Digital Twin-Assisted Resilient Planning for mmWave IAB Networks via Graph Attention Networks

Jie Zhang, Student Member, IEEE, Mostafa Rahmani Ghourtani, Member, IEEE, Swarna Bindu Chetty, Member, IEEE, Paul Daniel Mitchell, Senior Member, IEEE, and Hamed Ahmadi, Senior Member, IEEE School of Physics, Engineering and Technology

University of York

York, United Kingdom

Abstract-Digital Twin (DT) technology enables real-time monitoring and optimization of complex network infrastructures by creating accurate virtual replicas of physical systems. In millimeter-wave (mmWave) 5G/6G networks, the deployment of Integrated Access and Backhaul (IAB) nodes faces highly dynamic urban environments, necessitating intelligent DT-enabled optimization frameworks. Traditional IAB deployment optimization approaches struggle with the combinatorial complexity of optimization of joint coverage, connectivity, and resilience, often leading to suboptimal solutions that are vulnerable to the network disruptions. With this consideration, we propose a novel Graph Attention Network v2 (GATv2)-based reinforcement learning approach for resilient IAB deployment in urban mmWave networks. Specifically, we formulate the deployment problem as a Markov Decision Process (MDP) with explicit resilience constraints and employ edge-conditioned GATv2 to capture complex spatial dependencies between heterogeneous node types and dynamic connectivity patterns. The attention mechanism enables the model to focus on critical deployment locations maximize coverage and ensure fault tolerance through redundant backhaul connections. To address the inherent vulnerability of mmWave links, we train the GATv2 policy using Proximal Policy Optimization (PPO) with carefully designed balance between coverage, cost, and resilience. Comprehensive simulations across three urban scenarios demonstrate that our method achieves 98.5-98.7% coverage with 14.3-26.7% fewer nodes than baseline approaches, while maintaining 87.1% coverage retention under 30% link failures—representing 11.3-15.4% improvement in fault tolerance compared to state-of-the-art methods.

Index Terms—Graph Neural Networks, Integrated Access and Backhaul, mmWave Networks, Network Planning

I. Introduction

DT technology enables real-time virtual replicas of physical systems, providing unprecedented capabilities for network monitoring, analysis, and optimization [1]. In mmWave networks, operating in high-frequency bands above 24 GHz, the deployment of IAB nodes faces critical challenges due to severe propagation limitations, including high path loss and extreme susceptibility to blockages [2]. Critically, these blockage-prone characteristics make mmWave networks inherently vulnerable to frequent link failures, where temporary obstacles or environmental changes can instantly disconnect users or isolate network segments. In urban environments, these issues are compounded by dense user populations and complex topologies, necessitating a high density of base stations to ensure reliable connectivity. Deploying numerous base stations

with traditional wired backhaul, (such as fiber), is prohibitively expensive and logistically challenging. Integrated Access and Backhaul (IAB) technology addresses this by enabling nodes to simultaneously provide user access and wireless backhaul to the core network, significantly reducing deployment costs [3]. Optimizing IAB node placement is a combinatorial problem that requires balancing coverage, capacity, and resilience against link failures, particularly in dynamic urban settings where blockages and demand fluctuations are common.

A. Related Work and Contributions

Research on IAB deployment optimization primarily focuses on coverage maximization through traditional optimization approaches. Saha et al. [4] proposed a greedy heuristic algorithm which achieves 92-95% coverage in small scenarios but requires 30-40% more infrastructure than optimal solutions due to myopic decision-making that neglects resilience considerations. Polese et al. [3] formulated IAB deployment as Mixed-Integer Programming (MIP) problem, providing global optimality for networks with fewer than 50 candidate locations but exhibiting exponential complexity $\mathcal{O}(2^N)$ that becomes intractable for realistic urban scenarios exceeding 200 locations. Alzenad et al. [5] employed stochastic geometry for coverage analysis but relied on idealized assumptions including uniform distributions that do not capture urban deployment constraints [20].

While coverage optimization has received significant attention, resilience-aware IAB deployment remains largely unexplored, despite its critical importance in ensuring network reliability in dynamic environments. Resilience considerations are essential for IAB networks due to their multi-hop wireless backhaul nature, where single node failures can cascade through the network topology, potentially disconnecting entire service areas. The wireless nature of IAB links makes them inherently susceptible to environmental factors, interference, and physical obstructions that can cause temporary or permanent outages. Moreover, the hierarchical structure of IAB networks means that the failure of high-tier nodes has more severe consequences than traditional cellular deployments, making proactive resilience planning crucial rather than reactive recovery approaches.

