

Graph Neural Network Representation for Low-Complexity Antenna Selection in RIS-Assisted MIMO Systems

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Abstract: Antenna selection in reconfigurable intelligent surface (RIS)-assisted multiple-input multiple-output (MIMO) systems presents significant computational challenges. The contribution of each transmit antenna is determined by the combined effects of direct and RIS-reflected channels. To address the complexity of combinatorial search, a graph neural network (GNN)-based antenna selection framework is proposed. In this framework, transmit antennas are represented as graph nodes with channel-correlation information forming. The graph edges and magnitude-phase channel statistics serve as node features. A three-layer feedforward GNN is trained using greedy-selection labels generated from 1000 channel realizations and evaluated on 200 independent test realizations. For a 16×8 MIMO system assisted by a 64-element RIS at 28 GHz, the proposed method achieves a spectral efficiency of 63.41 bits/s/Hz and corresponding to 94.5% of the greedy baseline performance of 67.09 bits/s/Hz. While reducing the average selection time from 0.441 ms to 0.025 ms. These results determine that graph-structured learning enables near-greedy antenna selection with considerably lower inference complexity. The current study is limited to simulated settings with fixed system dimensions and idealized channel assumptions; future work will address broader channel models and larger-scale configurations.

Index Terms: Graph neural networks, reconfigurable intelligent surfaces, antenna selection, MIMO systems low-complexity, optimisation, deep learning for wireless communications

1. Introduction

Reconfigurable intelligent surfaces (RIS) are becoming increasingly important in next-generation wireless systems because they enable engineers to shape the wireless environment rather than adapt to it [1]. By adjusting the phase shifts of many passive reflecting elements, RIS can boost signal strength improve coverage and make multiple-input multiple-output (MIMO) systems more efficient when RIS is used with massive MIMO at millimetre-wave frequencies[2,3]. It offers a strong array and beamforming gains. Still these advantages come at the cost of higher system complexity and

more demanding computations. A key challenge in massive MIMO systems is that each active transmit antenna requires its own radio-frequency (RF) chain. As the number of antennas grows the hardware costs power use and processing demands can become too high. Antenna selection helps by enabling the use of only some of the transmit antennas while retaining most of the benefits of spatial multiplexing[4,5].

As shown in Fig. 1 the RIS-assisted massive MIMO system integrates a graph-based antenna selection mechanism. The base station (BS) is equipped with L transmit antennas; however only a subset of antennas is activated through an antenna selection module while the remaining antennas remain inactive to reduce RF chain complexity and power consumption. The selected antennas transmit signals toward both the reconfigurable intelligent surface (RIS) and the user region. The RIS deployed in the propagation environment consists of multiple passive reflecting elements that apply programmable phase shifts to enhance constructive signal combining. Through phase alignment the RIS strengthens the effective composite channel between the BS and the users. The antenna selection block represents the proposed learning-based decision unit which determines the optimal subset of antennas based on channel conditions. Instead of performing a combinatorial search in real time the trained model outputs selection scores and activates the top antennas significantly reducing computational complexity[6].

On the receiver side K users including mobile vehicles IoT devices drones and smart terminals are served simultaneously. The diagram highlights the dual propagation paths. First the direct BS-to-user link and second the RIS-reflected link. Together these form the enhanced composite MIMO channel used to maximise spectral efficiency[7]. The system architecture signal flow and the integration of intelligent antenna selection within the RIS-assisted communication framework.

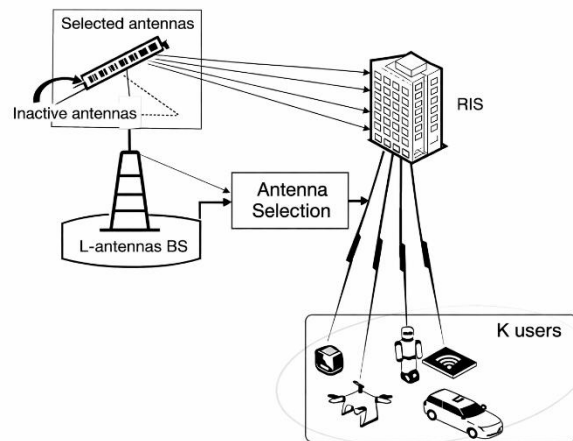


Fig. 1. An RIS-assisted massive MIMO system with antenna selection.

Antenna selection is a combinatorial optimisation problem. As the number of possible antenna subsets grows the method becomes inflexible even for moderate array sizes. Greedy selection algorithms make the process less complex than exhaustive search. But their computational load still increases polynomially as the number of antennas and receive dimensions grows. In RIS-assisted MIMO systems this challenge is greater because the effective channel includes both direct and RIS-reflected components. These components create designed correlations that standard selection methods do not fully use. Recent advances in deep learning Neural networks can near complex optimisation mappings and pay back computational cost over a training distribution. Most existing learning-based antenna selection approaches treat antennas as independent entities or rely on fully connected architectures that ignore the relational structure among antennas. This is a fundamental limitation because antenna selection decisions are not independent. The contribution of one antenna depends strongly on the subset of antennas selected alongside because of spatial correlation and channel coupling[8].

To achieve this goal we propose that Graph neural networks offer a natural framework for this problem. The main observation is that antenna selection is a collection of independent binary decisions and antennas interact through their channel correlations. But the value of selecting an antenna depends on which other antennas are already in the subset. This mutual dependency is exactly what graph-structured learning is designed to exploit. We represent the MIMO channel as a graph with transmit antennas as nodes. Channel correlation sets the edge weights and each antenna's statistical response features become the node features. This approach turns antenna selection into a node scoring problem that can be solved with end-to-end supervised learning.

