Vol. 08, No. 2 (2026) 699-710, doi: 10.24874/PES08.02.009

Proceedings on Engineering Sciences

www.pesjournal.net

GRAPH-BASED DEEP LEARNING APPROACH FOR EQUALIZATION IN IRS-AIDED MIMO COMMUNICATIONS

Shaik Jagadeesh Babu
Pradyumna Kumar Mohapatra [1]
Ravi Narayan Panda
Saroja Kumar Rout
Rojalin Samantaray

Received 11.02.2026.
Revised 25.05.2026.
Accepted 05.06.2026.

Keywords:

Graph Neural Network, Intelligent Reflecting Surface, MIMO Systems, Channel Equalization

A B S T R A C T

This paper presents a novel graph neural network (GNN)–based equalization scheme for intelligent reflecting surface (IRS)–assisted MIMO wireless communication systems operating over Rayleigh and Rician fading channels. Conventional equalization techniques, including linear methods such as zero-forcing (ZF) and minimum mean square error (MMSE), as well as metaheuristic optimization approaches like genetic algorithms (GA), particle swarm optimization (PSO), and simulated annealing (SA), often exhibit limited adaptability and high computational complexity in dynamically varying propagation environments. To overcome these challenges, the proposed GNN equalizer exploits the inherent structural relationships among received signals and IRS-induced channel correlations through a graph-based system representation. Extensive simulation results demonstrate that the proposed approach consistently outperforms conventional optimization-based equalizers in terms of mean squared error (MSE) convergence and bit error rate (BER) across a wide range of signal-to-noise ratios (SNRs). Notably, under both Rayleigh and Rician fading conditions, the GNN equalizer achieves faster convergence and up to an order-of-magnitude improvement in BER at high SNRs. Moreover, the proposed method maintains robust performance across diverse channel scenarios while reducing inference-time computational overhead. These results highlight the effectiveness of GNN-based equalization for enhancing the reliability and efficiency of IRS-assisted MIMO systems in next-generation wireless networks.

© 2026 Published by Faculty of Engineering

1. INTRODUCTION

Massive multiple-input multiple-output (MIMO) technology plays a crucial role in enhancing spectral efficiency and ensuring reliable performance in contemporary wireless communication networks (Marzetta et al., 2010). However, the practical performance of MIMO systems is severely affected by multipath fading and interference, especially in scenarios with non-line-of-sight (NLoS) conditions. To mitigate such impairments, precise channel equalization is vital for symbol detection at the receiver (Tse et al., 2005). Recently, intelligent reflecting surfaces (IRS) have emerged as a potentially useful technique to

[1] Corresponding author: Pradyumna Kumar Mohapatra
Email: er_pradyumna@yahoo.co.in

reshape the wireless propagation environment through passive, low-cost, and programmable elements (Wu & Zhang, 2019). By dynamically regulating the phase shifts of individual elements, an IRS can constructively enhance the desired signal or suppress interference at the receiver (Di Renzo et al., 2020). While this capability significantly improves link quality and coverage, it also introduces new challenges in signal processing, particularly in the design of channel equalizers that must now account for both direct and IRS-assisted paths (ElMossallamy et al., 2020).

Traditional equalization techniques like matched filter (MF), ZF, and MMSE estimators assume simplified linear models and often struggle to fully exploit the non-linear dependencies introduced by IRS phase shifts and the cascaded channel structure (Kay, 1993). Recent advancements in neural network-based equalizers have demonstrated significant improvements in mitigating nonlinear distortions in communication channels (Mohapatra et al., 2023; Das et al., 2025; Acharya et al., 2025;).

Furthermore, recent data-driven approaches using deep neural networks (DNNs) offer improved adaptability (Ye et al., 2018), but they cannot natively incorporate the spatial structure and topological dependencies of wireless links, especially in the presence of IRS nodes.

In this work, we suggested a novel equalizer which trained on GNN and designed specifically for IRS-assisted MIMO systems. By modelling the entire communication environment as a heterogeneous graph consisting of transmit antennas, IRS elements, and receive antennas. We enable structured message passing that naturally reflects the underlying channel topology. Our model incorporates both direct and IRS-reflected channel links as edge features and utilizes node-level information such as transmitted symbols, received signals, and phase shifts. This graph-based formulation allows the GNN to learn powerful representations for symbol recovery, even in highly complex wireless environments.

The core contributions of the proposed approach are outlined below:

- We develop a graph-based modelling context for IRS-assisted MIMO systems, where both direct and cascaded IRS paths are represented as edge connections in a heterogeneous graph.
- We design a phase-aware GNN equalizer that incorporates edge and node features derived from the wireless channel and IRS configuration.
- The performance of the proposed equalizer is comprehensively evaluated over both Rayleigh and Rician fading channels, offering insights into its robustness in diverse propagation environments.
- Extensive simulations demonstrate that the GNN-based equalizer significantly outperforms conventional techniques, including ZF, MMSE, GA, SA, and PSO, in terms of mean squared error (MSE) and bit error rate (BER).
- We analyse the impact of key system parameters, such as IRS size, SNR, and phase quantization levels, on the equalization performance.
- A tailored training strategy is introduced for optimizing the GNN parameters using synthetic complex-valued datasets that emulate real-world IRS-assisted MIMO channels.
- The manuscript includes qualitative assessments, such as constellation plots, to illustrate the symbol estimation accuracy of the GNN model compared to ground truth data.

The structure of the paper is as follows: Section 2 provides an overview of related work on equalization and IRS-assisted communication systems. Section 3 introduces the system model. In Section 4, the proposed GNN-based equalizer is explained in detail. Section 5 presents the simulation results along with a comprehensive discussion. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. BACKGROUND AND RELATED STUDIES

This section reviews the state of the art in four key areas relevant to this research: classical equalization techniques for MIMO systems, learning-based signal detection, intelligent reflecting surface (IRS)-assisted communication, and the recent adoption of graph neural networks (GNNs) in wireless communication.