Existing resilience methods focus primarily on reactive recovery rather than proactive deployment design. Madapatha et al. [11] developed reinforcement learning (RL) for dynamic routing in IAB networks, achieving a 15% improvement in

failure recovery but assuming a pre-deployed topology. Teymuri et al. [12] proposed pre-planned optimization for backhaul failures, improving availability by 12% but suffering from the same scalability limitations as MIP-based approaches. Madapatha et al. [13] surveyed IAB resilience techniques, emphasizing redundant connections but lacking concrete deployment optimization frameworks.

Graph Neural Networks (GNNs) have emerged as promising alternatives for network optimization across various scenarios. Yang et al. [6] developed a generic GNN-based node placement achieving 12-18% improvement over heuristics but lacking resilience constraints. Liu et al. [9] combined Graph Convolutional Network (GCN) with deep reinforcement learning for Virtual Network Function (VNF) orchestration, while Wang et al. [10] applied GNNs to Unmanned Aerial Vehicle (UAV) networks with fundamentally different constraints than terrestrial deployments. Recent advances include specialized architectures for user assignment in mmWave systems [8], multi-head GNNs for joint access point selection and beamforming [15], and heterogeneous GNNs for hybrid beamforming optimization [16], [17].

Existing GNN applications lack IAB-specific capabilities, however, particularly resilience-aware deployment optimization. Current approaches focus on coverage without resilience considerations or address resilience reactively rather than through proactive deployment design, failing to model IAB networks' unique hierarchical constraints.

B. Research Gap and Contributions

Most studies focus on coverage or throughput, with few addressing resilience under complex conditions and link failures. GNN-based methods show promise but have not been explored for IAB deployment. Our contributions are threefold:

- 1. Resilience-Aware MDP Formulation: We formulate IAB deployment as a MDP with resilience constraints, integrating fault tolerance directly into the optimization problem through penalty-based reward design.
- 2. Edge-Conditioned GATv2 Framework: We develop a novel reinforcement learning architecture using GATv2 with edge-conditioned attention, enabling effective modeling of heterogeneous node types and dynamic link utilization patterns in IAB networks.
- 3. Comprehensive multi-scenario evaluation: We conduct extensive performance analysis across diverse urban topologies with failure testing, demonstrating significant improvements in deployment efficiency (up to 26.7% node reduction) and fault tolerance (15.4% better coverage retention) compared to state-of-the-art baselines.

The paper is organized as follows: Section II presents the system model and problem formulation, Section III details the simulation setup and results, and Section IV concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider an urban mmWave IAB network deployment operating in the 60 GHz band, where the service area is

discretized into a grid of potential deployment locations, corresponding to existing infrastructure such as lamp posts and utility poles. The network architecture consists of fiberconnected IAB donors \mathcal{I} , which serve as gateways to the core network, and candidate IAB node locations $\mathcal J$ that extend coverage via wireless backhaul. Each IAB node must maintain at least m independent backhaul connections to ensure network resilience, where m represents the minimum connectivity requirement.

The communication model captures essential mmWave propagation characteristics at 60 GHz. For any link between any two potential nodes (or donor to nodes), the received power is given by:

$$P_r = P_{tx} + G_{\text{total}} - L_{\text{total}} \tag{1}$$

where P_{tx} denotes transmit power, G_{total} is the total antenna gain, and L_{total} represents aggregate propagation loss.

For access links serving user equipment, omni-directional antennas with constant gain G_0 are employed:

$$G_{\text{access}} = G_0 \tag{2}$$

In contrast, backhaul links utilize directional sector antennas to achieve higher gains and interference reduction. The effective backhaul gain is:

$$G_{\text{total}} = \begin{cases} G_t + G_r, & \text{if } |\theta| \le \frac{\theta_{\text{HPBW}}}{2} \\ 0, & \text{otherwise} \end{cases}$$
 (3)

where G_t and G_r are transmit and receive antenna gains, θ is the angular deviation, and θ_{HPBW} is the half-power beamwidth.

