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AdaptGNN: A self-supervised graph neural network with test-time adaptation for robust multiuser detection in MC-CDMA systems

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Multiuser detection in multicarrier-code-division multiple access (MC-CDMA) systems is a critical problem, especially in a situation where the user densities are high, channel conditions are dynamically changing, and therefore, labelled data is scarce. The current paper introduces AdaptGNN, a self-supervised graph neural network (GNN) receiver that learns the MC-CDMA uplink by treating the actors as a heterogeneous graph of users and subcarriers, meaning that the interference topology is explicitly represented in the receiver. The self-supervised tasks, including masked subcarrier reconstruction, interference-edge prediction, and contrastive representation learning, facilitate the direct learning of interference-aware embeddings from the received waveforms, without the need for manually annotated labels. To improve operational robustness, a self-supervised test-time adaptation (TTA) system is integrated; the system adapts a limited set of model parameters during inference on unlabeled test examples and therefore mitigates distributional change caused by changes in user load and channel statistics. Monte Carlo simulations under Rayleigh fading conditions demonstrate that AdaptGNN significantly reduces bit-error rate (BER) and outperforms traditional multiuser detection methods, particularly in highly congested interference environments. Besides, the method reduces the latency of detection and has a high resistance to channel estimation errors compared to traditional detectors and graph-based models. These results highlight that AdaptGNN is well-positioned to serve as a scalable and efficient receiver for deployment in dense and dynamic wireless environments.

Keywords: MC-CDMA, graph neural networks (GNNs), self-supervised learning, test-time adaptation (TTA), multiuser detection, wireless communications

1 Introduction

Recent developments in the wireless communication standard to the 6G generation have realized the need to reevaluate the development of robust access methods that will be able to support massive machine-type communications (mMTC). Multi-Carrier Code Division Multiple Access (MC-CDMA) is still a research topic of interest due to its special blend of frequency diversity of Orthogonal Frequency Division Multiplexing (OFDM) and the advanced multiple-access capability of Code Division Multiple Access (CDMA). MC-CDMA provides extremely high spectral efficiency by providing symbols on several subcarriers with distinct signature code sequences, and intrinsic resistance to frequency-selective fading. Theoretical potential of MC-CDMA is often lost in practice in the uplink case: once the number of active users (or users) surpasses the available number of subcarriers – an overloaded regime – the orthogonality of spreading codes is destroyed by the compound effects of multipath propagation and asynchronous transmissions [1]. This depreciation causes disastrous multiuser interference (MUI), which makes multiuser detection (MUD) problem more sophisticated.

Conventional detection models, e.g., Minimum Mean Square Error (MMSE) or Maximum Likelihood (ML) detectors have a devastating trade-off between computational efficiency and detection error. As much as ML detection offers an ideal bit error rate (BER), its exponential complexity makes it impractical to use in dense networks. Linear receivers like MMSE, on the other hand are computationally efficient but have a large performance floor with strong MUI and non-Gaussian noise.

The recent years have seen a paradigm shift to deep learning (DL) based receivers [2], which attempt to learn a mapping between received signals and bits transmitted by a transmitter. However, these data-based methods are mostly limited by their non-stochastic character: the vast majority of DL receivers have been trained on offline datasets that are produced at constant channel statistics, and thus perform poorly in generalization to out-of-distribution (OOD) conditions,

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including instantaneous changes in Rayleigh fading parameters or unexpected changes to the number of active users.

Research gap: Despite the proliferation of neural-based receivers, a critical gap remains in the literature. First, conventional CNNs and MLPs fail to exploit the relational topology of the MC-CDMA uplink, where the interference is intrinsically structured by the user-subcarrier bipartite mapping. Second, the reliance on labeled pilot signals for continuous retraining in dynamic environments imposes a prohibitive overhead on the limited spectral resources. Third, there is a lack of adaptive mechanisms that can refine the receiver's parameters at "test-time" without requiring ground-truth labels. While the work of Bendelhoum et al. [3] and Bendjillali et al. [4] has significantly advanced the state of channel coding in MC-CDMA through UTTCM, and Ilyas et al. [5] introduced temporal awareness via LSTMs, these methods still assume a relatively stable detection front-end that can provide reliable soft-estimates.

Contributions of this work: To address these fundamental limitations, we propose AdaptGNN, a self-supervised graph-based detection framework with the following contributions:

- **Topological representation learning:** We model the MC-CDMA uplink as a heterogeneous user-subcarrier graph, enabling the GNN to perform message-passing that explicitly captures the structure of MUI, leveraging the survey insights of Wu et al. [6] on GNN scalability.
- **Self-supervised objective triad:** We eliminate the need for labeled datasets by introducing a self-supervised learning strategy comprising masked reconstruction and contrastive representation, allowing the model to learn interference patterns directly from raw, unlabeled frames.
- **Test-time adaptation (TTA):** We integrate an online adaptation loop inspired by Wang et al. [7] and Shao et al. [8]. By minimizing prediction entropy during inference, AdaptGNN adjusts to instantaneous CSI errors and distribution shifts, ensuring robust MUD performance in dynamic environments.

2 Related works

Multi-user detection (MUD) in multi-carrier code-division multiple access (MC-CDMA) has developed multi-iterative signal-processing schemes to data-driven schemes. Here, we place our work in the existing environment of deep learning (DL) in MC-CDMA, graph-based receivers, and the emerging area of test-time adaptation. The first attempts to relate DL to the physical layer of MC-CDMA involved replacing the demapping and decoding processes. Bendelhoum et al. [3] and Bendjillali et al. [4] were the pioneers of neural-enhanced universal trellis-coded modulation (UTTCM), where deep architectures are demonstrated to significantly decrease the bit-error rate (BER) in frequency-selective fading channels. Based on this, Ilyas et al. [5] suggested attention enhanced long short term memory LSTM networks to emulate the temporal characteristics of uplink MC-CDMA channels, and hence provide an adaptive error correction system. However, these research works focused mostly on the channel coding, supposing a very simplistic detection phase. In pure detection, recent efforts have looked at deep-unfolding methods, which means that minimizing mean-square-error successive interference cancellation (MMSE-SIC) is brought to trainable neural networks, as depicted by Zhang et. al. [9]. Even though effective, these models are computationally intensive and require large labelled datasets to be trained. The AdaptGNN approach addresses these drawbacks with self-supervision. Graph representation modelling of interference is a recent development in wireless communications. Wu et al. defined the principles of the graph neural networks (GNNs) [6] and applied them to the interference management. Similar to MC-CDMA, Shao et al. [10] proposed a GNN-based receiver which outperforms the traditional message-passing algorithm (MPA) and pulls out the intrinsic factor graph. In addition, He et al. [11] came up with a heterogeneous GNN to detect multiple users in non-orthogonal multiple-access (NOMA) systems, and show that different types of nodes (user and resource) model nonlinear interference patterns more efficiently than traditional convolutional neural networks (CNNs). The proposed contribution, AdaptGNN, extends this paradigm to the MC-CDMA subcarrier user mapping, and therefore, the specific problem of code-domain interference, which has remained largely unaddressed in other GNN works, is tackled by Lu et al. [12]. The generalization gap effect of neural receivers with a decrease in performance when subjected to new channel conditions has stimulated the consideration of test-time adaptation (TTA). Shao et al. [8] demonstrated that TTA is capable of producing strong modulation recognition with the presence of unidentified distortions by performing online entropy minimization. This feature is especially relevant to MC-CDMA systems, where the number of active users is changing dynamically, as well as the fading statistics. While Wang et al. [7] introduced the Tent framework for general TTA, its application to graph-structured wireless data remained a challenge until the introduction of Graph TTA by Chen et al. [13]. AdaptGNN synthesizes these advancements, employing a self-supervised contrastive objective during the test phase to align the receiver's internal representations with the instantaneous channel state, a feat not achieved by existing MC-CDMA receivers.