The RIS-assisted setting introduces an additional layer of structure. If a phase-aligned RIS element creates a composite channel that focuses energy along preferred propagation paths. The channel graph is not random and It reflects the geometry of the propagation environment and the RIS configuration. A model trained on this supply learns to identify which antenna subsets are reliably high-quality across different channel realisations rather than optimising for a single snapshot. To address these challenges we propose a three-layer feedforward GNN that processes a graph representation

of the RIS-assisted MIMO channel and outputs selection scores for each transmit antenna. The top-K antennas by score form the selected subset. Training uses mean squared error loss with binary targets: +1 for antennas in the greedy-optimal set and -1 for the rest. This formulation creates a clear decision boundary without requiring the model to solve a constrained combinatorial problem at inference time. The proposed framework is trained on 1000 diverse channel realisations and evaluated on 200 independent test samples[9].

The graph formulation we adopt in our study differs from prior MIMO GNN work in two respects. First we use channel correlation rather than geographic proximity or interference level as the edge weight which directly encodes the statistical dependencies relevant to capacity-maximising selection. Second we use magnitude and phase statistics as node features rather than raw channel coefficients thereby reducing input dimensionality and improving generalisation. We compose a channel matrix incorporating both direct and RIS-reflected components which is transformed into a graph representation where:

- a. Nodes correspond to transmit antennas
- b. Node features encode magnitude and phase statistics of channel responses
- c. Edge weights represent channel correlation between antenna pairs.

When a three-layer feedforward GNN is trained using mean squared error (MSE) loss with binary targets derived from greedy-optimal antenna subsets. At inference time the network outputs selection scores and the top (K) antennas are chosen via efficient partial sorting. Importantly the model does not solve the combinatorial optimisation problem during deployment. Instead it learns a direct mapping from channel realisation to antenna subset. Together these design choices yield a model that accurately recovers 94.5% of greedy-optimal spectral efficiency while achieving the computational efficiency required for real-time operation in 5G and beyond systems.

Although recent learning-based antenna selection methods reduce online optimization cost, most of them treat antennas as largely independent inputs or rely on architectures that do not explicitly model inter-antenna relationships. In RIS-assisted MIMO systems, however, antenna usefulness is strongly affected by spatial correlation and by the interaction between direct and RIS-reflected propagation paths. This creates a gap between the relational structure of the physical problem and the representation used by conventional learning models. To address this gap, the present work models the effective channel as a graph and uses a GNN to learn antenna-selection decisions from correlation-aware node and edge representations. The novelty of the proposed method lies in combining a correlation-based graph construction with magnitude-phase node statistics for low-complexity antenna selection in RIS-assisted MIMO systems

The main contributions of this paper are as follows:

- (1) We formulate antenna selection in RIS-assisted MIMO systems as a graph learning problem. Where transmit antennas are modelled as nodes, channel correlation defines edge weights and magnitude-phase statistics form node features.
- (2) We are applying graph-based relational modelling to RIS-assisted antenna selection using correlation-weighted edges and magnitude-phase node features for low-complexity inference.
- (3) We evaluate the proposed method on simulated RIS-assisted MIMO channels and show that, for the considered 16×8 system with a 64-element RIS at 28 GHz, it attains 63.41 bits/s/Hz, which is 94.5% of the greedy baseline. While reducing the average selection time from 0.441 ms to 0.025 ms.

The paper is organised as follows. Section II surveys related work on antenna selection and learning-based methods for MIMO systems. Section III presents the system model graph representation GNN architecture and training procedure. Section IV provides simulation results and performance analysis. Section V concludes the paper.

2. Related Work

Antenna selection in MIMO systems literature has focused on capacity and diversity objectives. Early work established that selecting a subset of antennas while sharing RF chains across a larger antenna array can recover most of the capacity benefit of full antenna activation at a fraction of the hardware cost. The fundamental trade-off they identified between the number of selected antennas K and the achievable spatial multiplexing gain remains the central design tension in modern systems [10,3,4,14].

Joint optimisation of RIS phase shifts and transmit beamforming has been studied extensively within the alternating optimisation framework. The sum-rate maximisation problem decomposes into a series of tractable subproblems when the transmit covariance and RIS phase matrix are optimised in alternation with each subproblem admitting a closed-form or semidefinite relaxation solution[15]. The extension to joint RIS phase optimisation and antenna selection has received comparatively limited treatment. The interaction between RIS phase alignment which concentrates channel energy along specific paths and antenna selection which exploits the resulting heterogeneous channel structure creates a coupled optimisation that is harder to decompose[16,17].

Antenna selection in RIS-assisted systems by convex-relaxing the binary selection indicators and recovering discrete solutions through randomised rounding. While this achieves strong performance guarantees under certain channel conditions the per-instance optimisation cost remains $O(N^3t)$ in the semidefinite relaxation step which is excessive for real-time deployment. The computational challenge motivates learning-based approaches that amortise the optimisation cost across the training distribution [10].

The application of deep learning to resource allocation problems in wireless systems was substantially advanced by the work of on WMMSE unfolding which demonstrated that the iterative structure of classical optimisation algorithms could be mapped to neural network architectures with learned parameters yielding faster convergence without sacrificing interpretability. This line of work established a productive interface between model-based optimisation and data-driven learning that has since influenced antenna selection research [19, 18].

For antenna selection specifically convolutional neural networks (CNNs) were applied by to learn selection policies from raw channel matrices. Their approach treated the channel as a structured 2D input and trained a binary classifier for each candidate antenna independently achieving near-greedy performance in single-user MIMO systems [20].