The aggregate propagation loss at 60 GHz comprises multiple attenuation components:

$$L_{\text{total}} = L_{path} + L_{atm} + L_{rain} \tag{4}$$

accounting for path loss L_{path} , atmospheric absorption L_{atm} , and rain-induced attenuation L_{rain} .

Link feasibility is determined by the Signal to Noise Ratio (SNR) threshold requirement:

$$SNR = P_r - N_0 \ge SNR_{threshold}$$
 (5)

where thermal noise power $N_0 = -174 + 10 \log_{10}(W)$ dBm for bandwidth W.

B. Problem Formulation
We formulate the resilience-aware IAB deployment as a mixed-integer optimization problem that minimizes the number of deployed IAB nodes while ensuring coverage, connectivity, and resilience requirements. The problem is non-convex due to binary deployment variables and bilinear capacity constraints.

- 1) Decision Variables: Let \mathcal{I} denote the set of fiberconnected IAB donors and ${\mathcal J}$ the set of candidate IAB node locations. The decision variables are:
 - $\alpha_i \in \{0,1\}$: deployment indicator for candidate IAB node location $j \in \mathcal{J}$
 - $Y_{pq} \in \{0,1\}$: backhaul link activation from node p to IAB node q
 - $R_{pq} \ge 0$: traffic flow rate on link $p \to q$ (Mbps)
 - $U_k \in \{0,1\}$: coverage indicator for grid cell $k \in \mathcal{K}$

For all IAB donors $i \in \mathcal{I}$, we set $\alpha_i = 1$.

2) Coverage Constraints: The coverage requirement ensures adequate SNR levels across the service area:

$$U_k \le \sum_{i \in \mathcal{I}} C_{ik} + \sum_{j \in \mathcal{I}} C_{jk} \alpha_j, \quad \forall k \in \mathcal{K}$$
 (6)

where $C_{ik}, C_{jk} \in \{0, 1\}$ indicate whether IAB donor i or IAB node j provides coverage to cell k with SNR \geq SNR_{threshold}. The aggregate coverage constraint mandates:

$$\sum_{k \in \mathcal{K}} U_k \ge \theta_{cov} |\mathcal{K}| \tag{7}$$

ensuring at least fraction θ_{cov} of grid cells receive adequate coverage.

3) Resilience and Connectivity Constraints: Link activation follows logical consistency:

$$Y_{pq} \le L_{pq}\alpha_p\alpha_q, \quad \forall p \in \mathcal{I} \cup \mathcal{J}, q \in \mathcal{J}, p \ne q$$
 (8)

where $L_{pq} \in \{0,1\}$ indicates link feasibility based on SNR requirements from the communication model.

The resilience constraint ensures redundant connectivity:

$$\sum_{p \in \mathcal{I} \cup \mathcal{J}, p \neq j} Y_{pj} \ge m \cdot \alpha_j, \quad \forall j \in \mathcal{J}$$
(9)

requiring each deployed IAB node ($\alpha_j = 1$) to maintain at least m active backhaul connections for fault tolerance.

4) Capacity and Flow Constraints: Link capacity constraints reserve bandwidth for failure recovery:

$$R_{pq} \le (1-\beta)C_{pq}Y_{pq}, \quad \forall p \in \mathcal{I} \cup \mathcal{J}, q \in \mathcal{J}, p \ne q \quad (10)$$

where C_{pq} is the physical link capacity (Mbps) and $\beta \in [0,1]$ reserves fraction β of link capacity for traffic rerouting during link failures. This ensures that when primary paths fail, backup routes have sufficient capacity.

IAB donor capacity constraints limit fiber backhaul usage:

$$\sum_{i \in \mathcal{I}} R_{ij} Y_{ij} + R_o A_i \le F_i, \quad \forall i \in \mathcal{I}$$
 (11)

where F_i is IAB donor i's fiber capacity, $A_i > 0$ represents local access demand, and $R_o > 1$ accounts for protocol overhead including MAC layer framing, PHY layer pilot symbols, routing protocol signaling, and retransmission mechanisms.