3 Methodology

3.1 Mathematical model of the MC-CDMA system

The MC-CDMA system is a widely used communication technique where multiple users share the same frequency band, each utilizing a unique spreading code across different subcarriers. In this work, we model the MC-CDMA system with U active users and N subcarriers. The signal received at the n-th subcarrier is expressed as:

$$y_n = \sum_{u=1}^{U} h_{u,n} c_{u,n} x_u + w_n \tag{1}$$

where

- $h_{u,n}$ is the channel coefficient for user u on subcarrier n,
- $c_{u,n}$ is the spreading code for user u on subcarrier n,
- x_u is the transmitted symbol for user u,
- w_n represents additive white Gaussian noise (AWGN) at subcarrier n.

The objective is to recover the transmitted symbols x_u from the received signal y_n, while mitigating multi-user interference (MUI) that arises when users share subcarriers [14]. As shown in the following figure, the signal is received from different users and processed through the demodulation and multi-user interference mitigation techniques in the MC-CDMA system.

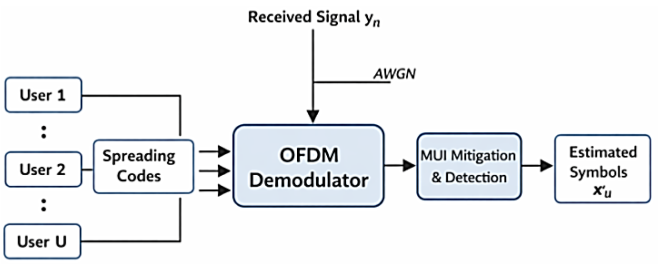

Fig. 1. Block diagram of the MC-CDMA receiver system

3.2 Graph-based representation of the MC-CDMA system

To enhance the detection process, we represent the MC-CDMA system as a heterogeneous graph. In this graph:

- User nodes v_u represent the active users.
- Subcarrier nodes v_n represent the available subcarriers.

The edges in the graph represent the interactions (or interference) between users and subcarriers, as well as the interference between users themselves due to shared subcarriers [15]. The graph is defined as:

$$\mathcal{G} = (\mathcal{V}_u \cup \mathcal{V}_n, \mathcal{E}) \tag{2}$$

where

- $\mathcal{V}_u$ is the set of user nodes,
- $\mathcal{V}_n$ is the set of subcarrier nodes,
- $\mathcal{E}$ is the set of edges representing interference relationships.

The edges are weighted based on the channel characteristics $h_{u,n}$ and the spreading codes $c_{u,n}$, which are crucial for modeling the interference patterns in the system. This graph-based representation allows the use of Graph Neural Networks (GNNs) to efficiently process and learn the complex interference dynamics between users and subcarriers.

3.3 Node features

In order to improve the performance of the model we come up with node features that reflect the important system properties that are examined in the process of detecting symbols [6]. These node features based on the signal and channel information are used to derive the node features on the users and subcarriers and thus add to the capacity of the model to correctly detect the symbols even in the context of interference.

3.3.1 User node features

$$f_u = \left[\sum_n \left|h_{u,n}\right|^2, \sum_n y_n c_{u,n}, SNR_{est}\right] \tag{3}$$

These characteristics include aggregated power of the subcarriers, interference pattern of each user and estimates signal to noises ratio (SNR).

3.3.2 Subcarrier node features

To be able to effectively describe the state of every subcarrier in the system, we present a feature vector which summarizes its core physical characteristics. For each subcarrier node v, the input feature vector x_v is constructed as follows:

$$x_v = [|y_v|^2, Re(y_n), Im(y_v)] \tag{4}$$

The purpose of these features is to have representation of the received power, i.e., the signal energy along with the phase and quadrature components. With these features, the GNN can better capture the interference dynamics and phase shift of the multi-user environment which is essential in the means of proper reconstruction of the signals [16]. In order to further improve the performance of the model, we design node features that make the model reflect important system-related characteristics that are relevant to the detection of symbols as shown in Fig. 2 below.

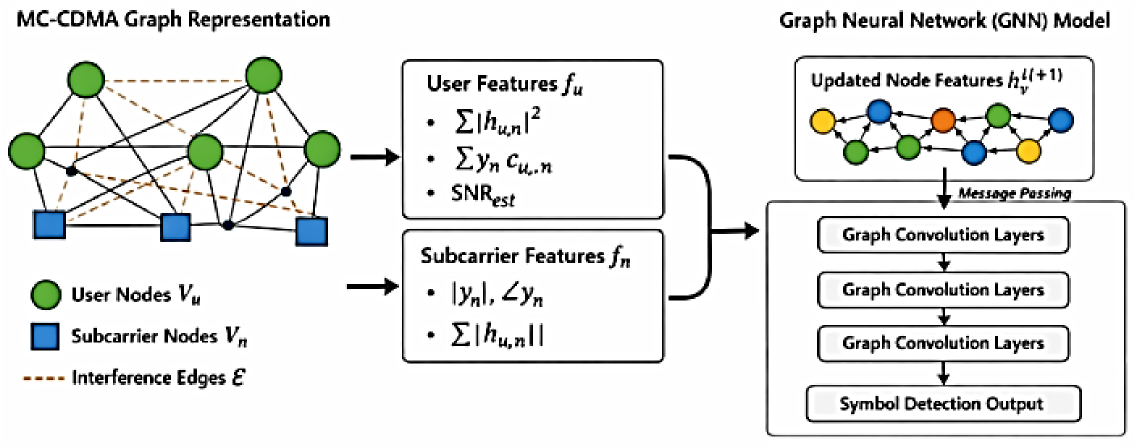

Fig. 2. Graph-based representation of the MC-CDMA system

Figure 2 shows the graphical diagram of MC-CDMA system, whereby users and subcarriers are represented by nodes and the interference edges link the nodes together. These edges are given weights based on the attributes of the channel used and utilised spreading codes which parameters are perceived essential in the assessment of the interference phenomena.

The graph representation allows the Graph Neural Network (GNN) to process complex interference dynamics between users and subcarriers, learning patterns that enhance symbol detection.

3.4 Graph neural network (GNN) architecture

We employ a multi-layer Graph Neural Network (GNN) to process the graph and learn interference patterns between users and subcarriers. The GNN uses graph convolution layers to pass messages between neighboring nodes [17, 18]. At each layer, the node representations are updated according to the following rule:

$$h_v^{(l+1)} = \sigma\left(W_0 h_u^{(l)} + \sum_{u\epsilon N(v)} \alpha_{vu} W_1 h_u^{(l)}\right) \tag{5}$$

where

- $h_u^{(l)}$ is the feature vector of node v at layer l,
- α_{vu} is the attenuation weight that determines the influence of neighboring nodes on the update of node v,
- $\sigma(\cdot)$ is a nonlinear activation function.

This message-passing mechanism allows the model to aggregate information from neighboring nodes, helping the GNN learn complex interference patterns and improving the accuracy of symbol detection.

3.5 Self-supervised learning tasks

To eliminate the need for labeled data, we train the model using self-supervised learning. This approach involves several tasks that help the model learn the interference patterns and signal representations without requiring labeled symbols [19, 20].

3.5.1 Masked subcarrier reconstruction

In this task, a random subset of subcarrier nodes is masked, and the model is trained to predict their values based on neighboring nodes:

$$\mathcal{L}_{mask} = \sum_{n\in M} ||\hat{y}_n - y_n||^2 \tag{6}$$

3.5.2 Interference edge prediction

This task involves predicting the presence and strength of interference between users. We define a binary variable $z_{u,u'}$ to indicate whether interference exists between users u and u':

$$z_{u,u'} = \begin{cases} 1, & if\ |w_{u,u'}| > \tau \\ 0, & otherwise \end{cases} \tag{7}$$

In this equation, $|w_{u,u'}|$ represents the absolute value of the weight $w_{u,u'}$, which can be considered as the L_1 norm. This absolute value is used to determine whether the interference between users exceeds a given τ threshold.

The loss function for this task is:

$$\mathcal{L}_{edge} = -\sum_{u,u'}\left(z_{u,u'}.\log\left(\hat{z}_{u,u'}+\epsilon\right) + \left(1-z_{u,u'}\right).\log\left(1-\hat{z}_{u,u'}+\epsilon\right)\right) \quad (8)$$

where ϵ is a small constant (e.g., 10^{-8}) added to avoid the issue of log(0) in the loss function.

3.5.3 Contrastive learning

This task maximizes the similarity between graph representations under different channel conditions (e.g., varying SNR, channel estimation errors) [21]:

$$\mathcal{L}_{con} = -\log\frac{\exp\left(\mathrm{sim}\left(z_u^{(1)},z_u^{(2)}\right)/\tau\right)}{\exp\left(\mathrm{sim}\left(z_u^{(1)},z_{u'}^{(2)}\right)/\tau\right)} \quad (9)$$

To illustrate the different tasks involved in self-supervised learning for interference pattern and signal representation learning, refer to Fig. 3 below.

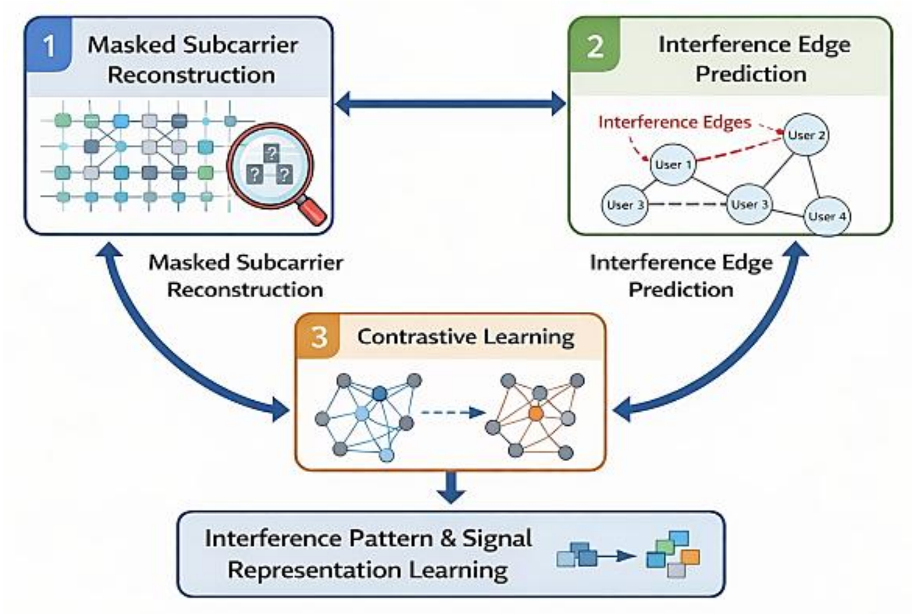

Fig. 3. Self-supervised learning tasks for interference and signal representation learning

As shown in Fig. 3, the three self-supervised learning tasks are executed in a cyclic sequence, aiding in the learning of interference patterns and signal representations without the need for labeled data.

3.6 Overall training objective

The final training objective is a weighted combination of the losses from the three self-supervised tasks:

$$\mathcal{L} = \lambda_1\mathcal{L}_{mask} + \lambda_2\mathcal{L}_{edge} + \lambda_3\mathcal{L}_{contrast} \quad (10)$$

where λ_1, λ_2, λ_3 are the weights assigned to each task.

3.7 Symbol detection

Once the model is trained, the transmitted symbols $\hat{x}_u$ are estimated by using the node representations from the final GNN layer:

$$\hat{x}_u = \mathrm{sign}\left(w^T h_u^{(L)}\right) \quad (11)$$

where w is the final detection weight vector.

3.8 Self-supervised test-time adaptation (TTA)

To mitigate train – test mismatch in practical MC-CDMA deployments (e.g., variations in load β, channel statistics, or residual hardware impairments), we augment the proposed receiver with a self-supervised test-time adaptation (TTA) procedure that refines a compact subset of model parameters during inference using only unlabeled received data [8]. Given a received frame $y = [y_1, \ldots, y_n]^T$ and its associated graph $\mathcal{G}$, we construct two stochastic graph views $\tilde{\mathcal{G}}^{(1)}$ and $\tilde{\mathcal{G}}^{(2)}$ by applying masking and mild perturbations to a subset of subcarrier nodes M. The adaptation objective reuses the self-supervised tasks previously defined, specifically the masked reconstruction and representation consistency tasks, the total adaptation loss is a weighted combination of these objectives:

$$L_{TTA} = \lambda_1 L_{mask}\left(\tilde{\mathcal{G}}^{(1)}\right) + \lambda_3 L_{con}\left(\tilde{\mathcal{G}}^{(1)},\tilde{\mathcal{G}}^{(2)}\right) \quad (12)$$

where L_{mask} captures the error from reconstructed masked subcarriers, and L_{con} enforces consistency between the graph representations under different augmentations [22].

To keep the online computational load manageable and avoid drift, we adapt only a small subset of parameters θ_{adapt} (e.g., the last message-passing block and normalization layers), while freezing the remaining parameters. Starting from the pretrained parameters $\theta_{adapt}^{(0)}$, we perform K gradient steps with a small learning rate η:

$$\theta_{adapt}^{(k+1)} = \theta_{adapt}^{(k)} - \eta \nabla_{\theta_{adapt}} L_{TTA} \left(\theta_{adapt}^{(k)} \right)$$
$$k = 0, \ldots, k-1 \tag{13}$$

After adaptation, symbol estimates are produced using the refined embeddings, following the same readout procedure as in Eqn. (11), but with the updated model parameters. This self-supervised test-time adaptation allows the receiver to adjust its interference representation to match instantaneous channel conditions without the need for labeled data, improving detection reliability under overload and channel impairments.

4 Results and discussion

4.1 Simulation setup

Simulations were conducted to assess the performance of the proposed self-supervised Graph Neural Network (GNN)-based detection framework in MC-CDMA systems, specifically under frequency-selective Rayleigh fading channels. The primary goal was to evaluate the framework's robustness across various operating environments and system parameters. The simulation setup, including data size and configuration, is as follows:

- Number of subcarriers N: 64
- Number of active users U: 32, 48, 64, 80
- Modulation scheme: BPSK (Binary Phase Shift Keying)
- Channel model: Rayleigh fading with additive white Gaussian noise (AWGN)
- Signal-to-noise ratio (SNR) Range: 0-20 dB
- Number of GNN layers L: 3
- Embedding dimension d: 64

The simulations were done in a range of SNR values with a dataset of 10,000 frames per setting. Each frame consisted of 64 subcarriers, and the payloads were created randomly in line with the modulation scheme as outlined in reference [23]. This experimental setup was useful in performing a comprehensive evaluation of the proposed model under a wide range of dynamic working conditions that are common in MC-CDMA domain. Besides, the simulation plan involved various user loads and channel implementations to ensure that the performance parameters of the detection framework were reflective of realistic communication situation.

4.2 Key methodology

4.2.1 Monte Carlo simulations

A Monte Carlo simulation system was used with 10 000 frames per point on the signal noise ratio. The approach provides statistically significant results across a wide range of channel realizations. To measure system performance under a variety of noise and interference, synthetic data were created using stochastic sampling in line with the nominal modulation alphabet, and the signal-to-noise ratio was varied between 0 and 20 dB, to evaluate the system performance under various conditions.

4.2.2 Performance metrics

To evaluate the effectiveness of the proposed GNN-based detection framework, Bit Error Rate (BER) and detection latency were the primary metrics. These metrics were calculated over a batch of 10,000 simulation runs for each SNR point, providing an accurate representation of the system's behavior under realistic conditions.

4.2.3 Training procedure

The GNN model was pre-trained using a set of self-supervised learning tasks, and the training was conducted on a dataset of 10,000 frames, where each frame contained randomly generated symbols and interference patterns. This dataset allowed the model to learn interference patterns and signal representations without requiring labeled data.

4.2.4 Simulation Environment

The simulations were run on a high-performance computing system configured as follows:

- Processor: Intel Core i7-9700K
- RAM: 32 GB
- GPU: NVIDIA RTX 2080 Ti
- Operating System: Ubuntu 20.04 LTS
- Software: TensorFlow 2.x, Python 3.8

The system was capable of handling the high computational demands of the GNN-based model, ensuring that the extensive 10,000 frame simulations could be processed efficiently under various configurations.

5 Simulation results

5.1 Performance analysis of AdaptGNN, GAT, and GCN with varying load factors (β)

In this section, we assess the performance of the AdaptGNN, GAT, and GCN models under different user load configurations (U=48, U = 64, and U=80) and load factors (β=0.75, β=1.0, and β=1.25). The evaluation is based on the Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR), providing insight into the effectiveness of each model across various loading conditions in multi-user communication systems, as shown in Figs. 4, 5, and 6.

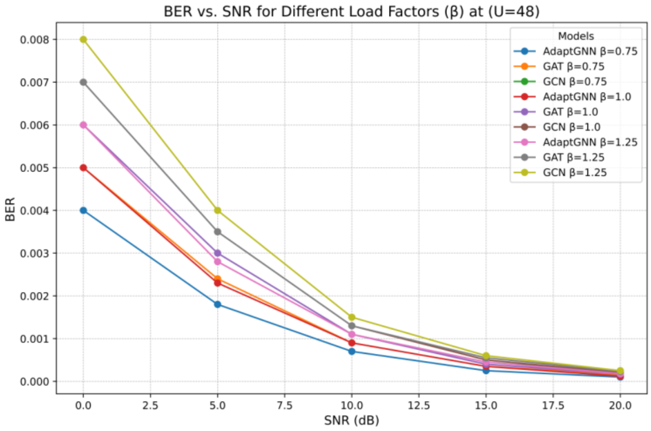

Fig. 4. BER vs. SNR for different load factors (β) at U=48

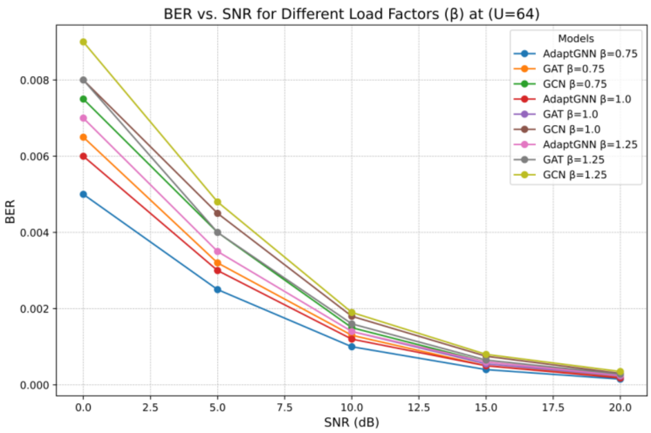

Fig. 5. BER vs. SNR for different load factors (β) at U=64

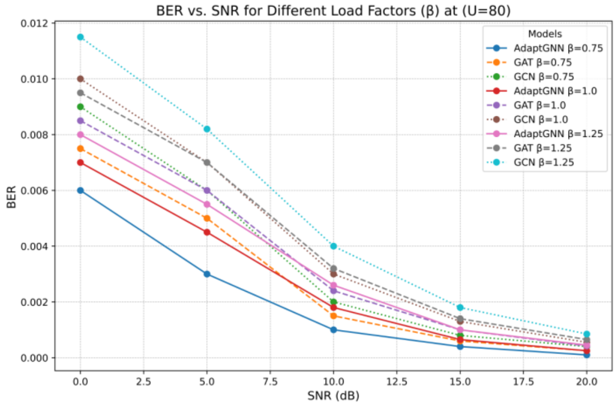

Fig. 6. BER vs. SNR for different load factors (β) at (U=80)

The results demonstrate that AdaptGNN consistently delivers superior performance compared to GAT and GCN across all configurations and loading conditions. At lower user configurations (such as U=48), AdaptGNN exhibits a significant reduction in BER, making it the most effective model for handling multi-user interference. As the user load increases, particularly in U=64 and U=80, the performance gap between AdaptGNN and the other models remains evident, with AdaptGNN continuing to outperform the GAT and GCN models at higher SNR values. This highlights the model's ability to effectively mitigate interference and adapt to varying channel conditions, which is crucial in environments where the number of active users increases.

5.2 Ablation study

A study of ablation was carried out to measure the effects of single self-supervised goals on the performance of the Self-Supervised Graph Neural Network (GNN). Figure 7 shows that the inclusion of each self-supersupplied module generates a statistically significant decrease in the Bit Error Rate (BER), and thus leads to an improved symbol detection and reduces multi-user interference. The evaluation of performance metrics was done in a thorough SNR sweep, which allowed providing a detailed assessment of the resilience of the model under realistic wireless conditions. As the comparative analysis indicates, the full architecture of AdaptGNN that considers all self-supervised modules is superior to the simple GNN that does not include these tasks. This finding supports the central role of self-directed learning in the representation of model performance. Moreover, the ablation highlights the importance of every task in suppressing interference and adapting channels, which supports the feasibility of a self-managed paradigm of wireless communication systems.

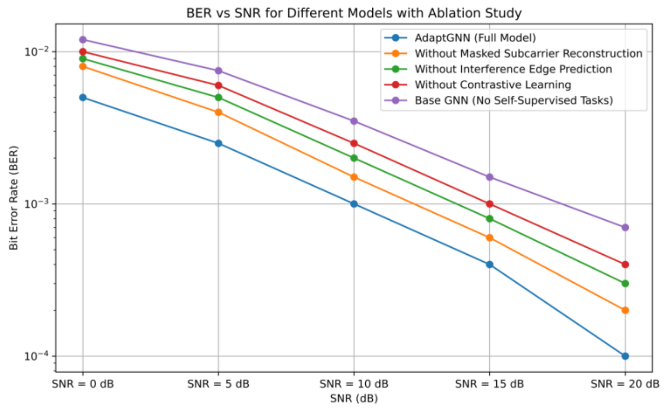

Fig. 7. Results of ablation study on the impact of self-supervised tasks

The ablation experiment indicates beyond reasonable doubt that the self-supervised activities are essential to complementing the performance of the self-supervised GNN model. In particular: The use of Masked Subcarrier Reconstruction is critical to the reduction of multi-user interference, since the model allows inference of missing subcarrier values, and allows to increase the accuracy of symbol-detection and the ability to reproduce patterns of interference more accurately. The contribution of Interference Edge Prediction is significant, as the approach models the correlation between users and subcarriers. This operation helps the model to warm the dynamic patterns of interference which is fundamental in terms of optimizing the detection accuracy in real-life complex multi-user settings. Contrastive Learning provides the greatest performance enhancement particularly in harsh channel conditions. Maximizing the similarity of graph representations when faced with different channel conditions helps the model to be adapted to different environments and hence improves the overall performance of the system. Comparatively, the single instance of the base GNN model, and therefore, the model that does not address any self-supervised tasks, has a significantly higher bit-error rate. These results indicate the importance of self-supervised learning in reducing interference and improving performance of detection in multi-user systems, and Contrastive Learning is the most significant task because it has a very large reduction in BER, especially at unfavorable channel conditions.

5.3 Detection latency

In this part, we compare the detection latency of the proposed AdaptGNN model with GAT and GCN under different numbers of active users. This test is conducted on the basis of time elapsed by each model to identify relayed symbols in real-time MC-CDMA systems. As shown in Tab. 1, the latency of each model with various user settings (U=32, 48, 64, and 80) is demonstrated.

Table 1. Detection latency comparison for MC-CDMA systems

Number of users (U)	AdaptGNN (ms)	GAT (ms)	GCN (ms)
32	4.5	8.2	7.8
48	6.1	10.1	9.4
64	7.3	13.2	12.0
80	9.0	15.5	14.3

The results indicate that AdaptGNN consistently achieves lower latency compared to GAT and GCN across all tested user configurations. Specifically:

- At lower user configurations (U=32), AdaptGNN demonstrates the fastest detection time of 4.5 ms, which is significantly lower than both GAT (8.2 ms) and GCN (7.8 ms). This shows AdaptGNN's superiority in handling real-time detection with minimal latency.
- As the user load increases, particularly at U=48 and U=64, AdaptGNN continues to outperform GAT and GCN in terms of latency. For instance, at U=64, AdaptGNN achieves a latency of 7.3 ms, while GAT and GCN take 13.2 ms and 12.0 ms, respectively.
- At U=80, AdaptGNN maintains a significant edge with a detection latency of 9.0 ms, while GAT (15.5 ms) and GCN (14.3 ms) exhibit higher latencies, especially as the number of users increases. This is primarily due to the higher computational complexity of GAT and GCN models, which struggle to handle the increased number of nodes and edges in the graph as the user load grows.

5.4 Robustness to channel estimation errors

In this section, we evaluate the robustness of the proposed AdaptGNN framework to channel estimation errors, comparing it with GAT and GCN. The results are presented for different user configurations: U=48, U=64, and U=80. Figures 8, 9 and 10 show the Bit Error Rate (BER) performance across varying levels of channel estimation errors ranging from 0% to 20%. This evaluation provides insights into how each model performs under realistic conditions where channel estimation may not be perfect, especially in multi-user environments with increasing interference.

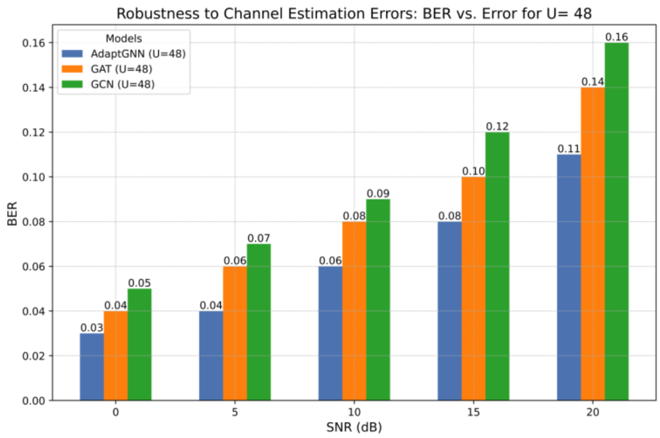

Fig. 8. BER performance under channel estimation errors for *U*=48: AdaptGNN, GAT, GCN models

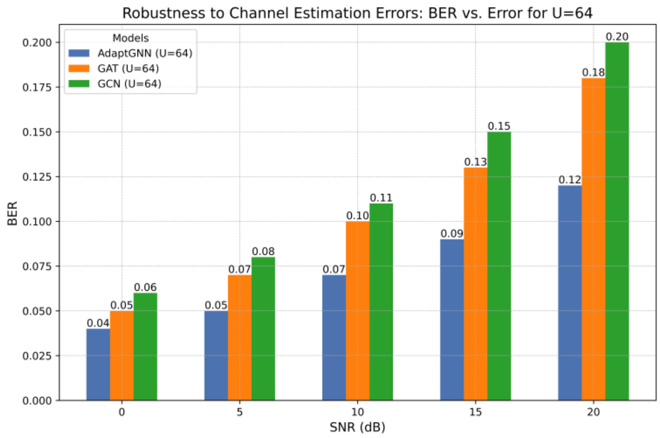

Fig. 9. BER performance under channel estimation errors for *U*=64: AdaptGNN, GAT, GCN models

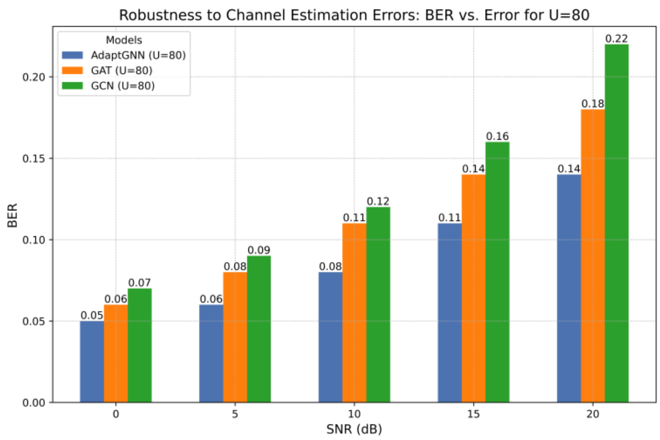

Fig. 10. BER performance under channel estimation errors for *U*=80: AdaptGNN, GAT, GCN models

The results demonstrate that AdaptGNN consistently outperforms both GAT and GCN across all user configurations (*U*=48, *U*=64, and *U*=80) and error levels. Specifically:

- For *U*=48: AdaptGNN maintains the lowest BER across all levels of channel estimation error, showcasing its superior robustness compared to GAT and GCN. Even as the estimation error increases from 0% to 20%, AdaptGNN shows minimal degradation in performance, while GAT and GCN exhibit significant increases in BER.
- For *U*=64: AdaptGNN continues to show clear superiority, with lower BER values at each error level compared to GAT and GCN. As the user load increases, AdaptGNN's ability to handle higher interference and adapt to changing channel conditions is evident, further cementing its strength in multi-user environments.
- For *U*=80: At the highest user density, AdaptGNN remains the most resilient to channel estimation errors, maintaining the lowest BER even under the most challenging conditions. GAT and GCN struggle more as the user count increases, with GAT showing moderate improvement over GCN, but still falling short of AdaptGNN's performance.

5.5 Computational complexity

In this section, we evaluate the computational complexity of the proposed AdaptGNN framework compared to GAT and GCN. The comparison focuses on three key metrics: training time, inference time, and memory usage. These metrics are crucial for determining the efficiency of each model in real-time symbol detection within MC-CDMA systems, particularly in large-scale, high-density user environments.

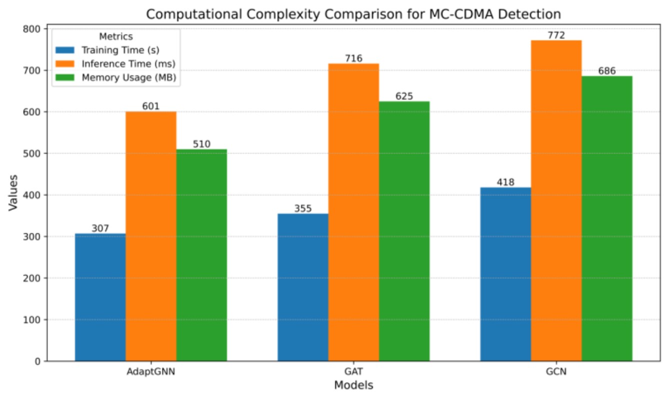

Fig. 11. Computational complexity comparison for MC-CDMA detection

The results presented in Fig. 11 highlight the computational efficiency of each model. AdaptGNN consistently shows lower computational complexity across all metrics compared to GAT and GCN. Specifically:

AdaptGNN demonstrates significantly faster inference times and lower memory usage than both GAT and GCN. This makes it particularly suitable for real-time applications, where efficiency in terms of speed and resource consumption is essential. GAT exhibits higher inference time and greater memory usage, primarily due to the attention mechanism, which requires storing and processing additional information during inference. GCN, while simpler than GAT, still requires more resources than AdaptGNN, particularly in terms of memory usage.

5.6 Impact of interference level and user density on AdaptGNN performance

To further investigate the robustness of the proposed AdaptGNN framework, Fig. 12 illustrates the Bit Error Rate (BER) performance under different interference levels and user densities across multiple Signal-to-Noise Ratio (SNR) conditions. The results are presented as heatmaps to provide a clear and intuitive comparison of how increasing interference and user density affect detection accuracy in multi-user MC-CDMA systems.

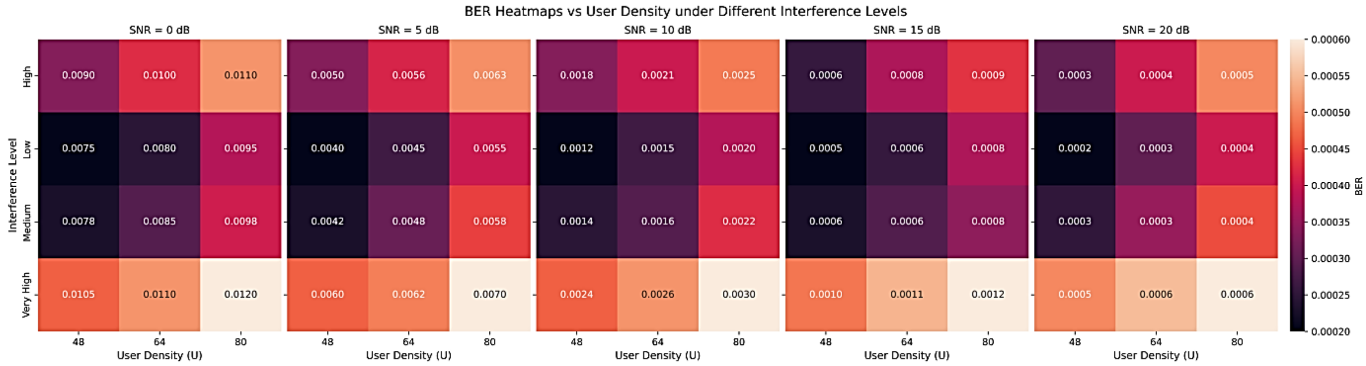

Fig. 12. Impact of interference level and user density on AdaptGNN BER performance across different SNR values

As observed in Fig. 12, the BER consistently decreeses with increasing SNR across all interference levels and user densities, confirming the expected behavior of the communication system. However, the figure also reveals that higher interference levels and larger numbers of users significantly increase the detection difficulty, particularly at low and moderate SNR values. For low interference scenarios, AdaptGNN maintains stable performance even as the user density increases from 48 to 80 users, demonstrating strong scalability. In contrast, under high and very high interference conditions, the BER degradation becomes more pronounced, especially at SNR values below 10 dB. Despite this, AdaptGNN continues to provide relatively low BER compared to what would typically be expected in dense multi-user environments, highlighting its ability to effectively model and mitigate multi-user interference.

Moreover, the gradual performance degradation with increasing user density indicates that the proposed self-supervised and adaptive mechanisms enable AdaptGNN to generalize well under varying network loads. This behavior is particularly important for practical deployments, where user density and interference levels are highly dynamic.

5.7 Impact of channel conditions and user density on AdaptGNN performance

To further evaluate the robustness of the proposed AdaptGNN framework under realistic propagation environments, Fig. 13 presents BER heatmaps across different channel conditions and user densities at multiple SNR levels. The visualization adopts a unified color scale to facilitate a fair comparison and to clearly highlight the combined effects of channel variability and network load on multiuser detection performance.

As illustrated in Fig. 13, AdaptGNN exhibits a consistent improvement in BER as the SNR increases across all channel conditions and user densities. Under stable channel conditions, the model maintains low error rates even at higher user densities, indicating strong generalization capability when channel statistics remain relatively predictable.

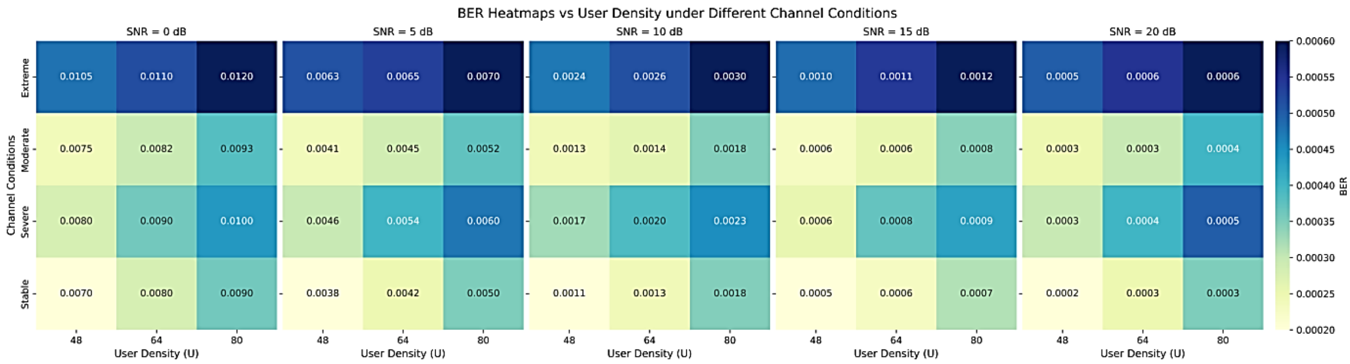

Fig. 13. BER heatmaps of AdaptGNN under different channel conditions and user densities across multiple SNR levels

As channel conditions become more challenging transitioning from moderate to severe and extreme fading the BER degradation becomes more noticeable, particularly at low and intermediate SNR values. This trend reflects the increased difficulty of symbol detection in the presence of rapid channel variations and stronger fading effects. Nevertheless, the degradation remains gradual rather than abrupt, demonstrating that AdaptGNN preserves robust detection behavior even under harsh propagation environments.

Furthermore, the results show that higher user densities amplify the impact of adverse channel conditions, especially in low-SNR regimes. Despite this compounded difficulty, AdaptGNN continues to provide reliable performance, highlighting the effectiveness of its adaptive and self-supervised learning mechanisms in capturing complex channel dynamics. Based on the results, AdaptGNN demonstrates strong potential for deployment in real-world wireless systems, where channel conditions and user density fluctuate dynamically. The observed robustness in challenging channel environments further highlights its suitability for dense, time-varying communication scenarios.

6 Conclusions and future perspectives

In this work, AdaptGNN, the paradigm shift of the conventional supervised receivers to self-supervised, graph-based, multiuser detector in MC-CDMA systems, was proposed. The approach to physical layer interactions as a heterogeneous graph lets us finally discontinue the strong dependence on labeled data, which has historically remained a bottleneck to the practical scalability of deep learning on practical wireless systems. The combination of masked reconstruction, interference-edge estimation, and contrastive learning demonstrates that a receiver can learn to detect by simply analyzing the inherent structure of the received signal. Moreover, the Test-Time Adaptation (TTA) is introduced that makes the model resilient even to the inevitability of distribution changes of the real-world propagation.

Nevertheless, the process of full autonomy and intelligent physical layer development is just starting. To push the boundaries of this research, several key areas must be explored:

Waveform evolution and 6G integration: Although this paper deals with MC-CDMA, the flexibility of GNNs makes them ideal candidates for adapting to next-generation waveforms. Subsequent versions will extend such a framework to a framework involving Orthogonal Time Frequency Space (OTFS) and RIS-assisted networks, whereby the reconfigurable nodes in the graph can be reconfigurable surface elements and model a truly programmable wireless environment.

Closing the sim-to-real gap: It is important to note that one of the most crucial steps toward Simulation to the Real World is to bridge the sim-to-real gap. We will test AdaptGNN with real world over-the-air (OTA) radio and software-defined radio (SDR) testbeds. This shall create exposure to the model of non-ideal hardware performance including IQ imbalance and non-linear power amplifier distortions that is frequently swept under the carpet in controlled simulations.

Distributed and semantic learning: Our vision is that we will shift to Federated Graph Learning, in which the base stations will be able to jointly optimize the models of interference without infringing upon the privacy of the users. Besides, combining AdaptGNN with the semantic communication principles would re-architecture detection; rather than restoring bits, the receiver would give more importance to restoring the meaning, the 6G bandwidth extremes.

Hardware-aware optimization: Future work needs to realize the energy-latency trade-off of TTA to make it more industrial friendly. The application of AdaptGNN to FPGA or AI-optimized edge silicon will be used to gain the insights needed regarding the computational footprint needed to support real-time, microsecond-scale adaptation at the network edge.

Stated further on real-life implementation: Besides having some encouraging simulation outcomes, one should think about the practical issues that can be encountered when implementing the suggested model into the real-world setting. The existence of hardware constraints is one of the most critical issues since it might impact the functioning of the model, in particular when utilizing it on edge devices with limited processing capacity, memory, and energy. Moreover, the model could be adversely affected by interference of non-ideal transmission channels, e.g., fading, multipath effects, and noise, especially in high-density or dynamic communication setting.

These factors may create a discrepancy between the simulation and real world systems performance. To resolve this, there is a need to consider how to enhance the capability of the model to deal with such issues. Adaptive mechanisms that vary the model parameters according to real-time feedback of the deployment environment is one possible solution. Also, the model can be optimized to run on hardware with fewer resources and model compression can be used to deploy the system to less powerful devices without compromising performance.

These are some of the practical issues that can be addressed to make the model more relevant and useful to the industry practitioners so that it addresses the needs of real-world communication systems.

With the transition to 6G as wireless standards, it is necessary to think about how models such as AdaptGNN can be used to meet the requirements of the next-generation networks, which will be characterized by more complicated patterns of interference, increased network density, and users with different needs. These issues might demand modifications on the model design and capability to handle new forms of interference and increased user densities. It will also be important to test the model in real world settings, both by over-the-air (OTA) radio data, and by using hardware testbeds to assess the performance of the model beyond idealized environments.

References

[1] F. A. Miloudi, M. S. Bendelhoum, F. Menezla, and R. I. Bendjillali, “Optimal Filter Selection for MIMO F-OFDM Systems in 5G Wireless Communication”, *JTIT*, vol. 101, no. 3, pp. 69–78, Sep. 2025, https://doi.org/10.26636/jtit.2025.3.2171

[2] R. I. Bendjillali, M. S. Bendelhoum, M. Kamline, A. Ouardas, M. R. Lahcene, and F. A. Miloudi, (2026). Attn-BiGRU: Angular-aware attention with curriculum learning for adaptive beamforming. *Radio Science*, *61*, e2025RS008432. https://doi.org/10.1029/2025RS008432

[3] M. S. Bendelhoum, F. Maliki, R. I. Bendjillali, A. A. Tadjeddine, and M. Kamline, "Enhancing Channel Coding in MC-CDMA Systems Using Deep Learning for Reduced Complexity and Improved Efficiency," *2024 International Conference of the African Federation of Operational Research Societies (AFROS)*, Tlemcen, Algeria, 2024, pp. 1-5. https://doi.org/10.1109/AFROS62115.2024.11037100

[4] R. I. Bendjillali, M. S. Bendelhoum, E. Abderraouf, and M. R. Lahcene, "Improving Performance of MC-CDMA Systems Using UTTCM Channel Coding," *Journal of Telecommunications and Information Technology*, vol. 2, no. 2, pp. 58–65, 2024. https://doi.org/10.26636/jtit.2024.2.1547

[5] B. R. Ilyas, B. M. Sofiane, T. A. Abderrazak, O. Asma, K. Miloud, and B. Linda, "Adaptive Channel Coding for MC-CDMA Systems: A Deep Learning Approach with Attention-Enhanced LSTMs for Efficient Error Correction," *2025 7th International Conference on Pattern Analysis and Intelligent Systems (PAIS)*, Laghouat, Algeria, 2025, pp. 1-7. https://doi.org/10.1109/PAIS66004.2025.11126054

[6] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A Comprehensive Survey on Graph Neural Networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 1, pp. 4-24, Jan. 2021. https://doi.org/10.1109/TNNLS.2020.2978386

[7] D. Wang, E. Shelhamer, S. Liu, B. Olshausen, and T. Darrell, "Tent: Fully Test-Time Adaptation by Entropy Minimization," *International Conference on Learning Representations (ICLR)*, 2021. Available: https://arxiv.org/abs/2006.10726

[8] Y. Shao, Y. Zeng, and Y. Gong, "Test-Time Adaptation for Robust Modulation Recognition Under Unknown Channel Distortions," *IEEE Communications Letters*, vol. 30, no. 2, pp. 657-661, Feb. 2026. https://doi.org/10.1109/LCOMM.2025.3647715

[9] H. Zhang, L. Zhang, and X. Gao, "Deep Unfolding ResNet for Multiuser Detection in Overloaded MIMO-MC-CDMA," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 8, pp. 10450-10465, Aug. 2023. https://doi.org/10.1109/TVT.2023.3267119

[10] S. Shao, G. Zhang, and J. Li, "Graph Neural Network-Based Detection for SCMA in Optical Wireless Communications," *IEEE Photonics Journal*, vol. 13, no. 4, pp. 1-12, Aug. 2021. https://doi.org/10.1109/JPHOT.2021.3090651

[11] X. He, Y. Chen, and L. Yang, "Heterogeneous Graph Neural Networks for Multiuser Detection in Uplink NOMA Systems," *IEEE Transactions on Wireless Communications*, vol. 23, no. 4, pp. 3120-3135, April 2024. https://doi.org/10.1109/TWC.2023.3325114

[12] Y. Lu, Y. Li, and J. Choi, "Graph Neural Networks for Wireless Networks: Graph Representation, Architecture and Evaluation," *IEEE Wireless Communications*, vol. 32, no. 1, pp. 1-10, 2025. https://doi.org/10.1109/MWC.2025.3412589

[13] G. Chen, J. Zhang, and R. Hu, "GraphTTA: Test Time Adaptation on Graph Neural Networks via Adversarial Contrast," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, no. 12, pp. 33354-33362, 2025. https://doi.org/10.1609/aaai.v39i12.33354

[14] B. M. Sofiane, B R. Ilyas, E. Abderraouf *et al.* Optimizing MC-CDMA System Performance via UTTCM Channel Coding Techniques. *Wireless Pers Commun* (2025). https://doi.org/10.1007/s11277-025-11815-2

[15] Z. Chen, W. Ge, H. Fei, H. Zhao, and B. Li, "A Lightweight Graph Neural Networks Based Enhanced Separated Detection Scheme for Downlink MIMO-SCMA Systems," *IEICE Transactions on Communications*, vol. E107-B, no. 4, pp. 368-376, April 2024. https://doi.org/10.23919/transcom.2023EBP3144

[16] S. Zhang, Z. Feng, Z. Peng, L. Xiao, and T. Jiang, "Sparse graph neural network aided efficient decoder for polar codes under bursty interference," *Digital Communications and Networks*, 2023. https://doi.org/10.1016/j.dcan.2023.12.002

[17] Y. Shen, Y. Shi, J. Zhang and K. B. Letaief, "Graph Neural Networks for Scalable Radio Resource Management: Architecture Design and Theoretical Analysis," in IEEE Journal on Selected Areas in Communications, vol. 39, no. 1, pp. 101-115, Jan. 2021, https://doi.org/10.1109/JSAC.2020.3036965

[18] K. Miloud, O. Asma, B. R. Ilyas, B. M. Sofiane, T. A. Abderrazak and M. F. Amel, "Graph Neural Network-Based Beam Selection for Massive MIMO Systems in Dynamic Wireless Environments," *2025 International Conference on Intelligent Computer Systems, Data Science and Applications (IC2SDA)*, Blida, Algeria, 2025, pp. 1-6, https://doi.org/10.1109/IC2SDA68097.2025.11331520

[19] S. Zhang, O. T. Ajayi and Y. Cheng, "A Self-Supervised Learning Approach for Accelerating Wireless Network Optimization," in IEEE Transactions on Vehicular Technology, vol. 72, no. 6, pp. 8074-8087, June 2023, https://doi.org/10.1109/TVT.2023.3244043

[20] Z. Zhang, T. Ji, H. Shi, C. Li, Y. Huang and L. Yang, "A Self-Supervised Learning-Based Channel Estimation for IRS-Aided Communication without Ground Truth," in IEEE Transactions on Wireless Communications, vol. 22, no. 8, pp. 5446-5460, Aug. 2023, https://doi.org/10.1109/TWC.2023.3233970

[21] X. Chen, