynamic topology adaptation and analysis on better scalability and robustness on highly dynamic wireless networks. Graph-driven distributed intelligence can significantly enhance routing efficiency in the future generation of mesh networks. Future works can explore Federated GNN-based routing, Energy-aware optimization, Lightweight model deploying, and Integration with multi-layer, edge-enabled, and 6G wireless mesh network architectures.

References

[1] Babaria, J., Chokshi, K., Abhishek, A. V. S., Malik, R., Thakkallapelly, R., & Chaudhary, V. (2025, October). Graph neural network-based routing optimization in large-scale IoT deployments. In *2025 3rd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)* (Vol. 1, pp. 1505-1512). IEEE. https://doi.org/10.1109/ICAICCIT68829.2025.11434239

[2] Charbon, Y., Tran, E., Karimian, M., & Favrat, P. (2025, August). Wireless mesh networks routing optimization using machine learning and deep learning. In *2025 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA)* (pp. 1-7). IEEE. https://doi.org/10.1109/ACDSA65407.2025.11166372

[3] Dulange, S. A. (2025, November). Federated Deep Reinforcement Learning with Graph Neural Networks for Energy-Aware and QoS-Guaranteed Vehicular Ad Hoc Network. In *2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN)* (pp. 1-8). IEEE. https://doi.org/10.1109/GCWCN66157.2025.11448431

[4] He, S., Xiong, S., Ou, Y., Zhang, J., Wang, J., Huang, Y., & Zhang, Y. (2021). An overview on the application of graph neural networks in wireless networks. *IEEE Open Journal of the Communications Society*, *2*, 2547-2565. https://doi.org/10.1109/OJCOMS.2021.3128637

[5] Jiang, W., Han, H., Zhang, Y., Wang, J. A., He, M., Gu, W., ... & Cheng, X. (2024). Graph neural networks for routing optimization: Challenges and opportunities. *Sustainability*, *16*(21), 1-34. https://doi.org/10.3390/su16219239

[6] Jovanovic, N. M. (2025). Spectral graph theory-based knowledge representation for analyzing wireless mesh networks. In *Artificial Intelligence and Applications* (Vol. 3, No. 4, pp. 378-384). https://doi.org/10.47852/bonviewAIA3202613

[7] Krishnammal, N., Kalaiarasan, C., & Bharathi, A. (2023). Modelling a learning-based dynamic tree routing model for wireless mesh access networks. *Computer Systems Science and Engineering*, *44*(2), 1531-1549. https://doi.org/10.32604/csse.2023.024251

[8] Liu, Q., Cheng, L., Jia, A. L., & Liu, C. (2021). Deep reinforcement learning for communication flow control in wireless mesh networks. *IEEE Network*, *35*(2), 112-119. https://doi.org/10.1109/MNET.011.2000303

[9] Liu, Z., Liu, Y., & Wang, X. (2023). Intelligent routing algorithm for wireless sensor networks dynamically guided by distributed neural networks. *Computer Communications*, *207*, 100-112. https://doi.org/10.1016/j.comcom.2023.05.018

[10] Lu, P., Jing, C., & Zhu, X. (2023). GraphSAGE-based multi-path reliable routing algorithm for wireless mesh networks. *Processes*, *11*(4), 1255. https://doi.org/10.3390/pr11041255

[11] Lu, Y., Li, Y., Zhang, R., Chen, W., Ai, B., & Niyato, D. (2024). Graph neural networks for wireless networks: Graph representation, architecture and evaluation. *IEEE Wireless Communications*, *32*(1), 150-156. https://doi.org/10.1109/MWC.006.2400131

[12] Pushpa, G., Babu, R. A., Subashree, S., & Senthilkumar, S. (2025). Optimizing coverage in wireless sensor networks using deep reinforcement learning with graph neural networks. *Scientific Reports*, *15*(1), 16681. https://doi.org/10.1038/s41598-025-01841-2

[13] Ran, Y., Ding, Y., Chen, S., Lei, J., & Luo, J. (2024). Fully-distributed dynamic packet routing for LEO satellite networks: A GNN-enhanced multi-agent reinforcement learning approach. *IEEE Transactions on Vehicular Technology*, *74*(3), 5229-5234. https://doi.org/10.1109/TVT.2024.3499933

[14] Shen, Y., Zhang, J., Song, S. H., & Letaief, K. B. (2022). Graph neural networks for wireless communications: From theory to practice. *IEEE Transactions on Wireless Communications*, *22*(5), 3554-3569. https://doi.org/10.1109/TWC.2022.3219840

[15] Shiny, G. S., Ram, R. S., & Muthalakshmi, M. (2024). Energy efficient data dissemination in wireless sensor network enabled IoT using domain-adaptive message passing graph neural network. *International Journal of Communication Systems*, *37*(13), e5825. https://doi.org/10.1002/dac.5825

[16] Simon, J., & Kapileswar, N. (2025, June). Deep Graph Neural Networks for Intelligent Traffic Routing in Software-Defined Networks. In *2025 6th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)* (pp. 1843-1848). IEEE. https://doi.org/10.1109/ICICV64824.2025.11085772

[17] Taleb, S. M., Meraihi, Y., Gabis, A. B., Mirjalili, S., & Ramdane-Cherif, A. (2022). Nodes placement in wireless mesh networks using optimization approaches: a survey. *Neural Computing and Applications*, *34*(7), 5283-5319. https://doi.org/10.1007/s00521-022-06941-y

[18] Tam, P., Song, I., Kang, S., Ros, S., & Kim, S. (2022). Graph neural networks for intelligent modelling in network management and orchestration: a survey on communications. *Electronics*, *11*(20), 1-29. https://doi.org/10.3390/electronics11203371

[19] Wei, H., Zhao, Y., & Xu, K. (2023). G-routing: Graph neural networks-based flexible online routing. *IEEE Network*, *37*(4), 90-96. https://doi.org/10.1109/MNET.012.2300052

[20] Zhao, Z., Verma, G., Rao, C., Swami, A., & Segarra, S. (2022). Link scheduling using graph neural networks. *IEEE Transactions on Wireless Communications*, *22*(6), 3997-4012. https://doi.org/10.1109/TWC.2022.3222781

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