Flow conservation at IAB nodes ensures traffic balance:

$$\sum_{p \in \mathcal{I} \cup \mathcal{J}, p \neq j} R_{pj} Y_{pj} \ge R_o \left(A_j \alpha_j + \sum_{n \in \mathcal{J}, n \neq j} R_{jn} Y_{jn} \right), \quad \forall j \in \mathcal{J}_{\text{optimization process.}}$$
(12)

where inbound traffic (left side) must satisfy local access demand A_j and outbound forwarding requirements (right side), both scaled by overhead factor R_o .

5) Optimization Objective: The objective minimizes the number of deployed IAB nodes:

$$\min \sum_{j \in \mathcal{J}} \alpha_j \tag{13}$$

subject to constraints (6)-(12).

This formulation ensures optimal IAB node placement while maintaining network resilience through redundant connectivity and capacity reservation for failure recovery.

C. Graph Representation

To enable GNN-based optimization, we transform the mixed-integer formulation into a heterogeneous attributed digraph $\mathcal{G}=(\mathcal{V},\mathcal{E},\mathbf{X},\mathbf{E},\mathbf{g})$ that captures network topology and deployment state.

- a) Vertices: $V = \mathcal{I} \cup \mathcal{J}$ comprise IAB donors $(i \in \mathcal{I})$ and candidate IAB node locations $(j \in \mathcal{J})$.
- b) Directed edges: $\mathcal{E} = \{(p,q) \mid L_{pq} = 1, p \in \mathcal{I} \cup \mathcal{J}, q \in \mathcal{J}, p \neq q\}$ represent feasible mmWave backhaul links satisfying SNR requirements.
- c) Node Features $\mathbf{X} \in \mathbb{R}^{|\mathcal{V}| \times d_v}$: Each vertex $v \in \mathcal{V}$ has feature vector:

$$\mathbf{x}_v = \left[\alpha_v, \frac{A_v}{A_{\text{max}}}, \frac{N_v}{m}, \mathbb{1}_{\{v \in \mathcal{I}\}}\right]$$

where $\alpha_v \in \{0,1\}$ is the deployment status, $\frac{A_v}{A_{\max}}$ is normalized access demand (with $A_{\max} = \max_{v \in \mathcal{V}} A_v$ from traffic analysis), $\frac{N_v}{m}$ represents resilience ratio (current connections over requirement m), and $\mathbb{1}_{\{v \in \mathcal{I}\}}$ indicates IAB donor type. Normalization prevents gradient instability caused by different feature scales.

d) Edge Features $\mathbf{E} \in \mathbb{R}^{|\mathcal{E}| \times d_e}$: Each directed link $(p,q) \in \mathcal{E}$ carries:

$$\mathbf{e}_{pq} = \left[\frac{C_{pq}}{C_{\max}}, \frac{R_{pq}}{C_{pq}}, L_{pq} \right]$$

where $\frac{C_{pq}}{C_{\max}}$ is normalized link capacity (with $C_{\max} = \max_{(p,q) \in \mathcal{E}} C_{pq}$ from strongest feasible link), $\frac{R_{pq}}{C_{pq}}$ represents current utilization ratio, and $L_{pq} = 1$ confirms link feasibility.

e) Global Features $\mathbf{g} \in \mathbb{R}^4$: Graph-level parameters:

$$\mathbf{g} = [\theta_{cov}, m, \beta, R_o]$$

encoding coverage target, resilience requirement, capacity headroom, and protocol overhead.

This representation enables the GNN to learn spatial dependencies while reasoning about deployment constraints, resilience requirements, and capacity utilization during the optimization process.

D. Markov Decision Process Formulation

We formulate the IAB deployment problem as a MDP (S, A, P, R, γ) to enable reinforcement learning optimization:

- a) State Space S: The state $s_t \in \mathcal{S}$ at step t is represented by the attributed graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}, \mathbf{X}_t, \mathbf{E}_t, \mathbf{g})$, where node and edge features encode current deployment status, traffic flows, and connectivity patterns.
- b) Action Space \mathcal{A} : At each step, the agent selects action $a_t \in \mathcal{A} = \{0\} \cup \{j \mid j \in \mathcal{J}, \alpha_j = 0\}$ to either deploy an IAB node at candidate location j $(a_t = j)$ or maintain current configuration $(a_t = 0)$.

c) Reward Function \mathcal{R} : The reward function balances coverage improvement against deployment costs and resilience violations:

$$r_t = \kappa_1 \Delta U_{cov} - \kappa_2 \alpha_{deploy} - \kappa_3 N_{vulnerable}$$

where ΔU_{cov} represents coverage percentage improvement, $\alpha_{deploy} \in \{0,1\}$ indicates new IAB node deployment, and $N_{vulnerable}$ penalizes nodes violating the resilience constraint m. The coefficients $\kappa_1, \kappa_2, \kappa_3$ control the relative importance of coverage gains versus deployment costs and constraint violations.

Algorithm 1 GATv2-PPO for Resilient IAB Deployment

Require: Donor configuration \mathcal{D} , candidate locations \mathcal{J} , training episodes E

Ensure: Optimized deployment policy π_{θ}^*

- 1: for e=1 to E do
- 2: Initialize environment with fixed donor topology \mathcal{D}
- 3: Reset deployment state s_0 and coverage metrics
- 4: **while** coverage threshold θ_{cov} not achieved **do**
- 5: Construct heterogeneous graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}, \mathbf{X}_t, \mathbf{E}_t)$
- 6: Apply GATv2 encoding: $\mathbf{H}^{(L)} = \text{GATv2}(\mathbf{X}_t, \mathbf{E}_t, \mathcal{E})$
- 7: Sample deployment action: $a_t \sim \pi_t$
- 8: Execute action a_t and observe transition (s_t, a_t, r_t, s_{t+1})
- 9: Compute reward r_t with resilience penalties
- Store experience $(\mathcal{G}_t, a_t, r_t, \mathcal{G}_{t+1}, d_t)$ in replay buffer
- Update graph state \mathcal{G}_{t+1} based on deployment changes
- 12: end while
- 13: end for
- 14: **return** Trained policy π_{θ}^* achieving resilient network deployment
- d) GATv2-based Policy Architecture: The policy $\pi_{\theta}(a|s)$ employs a GATv2 encoder with edge-conditioned attention to process the graph state:

$$\mathbf{h}_v^{(l+1)} = \text{GATv2}^{(l)}(\mathbf{h}_v^{(l)}, \{\mathbf{h}_u^{(l)}, \mathbf{e}_{uv}\}_{u \in \mathcal{N}(v)})$$

where $\mathbf{h}_v^{(l)}$ represents node embeddings at layer l, and edge features \mathbf{e}_{uv} condition the attention mechanism. A pointer-based actor network computes deployment probabilities over valid candidate locations, while a critic network estimates state values for PPO training.

III. SIMULATION AND RESULTS

A. Simulation setup

The simulation environment models urban mmWave IAB deployment across 1×1 km² service areas with 400 potential node locations distributed at 50m intervals to mimic realistic urban infrastructure density, corresponding to lamp posts and utility poles. This grid-based approach ensures fair algorithm comparison while maintaining practical relevance. Three deployment scenarios are used to evaluate algorithm performace: Pentagon (5 donors in pentagonal setting), Five-Dice (donors positioned as dice-5 pattern), and Vertical (linear arrangement). Table II summarizes the key simulation parameters used throughout the evaluation.

TABLE I
KEY SYMBOLS AND DEFINITIONS

Symbol	Definition
$\mathcal{I}, \mathcal{J}, \mathcal{K}$	IAB donor set, candidate IAB node set, grid cell set
α_i	Binary deployment variable for IAB node j
Y_{pq}	Binary link activation variable
U_k	Binary coverage indicator for cell k
C_{ik}, C_{jk}	Coverage indicators (0/1)
L_{pq}	Link feasibility indicator (0/1)
R_{pq}	Traffic flow on link $p \to q$ [Mbps]
C_{pq}	Physical capacity of link $p \rightarrow q$ [Mbps]
A_i, A_i	Access demand [Mbps]
F_i	Fiber capacity of IAB donor i [Mbps]
m	Minimum resilience degree (inbound links)
R_o	Protocol overhead factor (> 1)
β	Backup capacity fraction for resilience
θ_{cov}	Target coverage fraction
N_v	Number of active inbound connections to node v

TABLE II SIMULATION PARAMETERS AND MODEL CONFIGURATION

Parameter	Value	Reference
Transmit power P_{tx}	30 dBm	[19]
Antenna gain G_t, G_r	25 dBi	[19]
Noise figure	7 dB	[19]
Operating frequency	60 GHz	[19]
SNR threshold	10 dB	[20]
Coverage threshold θ_{cov}	98%	_
Backup capacity fraction for resilience β	0.2	-
Overhead R_o	1.2	
Resilience parameter m	2	_
Reward coefficients $\kappa_1, \kappa_2, \kappa_3$	4.0, 0.2, 0.5	_
Graph encoder	2-layer GATv2	_
Hidden units	64 per layer	
Attention heads	8	_
Learning rate	3×10^{-4}	-
Batch size	32	_
Discount factor γ	0.99	
Clip ratio	0.2	
Training episodes	8000	-

To address the resilience-aware IAB deployment challenge, we propose GATv2 with edge-conditioned attention mechanism detailed in Algorithm 1 to capture spatial dependencies and connectivity constraints inherent in IAB networks. The model's ability to process heterogeneous node types (IAB donors vs. candidate nodes) and dynamic edge features (link capacity, utilization) makes it particularly suited for modeling complex relationships between deployment decisions, network topology, and resilience requirements. The model is trained using Proximal Policy Optimization (PPO) within the MDP framework, enabling the agent to balance coverage objectives against deployment costs and constraint violations. Model performance is benchmarked against two established approaches:

- **Greedy Heuristic**: A greedy algorithm [25] that sequentially deploys nodes by maximizing immediate coverage improvement under data rate constraints and solved by Gurobi solver. Although fast and interpretable, its myopic nature leads to suboptimal long-term performance.
- Dueling DQN with GCN: Deep reinforcement learning

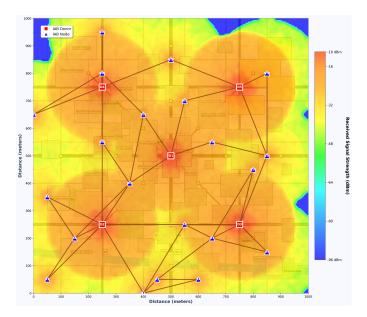


Fig. 1. GATv2-optimized IAB network deployment showing Five-Dice donor configuration (red squares D1-D5), deployed nodes (blue triangles), and signal strength heat map. Black lines indicate backhaul connections forming a resilient mesh topology with redundant paths.

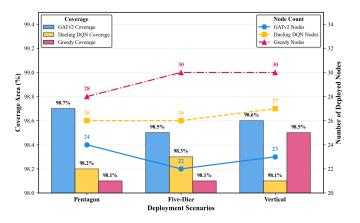


Fig. 2. Multi-scenario deployment efficiency comparison across Pentagon, Five-Dice, and Vertical donor configurations.

approach using a Graph Convolutional Network backbone with experience replay and target networks [24].

B. Result analysis

Fig. 1 demonstrates the spatial deployment achieved by GATv2 in the Five-Dice configuration. The heat map shows coverage zones from -96 dBm to -10 dBm, with deployed nodes (blue triangles) creating overlapping high-SNR areas that eliminate coverage gaps between donors D1-D5. The mesh connectivity pattern (black lines) ensures each node maintains multiple backhaul connections, satisfying the m=2 redundancy constraint through GATv2's learned policy that balances coverage and resilience requirements. Building upon this spatial optimization capability, Fig. 2 quantifies deployment efficiency across three donor configurations. GATv2 consistently outperforms baselines: Pentagon scenario achieves

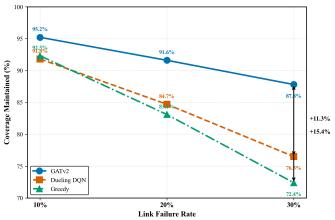


Fig. 3. Network resilience under progressive link failures, and progressive failure tests randomly disable 10%, 20%, and 30% of backhaul links to simulate mmWave blockage events.

98.7% coverage with 24 nodes versus 26 (DQN, 98.2%) and 28 (Greedy, 98.1%); Five-Dice requires only 22 nodes for 98.5% coverage, representing 26.7% reduction compared to Greedy's 30 nodes; Vertical uses 23 nodes versus 27 (DQN) and 30 (Greedy) for 98.6% coverage. These improvements result from GATv2's attention mechanism capturing multi-hop spatial dependencies for global topology optimization, surpassing greedy methods' myopic decisions and standard GCNs' limited graph representation.

Beyond deployment efficiency, the resilience-aware design proves critical under network stress conditions. To evaluate fault tolerance, we conduct link failure simulation using random failure models. The methodology randomly disables 10%, 20%, and 30% of backhaul links, with each failure rate tested across 100 independent trials. We measure coverage retention as the network robustness indicator. Fig. 3 demonstrates that GATv2 maintains superior performance across all failure scenarios: 95.2% coverage retention at 10% failure versus 91.3% (DQN) and 92.3% (Greedy); 91.6% at 20% failure versus 84.7% (DQN) and 83.1% (Greedy); 87.1% at 30% failure versus 76.6% (DQN) and 72.4% (Greedy). The 11.3-15.4% performance advantage stems from the explicit m connectivity constraint in the MDP formulation, preventing single-connected deployments that cause cascading failures in baseline methods.

C. Complexity Analysis

The computational complexity of GATv2-based deployment is analyzed for a network with N candidate nodes and E potential backhaul links. The graph attention mechanism requires $\mathcal{O}(E\cdot d_h)$ operations per attention head, where d_h is the hidden dimension. With 2 attention heads and 2 GATv2 layers, the encoding complexity is $\mathcal{O}(4E\cdot d_h)$. The actor network performs $\mathcal{O}(|\mathcal{A}|\cdot d_h)$ operations for action selection over valid action set \mathcal{A} .

For our urban scenarios with N=400 nodes and average node degree 8, $E\approx 1600$. With $d_h=32$, total complexity per episode is $\mathcal{O}(51200+32|\mathcal{A}|)$. This linear scaling contrasts fa-

vorably with mixed-integer programming approaches exhibiting exponential complexity $\mathcal{O}(2^N)$ for binary placement variables.

The PPO training complexity is $\mathcal{O}(B \cdot T \cdot C_{forward})$ per update, where B=32 is batch size, T is trajectory length, and $C_{forward}$ is the forward pass cost. Memory requirements scale as $\mathcal{O}(N \cdot d_h + E \cdot d_e)$ for node and edge embeddings, remaining manageable for large-scale deployments.

IV. CONCLUSION

This paper introduced a novel GATv2-based RL approach for resilient mmWave IAB network deployment. Our resilienceaware MDP formulation enables optimal deployment patterns balancing coverage, efficiency, and fault tolerance. Experimental results demonstrate superior performance: over 98% coverage with 14.3-26.7% fewer nodes than baselines, 87.1% coverage retention under 30% link failures (11.3-15.4% improvement over competing methods), and linear computational scaling suitable for large deployments. The edge-conditioned GATv2 architecture effectively captures mmWave spatial dependencies while preventing vulnerable single-connected deployments. These results validate GNN-based approaches for complex network optimization and suggest promising extensions to O-RAN architectures and 6G orchestration, particularly through integration with DT technology for realtime adaptive deployment in next-generation wireless systems.

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REFERENCES

- H. X. Nguyen, R. Trestian, D. To, and M. Tatipamula, "Digital Twin for 5G and Beyond," *IEEE Communications Magazine*, vol. 59, no. 2, pp. 10–15. Feb. 2021.
- [2] T. S. Rappaport, S. Sun, R. Mayzus, et al., "Millimeter Wave Mobile Communications for 5G Cellular: It Will Work!" *IEEE Access*, vol. 1, pp. 335–349, 2013.
- [3] M. Polese, M. Giordani, A. Roy, et al., "Integrated Access and Backhaul in 5G mmWave Networks: Potential and Challenges," *IEEE Communications Magazine*, vol. 58, no. 3, pp. 62–68, Mar. 2020.
- [4] C. Saha, M. Afshang, and H. S. Dhillon, "Integrated mmWave Access and Backhaul in 5G: Bandwidth Partitioning and Downlink Analysis," 2019 IEEE International Conference on Communications (ICC), pp. 1–6, May 2019.
- [5] M. Alzenad, M. Z. Shakir, H. Yanikomeroglu, et al., "Coverage and Rate Analysis for Vertical Heterogeneous Networks (VHetNets)," *IEEE Transactions on Wireless Communications*, vol. 17, no. 8, pp. 5533–5547, Aug. 2018.
- [6] Y. Yang, D. Zou, and X. He, "Graph Neural Network-Based Node Deployment for Throughput Enhancement," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 10, pp. 14810–14824, Oct. 2024.

- [7] A. Menapace, A. Zanfei, M. Herrera, et al., "Graph Neural Networks for Sensor Placement: A Proof of Concept towards a Digital Twin of Water Distribution Systems," Water, vol. 16, no. 13, p. 1835, 2024.
- [8] L. Kunz, M. Deronne, and S. Pollin, "Distributed Combinatorial Optimization of Downlink User Assignment in mmWave Cell-free Massive MIMO Using Graph Neural Networks," arXiv preprint arXiv:2406.05652, Jun. 2024.
- [9] J. Liu, Z. Xu, C. Wang, et al., "Graph Neural Networks for Intelligent Modelling in Network Management and Orchestration: A Survey on Communications," *Electronics*, vol. 11, no. 20, p. 3371, 2022.
- [10] X. Wang, L. Fu, N. Cheng, et al., "Joint Flying node Location and Routing Optimization for 6G UAV-IoT Networks: A Graph Neural Network-Based Approach," *Remote Sensing*, vol. 14, no. 17, p. 4377, Sep. 2022.
- [11] A. Madapatha, S. Parthasarathy, and S. Kalyanaraman, "Reinforcement Learning for Routing and Resource Allocation in 5G IAB Networks," *IEEE Transactions on Network and Service Management*, vol. 17, no. 3, pp. 1541–1554, Sep. 2020.
- [12] M. Teymuri, A. Sadeghi, and M. Haenggi, "Self-Backhaul Failure in 5G Networks: A Pre-Planned Optimization Approach," *IEEE Transactions on Wireless Communications*, vol. 20, no. 10, pp. 6741–6754, Oct. 2021.
- [13] A. Madapatha and S. Kalyanaraman, "A Survey on Resilience in 5G IAB Networks," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1041–1064, Secondquarter 2021.
- [14] Ericsson, "Integrated Access and Backhaul: New Option for 5G," Ericsson Technology Review, vol. 97, no. 2, pp. 1–10, 2020.
- [15] Y. Zhang, H. Zhou, and M. Tao, "A Lightweight Multi-Head Single-Body GNN for Access Point Selection and Beamforming in Cell-Free Networks," *IEEE Transactions on Wireless Communications*, to be published, 2024.
- [16] J. Li, X. Wang, and Y. Shi, "HGNN-HBF: Heterogeneous Graph Neural Network for Hybrid Beamforming in mmWave and sub-6 GHz Networks," *IEEE Transactions on Communications*, to be published, 2024.
- [17] Z. Chen, L. Zhang, and T. Q. S. Quek, "UserBeam-GNN: Graph Neural Network for User Association and Beam Management in Heterogeneous Networks," *IEEE Journal on Selected Areas in Communications*, to be published, 2024.
- [18] 3GPP, "Study on integrated access and backhaul," 3GPP TR 38.874 V16.0.0, Dec. 2018.
- [19] ITU-R, "Minimum requirements related to technical performance for IMT-2020 radio interface(s)," ITU-R M.2410-0, Nov. 2017.
- [20] 3GPP, "Study on channel model for frequencies from 0.5 to 100 GHz," 3GPP TR 38.901 V17.0.0, Jun. 2022.
- [21] OpenStreetMap Foundation, "OpenStreetMap," https://www.openstreetmap.org, 2023.
- [22] 3GPP, "NR; NR and NG-RAN Overall Description; Stage 2," 3GPP TS 38.300 V16.2.0, Sep. 2020.
- [23] Z. Wang, T. Schaul, M. Hessel, H. van Hasselt, M. Lanctot, and N. de Freitas, "Dueling network architectures for deep reinforcement learning," in *Proc. 33rd Int. Conf. Machine Learning (ICML)*, New York, NY, USA, Jun. 2016, pp. 1995–2003.
- [24] Y. Yang, D. Zou, and X. He, "Graph Neural Network-Based Node Deployment for Throughput Enhancement," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 10, pp. 14810–14824, 2024, doi: 10.1109/TNNLS.2023.3281643.
- [25] J. Zhang, Q. Wang, P. Mitchell, and H. Ahmadi, "An integrated access and backhaul approach to sustainable dense small-cell network planning," *Information*, vol. 15, no. 1, art. 19, 2024.