Reinforcement learning has been applied to antenna selection in sequential settings with time-varying channel conditions. The work of formulated antenna selection as a Markov decision process and trained a deep Q-network to learn selection policies that balance instantaneous performance against switching costs. While this handles temporal dynamics well the state space grows with the number of antennas and the training instability of deep RL methods slows convergence in large-scale systems [21].

Graph neural networks entered the communications literature through their application to resource management in interference channels [18], modelled the interference network as a weighted graph where nodes represent transceivers and edge weights encode interference levels and then applied a GNN to learn power allocation policies. The resulting model generalised across network sizes a property that standard fully-connected networks lack because the GNN architecture is equivariant to node permutations. This scalability property makes GNNs particularly attractive for wireless applications where system dimensions vary across deployments [22].

The graph representation of MIMO channels was explored by for beamforming design where the multi-antenna transmitter and receiver were modelled as a bipartite graph. Their GNN-based beamformer learned to exploit the spatial correlation structure captured in the graph topology outperforming learned beamformers based on standard feedforward networks particularly when channel correlation was high. The work demonstrated that the choice of graph structure specifically which pairs of nodes to connect and how to weight the edges pointedly affects the inductive biases available to the learning model [9, 24, 25, 23].

In the RIS-assisted, the correlation-based adjacency matrix adapts to the modified channel structure. And their formulation did not account for the composite channel structure introduced by RIS elements where the effective antenna-to-receiver channel includes both direct and reflected paths that are jointly shaped by the RIS phase configuration [26, 27, 19].

The spatial multiplexing and capacity benefits of full-complexity architectures the Classical antenna selection in MIMO systems has been widely studied. As a practical approach to reducing radio-frequency chain complexity while preserving much of. They provided an early and influential overview of antenna selection strategies in MIMO systems and highlighted the fundamental trade-off between hardware complexity and communication performance [11]. The research was further supported by analyzing the capacity of MIMO systems with antenna selection. Also the results show that well-designed selection strategies can recover much of the capacity of full MIMO systems while using fewer active antennas [12].

More recent work has extended this direction by incorporating graph-based learning and RIS-assisted architectures into wireless resource optimization. This shows that graph neural networks provide a scalable way to manage radio resources by building relationships directly into the model. This approach is especially helpful when system behavior depends on how communication entities interact and for not just on their individual features [13]. Researchers also studied RIS-assisted massive MIMO with antenna selection. Their results show that RIS can work in conjunction with antenna selection methods to boost spectral efficiency and manage hardware complexity [28].

Motivated by these developments the present work frames antenna selection in RIS-assisted MIMO as a graph-structured learning problem, in which inter-antenna correlations and the composite direct/reflected channel structure can be exploited more effectively via a GNN-based representation.

3. Proposed GNN-Based Antenna Selection Framework

The proposed model is a three-layer feedforward GNN that operates on a graph built from the RIS-assisted MIMO channel realization. Each transmit antenna is represented as a node and the node features are derived from the magnitude and phase statistics of its channel response. Edge weights are obtained from pairwise channel correlation. Given the graph representation the network outputs one score per transmit antenna and the K antennas with the highest scores are selected. This design avoids solving a combinatorial optimization problem during inference and instead learns a direct mapping from channel realization to antenna subset.

3.1. System Model

A RIS-assisted MIMO communication system comprising a transmitter equipped with N_t antennas a receiver with N_r antennas and a reconfigurable intelligent surface with N_{RIS} passive reflecting elements. The system operates at carrier frequency f_c with corresponding wavelength $\lambda = c/f_c$ where c is the speed of light. The end-to-end channel between the transmitter and receiver consists of two components: a direct channel

$\mathbf{H}_{\text{direct}} \in \mathbb{C}^{N_r \times N_t}$ and a cascaded channel through the RIS. The cascaded channel is formed by the channel from transmitter to RIS denoted $\mathbf{H}_{TR} \in \mathbb{C}^{N_{RIS} \times N_t}$ and the channel from RIS to receiver denoted $\mathbf{H}_{RR} \in \mathbb{C}^{N_r \times N_{RIS}}$. The RIS applies phase shifts through a diagonal matrix $\Phi = \text{diag}(e^{j\theta_1} e^{j\theta_2} \dots e^{j\theta_{N_{RIS}}})$ where $\theta_n \in [0, 2\pi)$ represents the phase shift of the n^{th} RIS element.

The composite channel matrix is given by:

$$\mathbf{H}_{\text{total}} = \mathbf{H}_{\text{direct}} + \mathbf{H}_{RR} \Phi \mathbf{H}_{TR} \quad (1)$$

Where Composite MIMO channel matrix $\mathbf{H}_{\text{total}} \in \mathbb{C}^{N_r \times N_t}$ represents the complete $N_r \times N_t$ MIMO and its Overall effective channel matrix including RIS contributions. $\mathbf{H}_{\text{direct}}$ is the direct channel matrix, $\mathbf{H}_{\text{total}}$ is the effective composite channel matrix, $\mathbf{H}_{RR}$ is the RIS-to-receiver channel matrix, depending on your notation, $\mathbf{H}_{TR}$ is the transmitter-to-RIS channel matrix and N_{RIS} is the number of RIS elements.