2.1 Traditional Equalization Techniques in MIMO Systems

Equalization in MIMO systems is fundamental for mitigating inter-symbol interference (ISI) and recovering transmitted symbols over multipath channels. Conventional linear equalizers such as the MF, ZF, and MMSE estimators are widely used due to their simplicity and analytical tractability. However, these techniques assume accurate channel state information (CSI) and often perform sub-optimally under realistic channel impairments, such as noise enhancement and correlated fading. The characteristics of channel behaviour and its integration with wireless communication systems are thoroughly discussed in (Mohapatra et al., 2016). In particular, the ZF equalizer eliminates interference at the cost of noise amplification, while MMSE offers a compromise by minimizing total error variance (Paulraj et al., 2004). These methods are not designed to exploit any non-linear structure or topological relationships that may

arise in advanced scenarios such as IRS-aided communication.

2.2 Deep Learning-Based Equalization

Driven by the remarkable achievements of deep learning in signal processing, neural networks have been utilized for symbol detection and equalization in MIMO and OFDM communication systems (He et al., 2018; O'shea & Hoydis, 2017). Deep learning architectures like deep neural networks (DNNs) and convolutional neural networks (CNNs) have demonstrated improved robustness against non-idealities, including channel uncertainty and interference. (Ye et al. 2018) suggested a DNN-based receiver for OFDM that jointly performs channel estimation and signal detection. Similarly, (Samuel et al. 2019) introduced a model-driven deep learning approach that mimics the unfolding of iterative algorithms for detection. While promising, these approaches typically treat the input data as flat vectors, neglecting the rich structural dependencies among transmitters, reflectors, and receivers in spatially-aware wireless systems.

2.3 Intelligent Reflecting Surface (IRS)-Assisted Communication

IRS technology enables passive control of the propagation environment by reflecting incident signals with programmable phase shifts (Wu et al., 2019; Di Renzo et al., 2020). By optimizing the IRS configuration, it is possible to enhance received signal strength and suppress interference (Zhang & Zhang, 2020; Zhang & Song, 2023). However, the presence of the IRS introduces a *cascaded channel* composed of both transmitter–IRS and IRS–receiver links, which significantly complicates channel estimation and equalization tasks Ding et al., 2021. Various works have addressed beam forming design for IRS-assisted systems (Huang et al., 2019), but the development of equalization strategies that fully exploit the potential of IRS remains underexplored. Some recent studies investigate IRS-aware MMSE designs, but they rely on linear models and fail to capture the complexity of IRS phase interaction.

2.4 Graph-Based Deep Learning Techniques in Wireless Communication

GNNs have gained prominence due to their robust learning capabilities on non-Euclidean data, where dealings are best modelled as graphs. In wireless communication, GNNs have been successfully applied to scheduling (Camargo et al., 2025), resource allocation (Wang et al., 2022), and channel estimation (Ye et al., 2024). GNNs enable structured message passing between entities (e.g., antennas or users) based on connectivity and feature similarity. Inspired by these developments, recent research has begun exploring GNNs for signal detection. For instance, (Sun et al., 2023) introduced a GNN-based model for MIMO detection under imperfect CSI, achieving notable performance gains. However, the use of GNNs for equalization in IRS-assisted MIMO scenarios remains largely unaddressed. The unique topology induced by the IRS: acting as a passive relay with trainable phase elements: naturally lends itself to a graph-based model where nodes represent physical entities (Tx, IRS, Rx) and edges encode channel coefficients and phase shifts.

2.5 Summary and Research Gap

In summary, while traditional and deep learning-based equalizers offer reasonable performance in standard MIMO settings, they are not well-suited for IRS-aided systems where channel complexity and spatial structure are critical. Moreover, although GNNs have shown promise in related tasks, their integration into IRS-MIMO equalization has not been fully investigated. This paper addresses this gap by designing a GNN-based equalizer that models IRS-assisted communication as a graph, incorporating both node-level features (e.g., received signals, IRS phases) and edge-level attributes (e.g., channel coefficients).

3. SYSTEM MODEL

To visually represent the communication framework, the schematic representation of the IRS-assisted MIMO system is depicted in Fig. 1. The system comprises a multiple-antenna transmitter (Tx) and receiver (Rx), with an Intelligent Reflecting Surface (IRS) positioned to assist the wireless link. Comprised of numerous affordable passive reflectors, the IRS can dynamically adjust the phase of reflected signals.

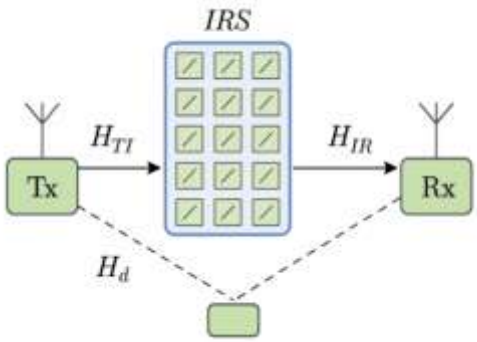


Figure 1. Schematic representation of an IRS- aided MIMO communication framework

As illustrated in Figure 1, the transmitter establishes communication with the receiver via two separate propagation paths: one is a direct link (if present) and an indirect link via the IRS. The effective IRS-reflected channel is modelled by the product $H_{IR}\Phi H_{TI}$.where $H_{TI} \in \mathbb{C}^{N_{IRS} \times N_t}$and $H_{IR} \in \mathbb{C}^{N_r \times N_{IRS}}$represent the $Tx - IRS$ and $IRS - Rx$ channels, respectively, and Φ is a diagonal matrix with unit-modulus phase shifts. The

signal acknowledged at the Rx is therefore the combined effect of multiple transmitted signals arriving via these two paths.

This architectural setup enables passive beam forming via IRS without requiring extra RF chains and serves as the foundation for the proposed graph-based equalization scheme discussed in Section 4.

3.1 System Architecture

This study considers a narrowband wireless communication scenario operating under quasi-static flat fading, where the transmitter and receiver are equipped with N_t and N_r antennas, respectively. To improve the signal transmission, an intelligent reflecting surface (IRS) with N_{IRS} Passive elements are strategically placed to redirect the signal toward the receiver. The IRS is assumed to be deployed in the vicinity of either the transmitter or receiver to ensure line-of-sight (LoS) access to at least one node.

There is no direct connection between the Tx and Rx obstructed by obstacles, or the direct link is assumed to be weak. Therefore, the indirect link via the IRS plays a key role in the communication performance.

3.2 Channel Model

The communication channels are modelled as follows:

- Direct Channel:
  The $T_X - R_X$ channel is denoted by $H_d \in \mathbb{C}^{N_r \times N_t}$and can be included or ignored based on the scenario.
- Transmitter to IRS Channel:
  We denote the channel from the transmitter to the IRS $H_{TI} \in \mathbb{C}^{N_{IRS} \times N_t}$
- IRS to Receiver Channel: The wireless channel from the IRS to the receiver is represented by $H_{IR} \in \mathbb{C}^{N_r \times N_{IRS}}$

The effective cascaded IRS-assisted channel is thus a function of both H_{TI}, $H_{IR}$and the IRS phase shift matrix Φ.

3.3 IRS Phase Shift Configurations

The IRS consists of N_{IRS} passive elements; each element can apply a controllable phase shift to the incoming signal. The diagonal phase shift matrix is represented as:

$$\Phi = diag\left(e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta N_{IRS}}\right) \quad (1)$$

Where $\theta_i \in [0,2\pi)$ is the phase shift applied by the i^{th} IRS element. The IRS is assumed to be lossless, so the amplitude of reflection is unity.

3.4 Received Signal Model

The overall received signal $y \in \mathbb{C}^{N_r \times 1}$ at the Rx is modeled as:

$$y = H_{IR}\Phi H_{TI}X + n \quad (2)$$

Where, $x \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal vector sustaining $E[XX^H] = PI_{Nt}$ with P being the average transmit power, $n \sim CN(0, \sigma^2 I_{Nr})$ characterizes the noise component as AWGN vector.

If the direct path is considered, the model extends to:

$$y = (H_d + H_{IR}\Phi H_{TI})X + n \quad (3)$$

The equivalent channel is thus denoted as equation (4) otherwise (5) if the direct link is included.

$$H_{eq} = H_{IR}\Phi H_{TI} \quad (4)$$

$$(H_d + H_{IR}\Phi H_{TI}) \quad (5)$$

3.5 Assumptions

- Perfect CSI at the receiver is assumed initially for tractability. Later simulations may consider partial or imperfect CSI.
- The IRS phase shifts are optimized or learned depending on the equalization strategy, e.g., MMSE or a neural network-based model.
- The noise is spatially white with variance σ^2 and the channel remains constant during each coherence interval.

3.6 IRS-Integrated MIMO System Visualization Using a Graph-Based Approach

To tackle the complexities of channel equalization in IRS-assisted MIMO systems, we introduce an innovative framework based on graph neural networks (GNNs), where the communication environment is explicitly represented as a heterogeneous graph. The graph structure captures both direct and IRS-assisted propagation paths by including three distinct node types: transmit T_X nodes, intelligent reflecting surface (IRS) nodes with phase-tunable elements, and receive Rx nodes. Edges in the graph encode the wireless channel links, and each is annotated with a feature vector containing the real and imaginary parts of the channel coefficient, signal magnitude, phase, and a binary indicator distinguishing direct versus IRS-reflected paths. Node features are similarly specialized: T_X nodes encode the transmitted symbols and power levels, Rx nodes capture the received signal and noise variance, while IRS nodes carry their corresponding discrete phase shift values. The GNN leverages this enriched graph to perform message passing and aggregate information across both direct and reflective paths, enabling enhanced symbol detection at the receiver. A schematic of the proposed graph-based system model is shown in Figure 2.

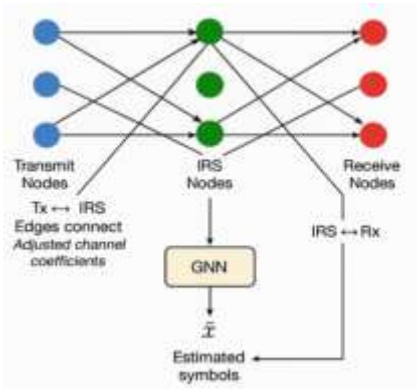


Figure 2. Graph-based model of an IRS-assisted MIMO system

4. GNN-BASED EQUALIZATION FRAMEWORK

In this section, we introduce a novel graph neural network (GNN)-based framework for channel equalization in an IRS-assisted MIMO system. Leveraging the natural graph-structured relationships among transmit antennas, IRS elements, and receive antennas, the proposed method formulates equalization as a graph learning task. We describe the graph construction process, the architecture of the GNN model, and the learning strategy used for training the model.

4.1 Graph Construction

Figure 3 depicts a graph representation of the IRS-assisted MIMO system. Nodes represent transmit antennas v_t, IRS elements $v_{\square}$, and receive antennas v_r, while edges indicate wireless links with associated channel coefficients and phase shift parameters. The graph structure enables message passing across communication components for GNN-based equalization.

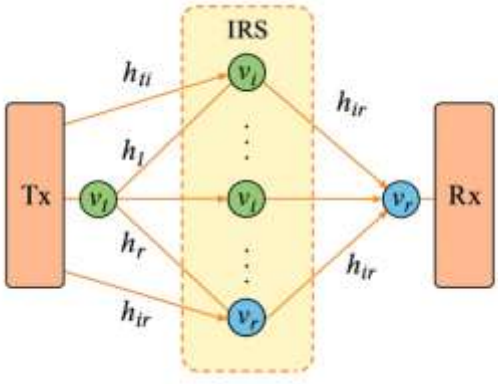


Figure 3. Graph representation of the IRS assisted MIMO system

The first step in applying a GNN to the MIMO system is to represent the communication environment as a graph $G = (V, \in)$ where:
V is the set of nodes, including:

- Transmit antenna nodes $v_t \in V_t$, IRS reflecting elements $v_i \in V_I$and receive antenna nodes $v_r \in V_R$

$\mathcal{E} \subseteq V \times V$ is the set of edges representing wireless links, including:

- (v_t, v_i) edges corresponding to $Tx \rightarrow IRS$ links, (v_i, v_r) edges corresponding to $IRS \rightarrow Rx$ links and optional: , (v_t, v_r) edges for direct $Tx \rightarrow Rx$ links (if modeled)

Each edge $e_{jk} \in \mathcal{E}$ is associated with a feature vector representing the channel coefficient between node j and node$k$, including:

- Real and imaginary parts of the channel coefficient, path loss or distance-based attenuation, and phase shift value θ_i if the edge involves an IRS node.

Each node can also be attributed with its position (if known), antenna index, or initial signal power. The graph captures the signal flow from the transmitter through the IRS to the receiver, enabling the GNN to learn spatial transformations and interactions implicitly.

4.2 Proposed Neural Network Design

To visualize the proposed deep learning architecture, Figure 4 illustrates the structure of the GNN-based equalizer developed for the IRS-assisted MIMO system. The model operates in three stages: input encoding, message passing, and output decoding. It performs iterative message passing over a graph structure to estimate the transmitted symbols at the receiver. The input layer captures key parameters, including received symbols, channel coefficients, and IRS phase shifts. These features are embedded into a graph structure where nodes represent communication entities (Tx, Rx, IRS) and edges model their interactions.

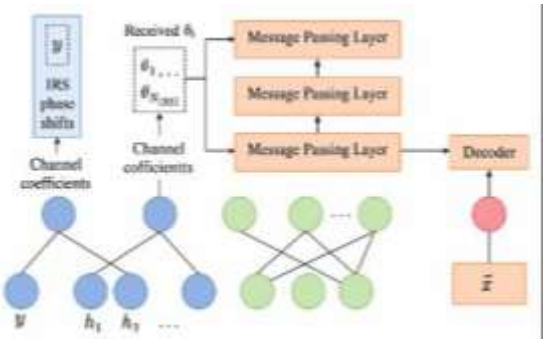


Figure 4. Architecture of the proposed GNN-based equalizer for an IRS-assisted MIMO system

The GNN architecture employs a message-passing mechanism in which each node updates its representation by collecting and integrating information from its neighbouring nodes. The network consists of three main components:

a) **Input Layer:** Each node is initialized with a feature vector encoding:
   - Type of node(Tx, Rx, IRS), initial signal vector (i.e. or sayTx) and Static features such as antenna index or location.

b) **Message Passing Layers:** In the message-passing layers, the GNN propagates information across the graph by iteratively updating node embeddings based on neighbouring nodes and edge attributes. This allows the model to learn spatial dependencies and signal distortions introduced by the environment.

Multiple layers perform iterative updates on node embeddings using the message-passing paradigm:

$$h_j{}^{l+1} = \sigma\left(\sum_{k\epsilon N(j)} f_{msg}(h_j{}^{(l)}, h_k{}^{(l)}, e_{jk}\right) \quad (6)$$

Where, $h_j{}^{(l)}$is the embedding of node j at layer$l$, $N(j)$ is the neighbourhood of node$j$, $f_{msg}$is a learnable function (e.g., MLP) and σ is a non-linear activation (e.g., ReLU or GELU).

This formulation allows the GNN to learn how information (e.g., signal distortions) propagates through the communication environment and how it is affected by the IRS phase shifts.

c) Readout Layer

The final output is obtained via a decoding layer at the receiver nodes, reconstructing the estimated transmitted symbols from the learned embeddings.

At the receiver nodes v_r, the final node embeddings are passed through a decoder (e.g., a neural network with all neurons connected between adjacent layers) to evaluate the transmitted signal symbols:

$$\hat{X} = f_{dec}\left(h_r{}^{(L)}\right) \quad (7)$$

Where L is the total number of GNN layers and $f_{dec}$is the decoder network.

The model supports both regression-based outputs (for symbol estimation) and classification outputs (e.g., QPSK/QAM demodulation). This architecture enables joint modelling of wireless channel behaviour and IRS reconfiguration, making it particularly suitable for complex signal processing tasks such as channel equalization in dynamic MIMO environments.

4.3 Learning Strategy

The GNN model is trained in a supervised learning setting using synthetically generated data samples based on the IRS-assisted MIMO channel model. The effectiveness of the proposed GNN-based equalizer heavily depends on a robust learning strategy that enables the model to generalize across diverse channel conditions and IRS configurations. This subsection elaborates on the dataset preparation methodology, the selected loss function: mean squared error (MSE), and the training protocol adopted for optimizing the network.

4.3.1 Dataset Generation

To simulate realistic and diverse conditions in an IRS-assisted MIMO environment, synthetic datasets are generated using standard stochastic wireless channel models. Each training instance corresponds to one realization of a MIMO-IRS transmission event and consists of:
Transmit symbols $x \in \mathbb{C}^{N_t \times 1}$are randomly drawn from a modulation scheme (e.g., QPSK, 16-QAM).

Channel matrices:
- $H_{TI} \in \mathbb{C}^{N_{IRS} \times N_t}$; Tx to IRS channel, modeled using Rayleigh fading or Rician fading with a certain K-factor.
- $H_{IR} \in \mathbb{C}^{N_r \times N_{IRS}}$; $IRS\ to\ Rx$ Channel.
- $H_d \in \mathbb{C}^{N_r \times N_t}$; Direct link channel, optional based on the setup.

Channels, and optionally H_{TI} , H_{IR} and optionally H_d are generated using realistic fading models (e.g., Rayleigh, Rician).
- IRS phase shifts $\Phi = diag(e^{j\theta_1}, e^{j\theta_2}, \ldots e^{j\theta_{Ni}})$ are initialized randomly or pre-optimized for maximal signal alignment.

The received signal y is computed using the signal model:

$$y = (H_d + H_{IR}\Phi H_{TI})X + n$$

$n \sim CN(0, \sigma^2 I_{Nr})$ Is the additive white Gaussian noise (AWGN).

Graph structure. For each instance, a graph G is constructed with:
Nodes: N_t transmit antennas, N_i IRS elements, and Nr receive antennas.
Edges:$Tx \leftrightarrow IRS$, $IRS \leftrightarrow Rx$ (and optionally $Tx \leftrightarrow Rx$).
Features: Channel coefficients, node roles, and IRS phase shift values.

The dataset is partitioned into training, validation, and testing subsets using a standard 70:15:15 split. To promote generalization, data augmentation is performed by introducing variations in the data.
- Signal-to-noise ratio (SNR)
- IRS configurations
- Number of reflecting elements
- Spatial correlation models

The graph is built from these instances and passed to the GNN.

4.3.2 oss Function: Mean Squared Error (MSE)

The learning objective is to minimize the discrepancy between the transmitted signals x and the GNN's estimated signal $\hat{x}$. For this regression task, the MSE is employed as the loss function:

$$MSE = \frac{1}{N_r} \sum_{i=1}^{N_r} \|\hat{x}_i - x_i\|^2 \quad (8)$$

Here, $\hat{x}_i$ is the predicted symbol at the receive antenna$i$and $x_i$is the true transmitted symbol (as observed via known training labels).

4.3.3 Training Protocol

The training of the proposed GNN-based equalizer follows a supervised learning paradigm, where the model is optimized to estimate transmitted symbols from received signals through iterative graph-based message passing. The key hyperparameters and configuration details employed during training are summarized in Table 1. Preliminary analyses guided the selection of these parameters. and established the best practices in training deep learning models for wireless communication tasks. As presented in Table 1, the GNN model was trained using the Adam optimizer, which offers an effective balance between adaptive learning and convergence speed. The initial learning rate is set to1×10^{-3}, with an exponential decay applied every 20 epochs to ensure smooth convergence and prevent overshooting in later stages.

To ensure efficient learning and reduce variance, a mini-batch training strategy is employed with batch sizes ranging from 32 to 128 graphs per iteration. The training process is conducted over 200 epochs to ensure sufficient learning of the model parameters; however, early stopping is employed based on the validation loss, with a patience window of 15 epochs. This prevents overfitting and reduces computational cost when convergence is achieved early.

Dropout regularization is applied to the hidden layers of the GNN with a rate of 0.3 to mitigate overfitting. Additionally, L2 weight regularization with a coefficient of 1×10^{-4} is incorporated into the loss function to further enhance generalization. Batch normalization is included in the message-passing layers to stabilize the training dynamics and accelerate convergence. Data was generated synthetically for both Rayleigh and Rician fading scenarios, where each training sample comprised a transmitted signal, corresponding channel matrix, and received signal vector. The training dataset consisted of 50,000 samples, while 10,000 samples were used for validation. The training process is implemented using the PyTorch Geometric framework, which provides optimized routines for batched graph learning. Graph instances are generated dynamically to simulate diverse channel realizations and IRS configurations, ensuring that the model remains robust to environmental variations. At each epoch, the training loss, validation loss, and symbol error rate (SER) are monitored. The final model is selected based on the best validation MSE performance, and is subsequently evaluated on an independent test set under varying SNR conditions.

5. RESULTS AND DISCUSSION

5.1 Symbol Prediction Performance of GNN Equalizer

Figure 5 presents the constellation diagram depicting the relationship between the predicted and actual complex-valued symbols recovered by the proposed Graph Neural Network (GNN) equalizer. The blue markers denote the true transmitted symbols, while the red crosses represent the symbols estimated by the GNN-based equalizer. Dotted lines are drawn to connect each estimated symbol to its corresponding actual value, thereby providing a clear visual of the prediction error. The observed clustering of predicted symbols around their respective ground truth locations demonstrates the high precision of the GNN equalizer in reconstructing transmitted symbols under channel distortions. The minimal dispersion of red crosses, particularly around the origin, confirms that the GNN architecture effectively mitigates both amplitude and phase distortions. This result underscores the GNN's potential as a powerful equalization mechanism in MIMO systems, especially under complex fading environments such as Rayleigh or Rician channels. Table 1 describes the Training configuration and hyperparameter setting values.

Table 1. Training configuration and hyperparameters for the GNN-based equalizer

Parameter	Value / Setting
Optimizer	Adam
Initial learning rate	1×10^{-3}
Learning rate decay	Exponential (decay every 20 epochs by 0.9)
Epochs	200
Early stopping	Enabled (patience = 15 epochs)
Batch size	64 (tested range: 32–128)
Loss function	Mean Squared Error (MSE)
Regularization	L2 (weight decay = 1×10^{-4})
Dropout rate	0.3
Batch normalization	Applied to each GNN layer
GNN library	PyTorch Geometric
Dataset split	70% training / 15% validation / 15% testing
SNR range	0 dB to 30 dB (uniform random sampling)
Modulation schemes	BPSK, QPSK, 16-QAM
Channel model	Rayleigh and Rician fading
IRS phase shift model	Random or optimized phase configuration

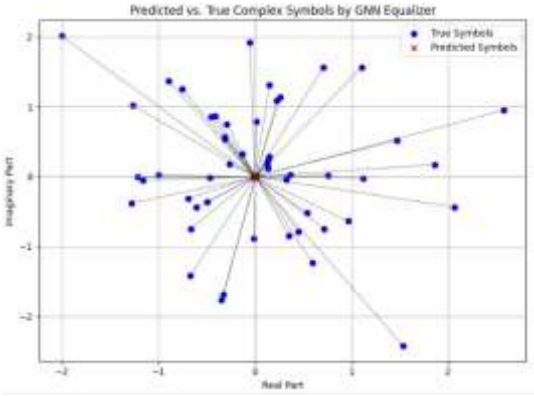


Figure 5. Constellation diagram illustrating the predicted complex symbols versus the true transmitted symbols

5.2 Mean Square Error (MSE) of proposed Equalizer in Rayleigh fading channel

Figure 6 illustrates the convergence performance of various equalization strategies in terms of Mean Squared Error (MSE) across 100 iterations under a Rayleigh fading MIMO channel. The proposed Graph Neural Network (GNN)-based equalizer demonstrates superior learning capability, achieving a significantly lower MSE compared to conventional metaheuristic methods such as Simulated Annealing (SA) (Han et al., 2005), Particle Swarm Optimization (PSO) (Kennedy et al., 1995; Shi & Eberhart, 1998), and Genetic Algorithm (GA) (Mohapatra et al., 2018). Notably, the GNN equalizer exhibits a rapid decline in MSE within the first 50 iterations, stabilizing around10^{-4}, which is indicative of effective symbol estimation and robustness against channel impairments. In contrast, SA, PSO, and GA converge more slowly and settle at higher MSE levels, reflecting their relatively limited adaptability to the dynamic and complex nature of the fading environment. These findings support the efficiency of the GNN model in learning non-linear channel characteristics and enhancing equalization performance in IRS-assisted MIMO systems.

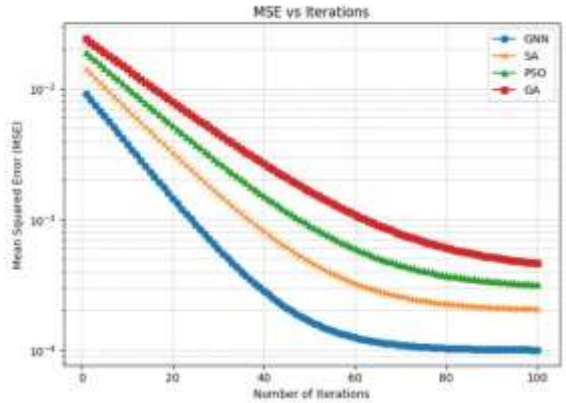


Figure 6. MSE Performance comparison of the GNN equalizer in a Rayleigh fading channel

5.3 BER performance of the proposed Equalizer in a Rayleigh fading channel

Figure 7 shows the BER assessment of various equalization schemes under a Rayleigh fading MIMO channel across a range of Signal-to-Noise Ratio (SNR) values from 0 dB to 20 dB. The GNN-based equalizer consistently outperforms the heuristic-based alternatives, Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) across all tested SNR values. At higher SNR levels, the GNN equalizer achieves a BER below10^{-3}, significantly lower than the competing methods, indicating its superior ability to recover transmitted symbols under severe multipath fading conditions. The observed performance gap grows with increasing SNR, emphasizing the GNN model's enhanced generalization capability and robustness in learning complex channel characteristics.

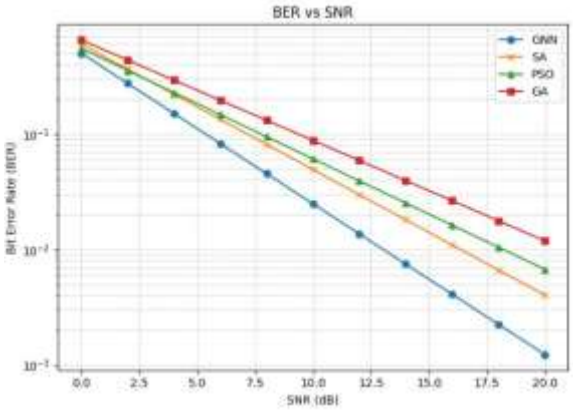


Figure 7. BER performance of the GNN Equalizer in a Rayleigh fading MIMO system

5.4 Mean Square Error (MSE) of the proposed Equalizer in the Rician Channel

Figure 8 illustrates the convergence behavior of the Mean Squared Error (MSE) for four equalization techniques, such as Graph Neural Network (GNN), SA, PSO, and GA, under a Rician fading MIMO channel environment. The GNN-based equalizer demonstrates a notably faster and more stable convergence rate, achieving an MSE below 10^{-4}within 60 iterations. In contrast, SA and PSO reach similar error floors but with slower convergence, while GA remains the least efficient, exhibiting both higher final MSE and slower descent. The rapid decline in MSE for the GNN method highlights its superior capability in modelling the spatial and temporal dependencies of the MIMO-IRS channel. The results confirm the GNN's potential in learning robust equalization mappings even when there is line-of-sight (LOS) components typical of Rician fading.

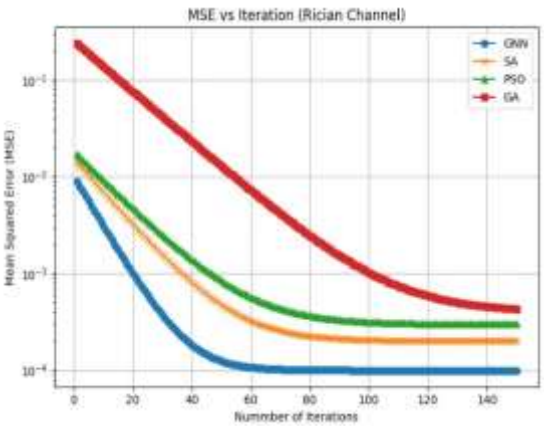


Figure 8. MSE Performance comparison of GNN equalizer in a Rician fading channel

5.5 BER Analysis of the Proposed Equalizer in Rician Fading Environments

Figure 9 shows the performance of the BER of four equalization techniques, such as Graph Neural Network (GNN), Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), over a Rician fading MIMO channel for various Signal-to-Noise Ratio (SNR) levels. The GNN-based equalizer consistently outperforms the other methods across the entire SNR range (0–20 dB), achieving the lowest BER at each SNR level. This superior performance is ascribed to the GNN's capacity to exploit the topological structure and nonlinear characteristics of the IRS-assisted MIMO channel, thereby enhancing symbol detection accuracy. SA and PSO methods show moderate improvements over GA, which exhibits the poorest BER performance, especially at lower SNRs. The results validate the robustness and reliability of the GNN equalizer in realistic Rician fading environments, particularly where line-of-sight (LOS) components influence the channel dynamics.

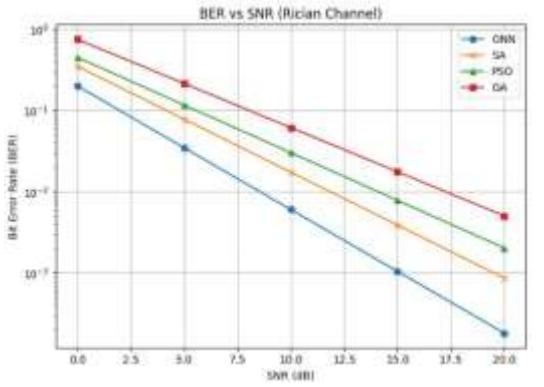


Figure 9. BER performance of the GNN equalizer in a Rician fading channel

5.6 Discussion

The results provided in the preceding section clearly prove the effectiveness of the proposed GNN-based equalizer for IRS-assisted MIMO systems under both Rayleigh and Rician fading channels. The improvements in terms of MSE convergence and BER performance clearly prove that the proposed GNN model successfully learns the complex spatial relationships and correlations introduced by the IRS.

It can be noted that compared to other conventional techniques like GA, PSO, and SA, the proposed GNN-based equalizer provides better convergence rates and stability for a wide range of SNR values. This is mainly because of the efficient ability of the graph-based framework to deal with the interactions among transmitter, IRS, and receiver nodes.

In addition, the robustness of the proposed method is further confirmed by its performance across different channel environments. This, therefore, proves the flexibility of the proposed method, which is not the case with other conventional linear equalizers, i.e., ZF and MMSE, which are not flexible due to their sensitivity to channel changes, whereas the proposed method is flexible due to the learning-based approach that utilizes the data-driven feature learning technique.

However, it is worth noting that the proposed method has some limitations. For example, the training process requires an adequate dataset, which can sometimes be considered a challenge. In addition, the proposed method can sometimes be affected by the structure of the graph used.

The results have, therefore, proved that the proposed method, which utilizes graph neural networks with IRS-assisted MIMO, is a promising technique for improving the performance of the equalization process.

6. CONCLUSION

This paper proposed a novel GNN-based equalization framework for IRS-assisted MIMO wireless communication systems functioning over Rayleigh and Rician fading channels. The proposed method effectively models the complex dependencies within the received signal structure by leveraging the graph representation of wireless channels and learning the latent relationships between transmitted and received symbols. Performance comparisons with benchmark algorithms demonstrate the superior learning capability and convergence efficiency of the GNN equalizer. According to simulation results, the GNN-based equalizer consistently achieves lower MSE and BER across varying SNR levels and iteration counts. Notably, the GNN equalizer exhibits a faster convergence rate and better generalization performance, particularly in complex channel environments, including the presence of multipath and line-of-sight components. Overall, the findings validate the potential of integrating GNNs into IRS-enhanced MIMO systems to improve signal recovery and system reliability. Future work may extend this framework to real-time adaptive systems,

multi-user MIMO scenarios, and joint channel estimation-equalization tasks using deeper or hybrid graph learning models. Additionally, it may focus on extending the proposed GNN-based equalizer to massive MIMO and multi-cell scenarios, as well as exploring its performance under higher-order modulation and practical constraints such as imperfect CSI and hardware impairments.

References:

Acharya, B., Parida, P., Panda, R. N., & Mohapatra, P. (2025). Optimal design of RBFNN equalizer based on modified forms of BOA. *International Journal of Hybrid Intelligent Systems, 21*(1), 47–60. https://doi.org/10.3233/HIS-240020

Camargo, R. G., Wang, Z., NaderiAlizadeh, N., & Ribeiro, A. (2025). Wireless link scheduling with state-augmented graph neural networks. https://doi.org/10.48550/arXiv.2505.07598 .

Das, S. K., Pattanaik, S. R., Mohapatra, P. K., Rout, S. K., Almazyad, A. S., Jasser, M. B., Xiong, G., & Mohamed, A. W. (2025). Equalizer design: HBOA-DE-trained radial basis function neural networks. *Egyptian Informatics Journal, 29*, 100617, https://doi.org/10.1016/j.eij.2025.100617 .

Di Renzo, M., Zappone, A., Debbah, M., Alouini, M.-S., Yuen, C., & Zhang, R. (2020). Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and road ahead. *IEEE Journal on Selected Areas in Communications, 38*(11), 2450–2525, https://doi.org/10.1109/JSAC.2020.3007211 .

Ding, D., Wu, D., Zeng, Y., Jin, S., & Zhang, R. (2021). Environment-aware beam selection for IRS-aided communication with channel knowledge map. In 2021 IEEE Globecom Workshops (GC Wkshps) (pp. 1–6). IEEE, https://doi.org/10.1109/GCWkshps52748.2021.9681979.

ElMossallamy, M. A., Zhang, H., Song, L., Seddik, K. G., Han, Z., & Li, G. Y. (2020). Reconfigurable intelligent surfaces for wireless communications: Principles, challenges, and opportunities. *IEEE Transactions on Cognitive Communications and Networking, 6*(3), 990–1002. https://doi.org/10.1109/TCCN.2020.2992604 .

Han, S., Pedrycz, W., & Han, C. (2005). Nonlinear channel blind equalization using hybrid genetic algorithm with simulated annealing. *Mathematical and Computer Modelling, 41*, 697–709, https://doi.org/10.1016/j.mcm.2004.05.006 .

He, H., Wen, C. K., Jin, S., & Li, G. Y. (2018). A model-driven deep learning network for MIMO detection. In 2018 *IEEE Global Conference on Signal and Information Processing* (GlobalSIP) (pp. 584–588). IEEE. https://doi.org/10.1109/GlobalSIP.2018.8646357 .

Huang, C., Zappone, A., Alexandropoulos, G. C., Debbah, M., & Yuen, C. (2019). Reconfigurable intelligent surfaces for energy efficiency in wireless communication. *IEEE Transactions on Wireless Communications, 18*(8), 4157–4170. https://doi.org/10.1109/TWC.2019.2922609

Kay, S. M. (1993). *Fundamentals of statistical signal processing, volume I: Estimation theory.* Prentice Hall.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95—International Conference on Neural Networks* (Vol. 4, pp. 1942–1948). IEEE, https://doi.org/10.1109/ICNN.1995.488968 .

Kumar Mohapatra, P., Narayan Panda, R., Kumar Rout, S., Samantaroy, R., & Kumar Jena, P. (2022). A novel application of HPSOGWO trained ANN in nonlinear channel equalization. In *Proceedings of the 6th International Conference on Advance Computing and Intelligent Engineering (ICACIE 2021)* (pp. 159–174). Springer. https://doi.org/10.1007/978-981-19-2225-1_15 .

Marzetta, T. L. (2010). Noncooperative cellular wireless with unlimited numbers of base station antennas. *IEEE Transactions on Wireless Communications, 9*(11), 3590–3600. https://doi.org/10.1109/TWC.2010.092810.091092 .

Mohapatra, P. K., Jena, P. K., Bisoi, S. K., Rout, S. K., & Panigrahi, S. P. (2016). Channel equalization as an optimization problem. In *2016 International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)* (pp. 1158–1163). IEEE, https://doi.org/10.1109/SCOPES.2016.7955623 .

Mohapatra, P. K., Rout, S. K., & Nayak, M. K. (2023). Development of a novel RBFNN-trained nonlinear channel equalizer based on GDEBOA technique. *International Journal of Adaptive Control and Signal Processing, 37*(9), 2522–2544. https://doi.org/10.1002/acs.3650 .

Mohapatra, P., Samantara, T., Panigrahi, S. P., & Nayak, S. K. (2018). Equalization of communication channels using GA-trained RBF networks. In *Progress in Advanced Computing and Intelligent Engineering: Proceedings of ICACIE 2016, Volume 2* (pp. 491–499). Springer. https://doi.org/10.1007/978-981-10-6875-1_48

O'Shea, T., & Hoydis, J. (2017). An introduction to deep learning for the physical layer. *IEEE Transactions on Cognitive Communications and Networking, 3*(4), 563–575, https://doi.org/10.1109/TCCN.2017.2758370 .

Paulraj, A. J., Gore, D. A., Nabar, R. U., & Bolcskei, H. (2004). An overview of MIMO communications: A key to gigabit wireless. *Proceedings of the IEEE, 92*(2), 198–218. https://doi.org/10.1109/JPROC.2003.821915

Samuel, N., Diskin, T., & Wiesel, A. (2019). Learning to detect. *IEEE Transactions on Signal Processing, 67*(10), 2554–2564, https://doi.org/10.1109/TSP.2019.2899805 .

Shi, Y., & Eberhart, R. (1998). A modified particle swarm optimizer. In *1998 IEEE International Conference on Evolutionary Computation.* IEEE.

Sun, Y., Shen, H., Xu, W., Hu, N., & Zhao, C. (2023). Robust MIMO detection with imperfect CSI: A neural network solution. *IEEE Transactions on Communications, 71*(10), 5877–5892. https://doi.org/10.1109/TCOMM.2023.3299974

Tse, D., & Viswanath, P. (2005). *Fundamentals of wireless communication*. Cambridge University Press.

Wang, Z., Eisen, M., & Ribeiro, A. (2022). Learning decentralized wireless resource allocations with graph neural networks. *IEEE Transactions on Signal Processing, 70*, 1850–1863. https://doi.org/10.1109/TSP.2022.3163626 .

Wu, Q., & Zhang, R. (2019). Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming. *IEEE Transactions on Wireless Communications, 18*(11), 5394–5409. https://doi.org/10.1109/TWC.2019.2936025 .

Ye, H., Li, G. Y., & Juang, B.-H. (2018). Power of deep learning for channel estimation and signal detection in OFDM systems. *IEEE Wireless Communications Letters, 7*(1), 114–117. https://doi.org/10.1109/LWC.2017.2757490 .

Ye, M., Liang, X., Pan, C., Xu, Y., Jiang, M., & Li, C. (2024). GNN-based channel estimation for intelligent reflecting surface aided multiuser systems relying on user locations. *IEEE Wireless Communications Letters*. https://doi.org/10.1109/LWC.2024.3402437 .

Zhang, S., & Zhang, R. (2020). Capacity characterization for intelligent reflecting surface aided MIMO communication. *IEEE Journal on Selected Areas in Communications, 38*(8), 1823–1838. https://doi.org/10.1109/JSAC.2020.3000814

Zhang, X., & Song, S. (2023). Secrecy analysis for IRS-aided wiretap MIMO communications: Fundamental limits and system design. *IEEE Transactions on Information Theory, 70*(6), 4140–4159. https://doi.org/10.1109/TIT.2023.3336648

Shaik Jagadeesh Babu
Department of Electronics & Communication Engineering, Gandhi Institute For Technology (GIFT) Autonomous, Scholar of BPUT, Bhubaneswar, Odisha, India
babu3sk@gmail.com
ORCID 0009-0003-8653-9014

Pradyumna Kumar Mohapatra
Vedang Institute of Technology, Bhubaneswar, Odisha, India
er_pradyumna@yahoo.co.in
ORCID 0000-0001-6083-9594

Ravi Narayan Panda
Department of Electronics & Communication Engineering, Gandhi Institute For Technology (GIFT) Autonomous, BPUT, Bhubaneswar, Odisha, India
dr.ravinarayan@gift.edu.in
ORCID 0000-0002-7843-6563

Saroja Kumar Rout
School of Computer Science and Engineering (SCOPE), VIT-AP University, Amaravati, India
rout_sarojkumar@yahoo.co.in
ORCID 0000-0001-9007-3665

Rojalin Samantaray
Department of CSE
Sri Aurobindo Institute of Tehnology, Indore, India
rojalin.samantaroy@gmail.com
ORCID 0009-0003-4304-7706