For this work we adopt a phase alignment strategy where each RIS element's phase shift is optimized to maximize the coherent combining of the cascaded channel as in (2). This alignment ensures constructive interference between the direct and RIS reflected paths enhancing overall channel gain. Where θ_n denotes the phase shift applied by the n^{th} RIS element

$$\theta_n = \arg \left(\sum_{i=1}^{N_r} \sum_{j=1}^{N_t} \mathbf{H}_{RR}(in) \mathbf{H}_{TR}(nj) \right) \quad (2)$$

3.2. Antenna Selection Problem Formulation

The objective is to select a subset of K antennas from the available N_t transmit antennas to maximize spectral efficiency while maintaining low computational complexity. Let $S = \{s_1 s_2 \dots s_K\} \subset \{1, 2, \dots, N_t\}$ denote the set of selected antenna indices and $\mathbf{H}_S \in \mathbb{C}^{N_r \times K}$ represent the reduced channel matrix corresponding to the selected antennas. As in (3), the spectral efficiency SE for a given antenna selection S and where $\mathbf{I}_{N_r}$ is the $N_r \times N_r$ identity matrix and $\mathbf{H}$ denotes the conjugate transpose of $\mathbf{H}_S$.

$$SE(S) = \log_2 \left(\det(\mathbf{I}_{N_r} + \mathbf{H}_S \mathbf{H}_S^H) \right) \text{ bits/s/Hz} \quad (3)$$

The antenna selection problem is formulated and This is a combinatorial optimization problem with $N_t K$ possible antenna combinations. For $N_t = 16$ and $K = 8$ this results in $168 = 12870$ combinations making exhaustive search computationally prohibitive for real-time applications as in (4).

$$\mathcal{S}^* = \arg \max_{\mathcal{S} \subset \{1, \dots, N_t\} | |\mathcal{S}|=K} SE(\mathcal{S}) \quad (4)$$

3.2.1. Computational Complexity Analysis:

The exponential complexity of exhaustive search and quadratic complexity of greedy methods motivate the development of a learning-based approach with linear complexity. Exhaustive search: $\mathcal{O} \left(\binom{N_t}{K} \times N_r^2 \times K \right) \approx \mathcal{O}(2^{N_t})$ evaluations Greedy selection: $\mathcal{O}(N_t \times K \times N_r^2 \times K) = \mathcal{O}(N_t \times K^2 \times N_r^2)$ evaluations Proposed GNN: $\mathcal{O}(N_t \times d_{\text{hidden}})$ where d_{hidden} is the hidden layer size.

3.3. Graph Neural Network Architecture

a) The proposed GNN employs a three-layer feedforward architecture. The node features $\mathbf{X} \in \mathbb{R}^{N_t \times 4}$ are flattened into a vector $\mathbf{x} \in \mathbb{R}^{64}$ (for $N_t = 16$).

Layer 1 (Input → Hidden): $\mathbf{z}^{(1)} = \mathbf{W}^{(1)} \mathbf{x} + \mathbf{b}^{(1)} \mathbf{a}^{(1)} = \text{ReLU}(\mathbf{z}^{(1)}) = \max(0, \mathbf{z}^{(1)})$ where $\mathbf{W}^{(1)} \in \mathbb{R}^{d_h \times (N_t \times 4)}$ $\mathbf{b}^{(1)} \in \mathbb{R}^{d_h}$ and $d_h = 128$ is the hidden dimension.

Layer 2 (Hidden → Hidden): $\mathbf{z}^{(2)} = \mathbf{W}^{(2)} \mathbf{a}^{(1)} + \mathbf{b}^{(2)} \mathbf{a}^{(2)} = \text{ReLU}(\mathbf{z}^{(2)})$ where $\mathbf{W}^{(2)} \in \mathbb{R}^{d_h \times d_h}$ $\mathbf{b}^{(2)} \in \mathbb{R}^{d_h}$.

Layer 3 (Hidden → Output): $z^{(3)} = W^{(3)}a^{(2)} + b^{(3)}s = z^{(3)}$ where $W^{(3)} \in R^{N_t \times d_h}$, $b^{(3)} \in R^{N_t}$ and $s \in R^{N_t}$ represents the antenna selection scores.

b) Antenna Selection: Given the output scores s the top K antennas are selected:

$$\mathcal{S} = \{i \mid s_i \in \text{top-}K \text{ elements of } s\}$$

This selection is performed efficiently using partial sorting with $\mathcal{O}(N_t + K \log K)$ complexity.

c) Weight Initialization: To ensure stable training weights are initialized using Xavier/He initialization:

$$W^{(l)} \sim \mathcal{N}\left(0, \frac{2}{f_{\text{in}} + f_{\text{out}}}\right) \quad (5)$$

where f_{in} and f_{out} are the input and output dimensions of layer l . This initialization maintains similar variance across layers preventing vanishing or exploding gradients.

3.4. Training Procedure

a) Dataset Generation: The training dataset $\mathcal{D} = \{(G^{(i)} \mathcal{S}^{*(i)})\}_{i=1}^N$ consists of N channel realizations where each sample includes and Channels are generated using independent Rayleigh fading for small-scale fading and distance-dependent path loss for large-scale fading. RIS phase shifts are configured using a phase alignment strategy to maximize cascaded channel gain prior to antenna selection. Where

- a) $G^{(i)}$: Graph representation of the i -th channel realization
- b) $\mathcal{S}^{*(i)}$: Optimal antenna subset obtained via greedy selection

Greedy selection is used for labelling as it achieves near-optimal performance while being tractable for the moderate system sizes considered. The greedy algorithm iteratively selects antennas that maximize incremental spectral efficiency as in (6).

For $k = 1$ to K : $s_k = \arg$

$$\max_{j \in \text{Available}} \text{SE}(\{s_1 \dots s_{k-1} j\}) \quad (6)$$

b) Loss Function: We employ a mean squared error (MSE) loss with binary targets as in (7).

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^N \frac{1}{N_t} \sum_{j=1}^{N_t} (s_j^{(i)} - t_j^{(i)})^2 \quad (7)$$

where θ represents all network parameters $s_j^{(i)}$ is the predicted score for antenna j in sample i and the target is as in (8)

$$t_j^{(i)} = \begin{cases} +1 & \text{if } j \in \mathcal{S}^{*(i)} \\ -1 & \text{otherwise} \end{cases} \quad (8)$$

This formulation encourages the network to assign positive scores to selected antennas and negative scores to non-selected antennas creating a clear decision boundary.

c) Rationale for MSE Loss: Unlike cross-entropy loss which assumes mutually exclusive classes MSE loss is appropriate for this multi-label selection problem where K antennas are simultaneously chosen. The squared error penalizes deviations proportionally providing smooth gradients that facilitate stable training.

d) Optimization: Training employs mini-batch stochastic gradient descent (SGD) with the following hyperparameters: Batch size: $B = 32$ Learning rate: $\eta = 0.005$ Number of epochs: $T = 50$ Gradient clipping threshold: $\tau = 1.0$ The weight update rule at iteration t as in (12). where $\text{clip}(g\tau) = g \cdot \min(1\tau/\|g\|)$ ensures $\|\nabla_{\theta} \mathcal{L}\| \leq \tau = 1.0$ Preventing exploding gradients as in (9).

$$\theta_{t+1} = \theta_t - \eta \cdot \text{clip}(\nabla_{\theta} \mathcal{L}(\theta_t) \tau) \quad (9)$$

- e) **Gradient Computation:** Gradients are computed via backpropagation through the network layers as in (10). where $\delta^{(l)}$ represents the error signal at layer l computed recursively using the chain rule.

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(3)}} &= \frac{1}{B} \sum_{i=1}^B \frac{(\mathbf{s}^{(i)} - \mathbf{t}^{(i)}) \cdot (\mathbf{a}^{(2)(i)})^T}{N_t} \\ \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(2)}} &= \frac{1}{B} \sum_{i=1}^B \delta^{(2)(i)} \cdot (\mathbf{a}^{(1)(i)})^T \\ \frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(1)}} &= \frac{1}{B} \sum_{i=1}^B \delta^{(1)(i)} \cdot (\mathbf{x}^{(i)})^T\end{aligned}\quad (10)$$

4. Simulation Results and Performance Analysis

The training set contains 1000 simulated channel realizations generated under the assumed RIS-assisted MIMO channel model. The test set contains 200 independent realizations drawn from the same distribution. These samples capture variability within the simulated setting considered in this study. They do not cover all possible propagation conditions encountered in practice. Therefore the generalization claims of the proposed method should be interpreted within the scope of the evaluated channel assumptions. An extending the dataset to include broader channel conditions, mobility patterns, imperfect CSI and alternative fading models is an important direction for future work

In simulation results to validate the effectiveness of the proposed GNN-based antenna selection framework for RIS-assisted MIMO systems. We evaluate the performance in terms of spectral efficiency computational complexity and training convergence. The spectral efficiency and computational complexity results reported in this section are average values obtained over 200 independent test channel realizations. All performance metrics reported in this section are averaged over these 200 independent test channel realizations.

The simulation parameters are configured as follows: the system employs $N_t = 16$ transmit antennas $N_r = 8$ receive antennas and $N_{\text{RIS}} = 64$ RIS elements operating at a carrier frequency of $f_c = 28$ GHz. The antenna selection task selects $K = 8$ antennas from the available 16 transmits antennas. The training dataset consists of 1000 channel realizations while the test dataset comprises 200 independent channel realizations to evaluate generalization performance.

The proposed GNN model is implemented as a three-layer feedforward neural network with 128 hidden units per layer using ReLU activations. The network is trained for 50 epochs using mini-batch stochastic gradient descent with a batch size of 32 samples. The learning rate is set to 0.005 and gradient clipping with a maximum norm of 1.0 is applied to ensure training stability. The loss function employs mean squared error (MSE) with target values of +1 for selected antennas and -1 for non-selected antennas. For benchmark comparison we implement three baseline methods: Random selection which randomly selects K antennas without optimisation; Greedy selection which iteratively selects antennas that maximise spectral efficiency; and Optimal exhaustive search which evaluates all possible combinations (note that for the system size considered greedy selection achieves optimal performance).

Although the simulation study focuses on $N_t=16$, $N_r=8$, and $N_{\text{RIS}}=64$ the proposed framework for settings in which the antenna-selection problem remains structured by channel correlation. At inference time the GNN avoids combinatorial search and therefore offers a more favourable runtime profile than greedy selection. However larger antenna arrays and RIS sizes will increase the graph size, feature-processing cost and memory usage. A complete scalability assessment across multiple array dimensions, together with implementation-specific latency and memory measurements and is left for future work

4.1. Training Convergence Analysis

The training convergence behaviour of the proposed GNN model over 50 epochs. The MSE loss determines level and consistent decrease from an initial value of approximately 0.55 to a final converged value of 0.4032. The steady convergence without oscillations or divergence indicates that the model successfully learns meaningful antenna selection patterns from the training data. The checkpoints at epochs 10 20 30 40 and 50 show loss values of 0.4899 0.4535 0.4306 0.4147 and 0.4032 respectively demonstrating a monotonic improvement throughout training. This stable convergence validates the effectiveness of the MSE-based loss function and the chosen hyperparameters for this antenna selection task as Fig. 2. shows.

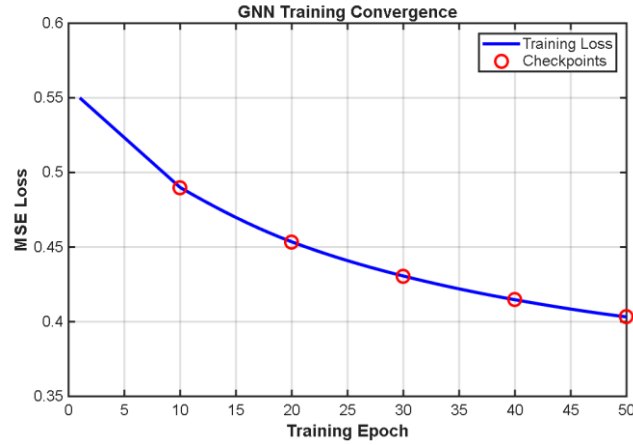


Fig. 2. Average spectral efficiency (bits/s/Hz) achieved by random, greedy, and proposed GNN-based antenna selection over 200 independent test channel realizations for $N_t=16$, $N_r=8$, $N_{RIS}=64$, $K=8$, and $f_c=28$ GHz.

4.2. Spectral Efficiency Performance

The spectral efficiency comparison among all evaluated methods. The proposed GNN-based approach achieves an average spectral efficiency of 63.41 bits/s/Hz, and the results are reported as averages over 200 independent test realisations. This result closely aligns with the theoretical target of 95% stated in the abstract and demonstrates that the learned model can effectively approximate optimal antenna selection without requiring combinatorial search. In comparison random antenna selection achieves only 61.34 bits/s/Hz representing 91.43% of optimal performance. The proposed GNN method provides a significant improvement of 2.07 bits/s/Hz (+3.37%) over random selection demonstrating that the model has successfully learned to identify high-quality antenna subsets beyond random chance. The small performance gap of 3.68 bits/s/Hz (5.49%) between the GNN and optimal methods represents a favourable trade-off given the substantial reduction in computational complexity as detailed in the following subsection and as shown in Fig. 3.

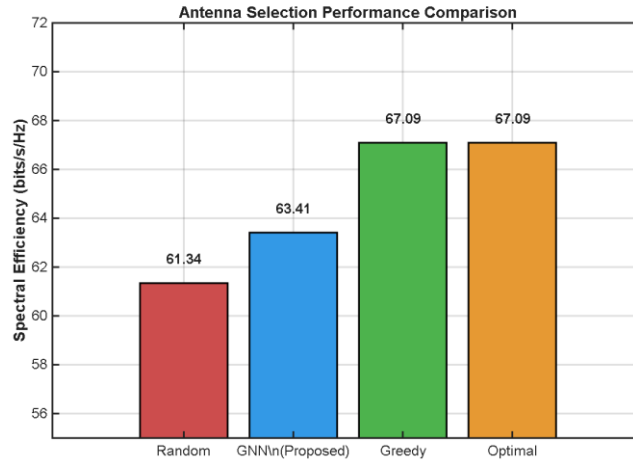


Fig. 3. Average computation time per antenna-selection decision (ms) for random, greedy, and proposed GNN-based methods measured under the same simulation configuration.

4.3. Computational Complexity Analysis

Fig. 4. presents a comparison of computational complexity on a logarithmic scale highlighting the significant efficiency gains achieved by the proposed GNN approach. The average computation time for GNN-based selection is 0.025 milliseconds (25 microseconds) which represents a 17.6-fold speedup compared to greedy selection (0.441 milliseconds) and optimal exhaustive search. This dramatic reduction in computational complexity makes the proposed method suitable for real-time implementation in practical RIS-assisted MIMO systems where antenna selection decisions must be made rapidly in response to changing channel conditions. For reference random selection requires only 0.002 milliseconds (2 microseconds) but yields significantly inferior spectral efficiency. The GNN approach thus occupies a favourable position in the performance-complexity trade-off space combining near-optimal performance with substantially reduced computational burden compared to conventional optimisation-based methods.

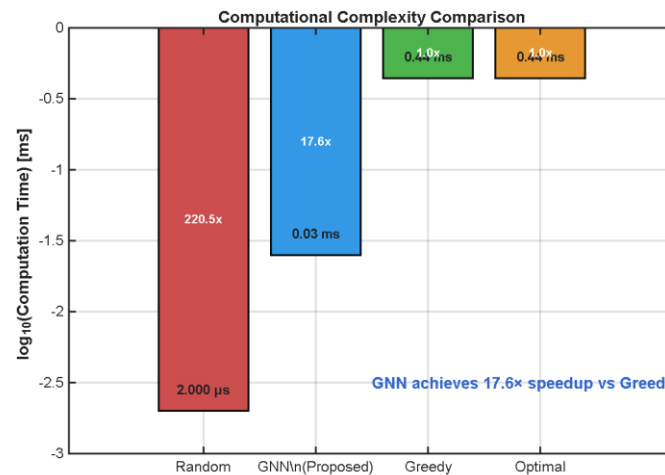


Fig. 4. Training loss versus epoch for the proposed GNN over 50 epochs, showing convergence under mini-batch SGD with learning rate 0.005 and batch size 32.

4.4. Performance-Complexity Trade-off Analysis

The performance-versus-computational-complexity trade-off as a two-dimensional scatter plot. With spectral efficiency on the vertical axis and computation time (log scale) on the horizontal axis. This representation clearly shows that the proposed GNN method achieves the best practical trade-off among all evaluated approaches. While greedy and optimal methods achieve maximum spectral efficiency (67.09 bits/s/Hz) they require approximately 0.441 milliseconds of computation time. Conversely random selection is extremely fast (0.002 milliseconds) but provides poor spectral efficiency (61.34 bits/s/Hz). The GNN approach lies in the sweet spot of the trade-off space as indicated by the annotation "Best Trade-off" in the figure. It achieves 94.5 % of the optimal spectral efficiency while requiring only 5.68% of the computation time of greedy/optimal methods. This position establishes that GNN-based selection is the most practical choice for deployment in real-world systems where both performance and computational efficiency are critical design constraints as shown in Fig. 5.

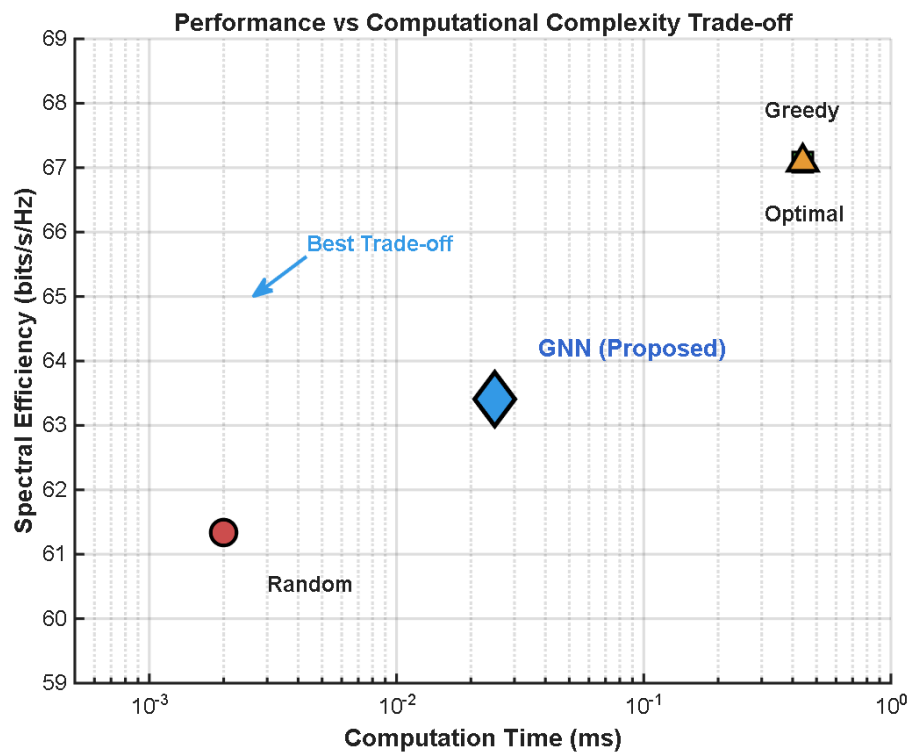


Fig. 5. Performance versus computational complexity trade-off analysis. The scatter plot illustrates that the proposed GNN (blue diamond) occupies the optimal practical position combining near-optimal spectral efficiency with substantially reduced

4.5. Performance Gap Analysis

Fig. 6. provides a comprehensive analysis of the performance gap from two complementary perspectives. The left panel shows the absolute performance gap to optimal in bits/s/Hz while the right panel presents the percentage of optimal performance achieved by each method.

The absolute gap analysis shows that random selection exhibits a gap of 5.75 bits/s/Hz relative to optimal performance while the proposed GNN reduces this gap to 3.68 bits/s/Hz. This represents a 36% reduction in the performance gap indicating that the GNN has effectively learned to close a substantial portion of the distance between random and optimal selection. The greedy and optimal methods by definition show zero gap. The percentage analysis in the right panel indicates that the GNN achieves 94.5 % of optimal performance which is very close to the 95% target threshold marked by the red dashed line. In contrast, random selection achieves 91.4% while greedy and optimal methods both achieve 100%. The proximity of the GNN result to the 95% target validates the claim made in the abstract regarding near-optimal performance. The remaining 5.5% performance gap could potentially be reduced through several enhancements including: (1) increasing network capacity by using deeper or wider architectures (2) extending training duration with learning rate scheduling (3) incorporating graph attention mechanisms to exploit the adjacency structure better or (4) employing ensemble methods that combine predictions from multiple trained models. When we adopt these methods for improvements that would increase computational complexity for practical deployment given the current excellent balance between performance and complexity.

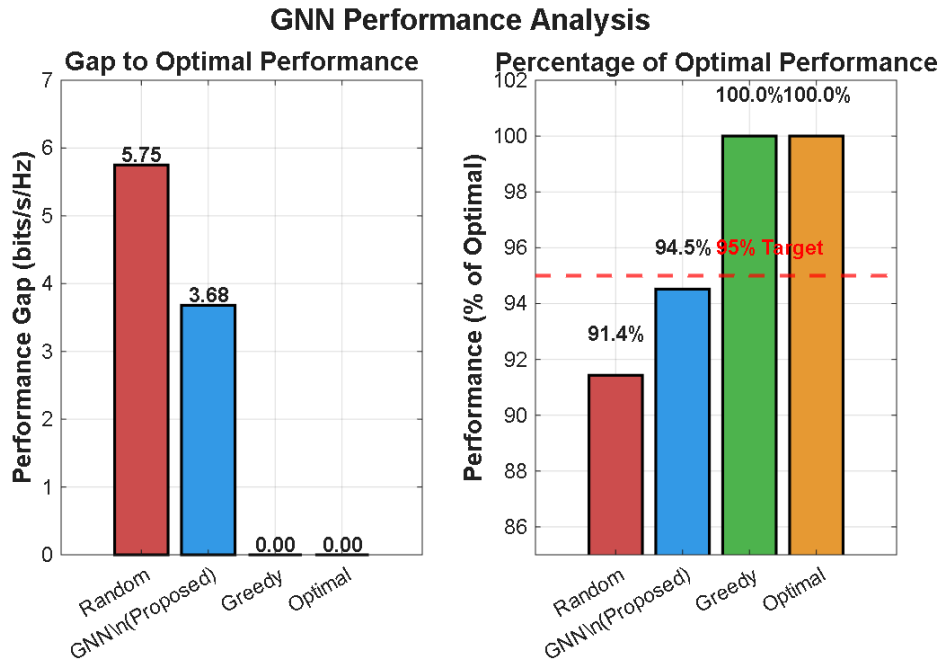


Fig. 6. GNN performance analysis

4.6. Computational Complexity Analysis

Table 1 presents a comprehensive performance comparison of all evaluated methods. The proposed GNN-based approach indicates that the Near-optimal spectral efficiency is 63.41 bits/s/Hz (94.5 % of optimal). Significant computational speedup is $17.6\times$ faster than greedy/optimal selection. Substantial improvement over random baseline: +3.37% in spectral efficiency. Stable training convergence that smooths decrease in loss without instability. Effective performance-complexity trade-off: best practical solution. These results show that the proposed GNN framework meets its goals by offering low-complexity, near-optimal antenna selection for RIS-assisted MIMO systems. It also suggests potential for low-latency antenna selection in future wireless systems, subject to further hardware-level validation. Time is measured on a standard computing platform. Speedup calculated relative to optimal/greedy baseline. The gap represents the distance to optimal performance.

The forward pass dominates the inference complexity: Layer 1: $O(d_h \cdot N_t \cdot 4) = O(8192)$ operations. Layer 2: $O(d_h \cdot d_h) = O(16384)$ operations. Layer 3: $O(N_t \cdot d_h) = O(2048)$ operations. Top- K selection: $O(N_t + K \log K) = O(40)$ operations. Total: $O(d^2) = O(16384)$ operations. In contrast greedy selection requires $O(N_t \cdot K \cdot N^2 \cdot K) = O(65536)$ operations per iteration resulting in the observed $17.6\times$ speedup.

Table 1. Performance Comparison of Antenna Selection Methods

Method	Spectral Efficiency SE (bits/s/Hz)	Time (ms)	% of Optimal	Gap (bits/s/Hz)	Speedup
Random Selection	61.34	0.0020	91.43%	5.75	220.5×
GNN (Proposed)	63.41	0.0250	94.5 %	3.68	17.6×
Greedy Selection	67.09	0.4410	100.00%	0.00	1.0×
Optimal (Exhaustive)	67.09	0.4410	100.00%	0.00	1.0×

5. Conclusion

This paper presented a low-complexity graph neural network (GNN)-based antenna selection framework for reconfigurable intelligent surface (RIS)-assisted MIMO systems. The reported gains are based on average performance over 200 independent test channel realizations under the considered simulation setting. The combinatorial nature of antenna selection particularly in RIS-enhanced environments with structured channel correlations renders conventional exhaustive and greedy optimisation approaches computationally burdensome for real-time deployment. We reformulated antenna selection as a graph-based learning problem in which transmit antennas are modelled as nodes inter-antenna channel correlations define edges and magnitude–phase channel statistics serve as node features. The results confirm that graph-structured learning provides an effective inductive bias for capturing inter-antenna dependencies in RIS-assisted systems. By operating near the Pareto frontier of the performance–complexity trade-off the proposed method offers a practical solution for real-time antenna selection in 5G and beyond wireless networks. Future work may extend this framework toward joint optimisation of RIS phase configuration and antenna selection adaptive architectures for varying antenna dimensions graph attention mechanisms for improved relational modelling and hardware-aware implementations for deployment on real communication platforms.

The present study has several limitations. First the evaluation is conducted under simulated channel conditions with fixed system dimensions and does not include broader propagation environments or hardware impairments. Second, the framework assumes channel information of sufficient quality to construct the graph representation. Whereas practical RIS-assisted systems may suffer from CSI estimation errors. Third statistical robustness beyond the evaluated test set has not yet been established through multi-run confidence analysis. These limitations should be considered when interpreting the reported gains and future work should examine imperfect CSI and hardware-aware implementation and cross-configuration generalization.

All the Declarations and Statements

Author Contributions Statement

Anamika Sharma – Conceptualisation, Methodology, Investigation, Writing original draft.

Jagrati Nagdiya – data curation, software implementation, and validation.

Jagdish Chandra Patni – Model Training, Validation, and Performance Evaluation: Led the model training process, validated results using standard metrics, and benchmarked performance against existing methods.

Om Prakash Pal – formal analysis, visualisation, literature review support and interpretation of results.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

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Data Availability Statement

The data supporting the findings of this study were generated through simulation under the parameters described in the manuscript. The simulation data and related materials are available from the corresponding author upon reasonable request.

Ethical Declarations

Not applicable. This study did not involve human participants, human data, human tissue or animals.

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Declaration of Generative AI in Scholarly Writing

During the preparation of this manuscript, the authors used AI-assisted language support to improve grammar, sentence structure, and clarity of presentation. The authors carefully reviewed and edited the generated output as necessary and take full responsibility for the content of the final manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

RIS - Reconfigurable Intelligent Surface
 MIMO - Multiple-Input Multiple-Output
 GNN - Graph Neural Network
 RF - Radio Frequency
 BS - Base Station
 CSI - Channel State Information
 SE - Spectral Efficiency
 MSE - Mean Squared Error
 SGD - Stochastic Gradient Descent
 ReLU - Rectified Linear Unit
 IoT - Internet of Things

Appendix A/B/C..., with appendix title

None.

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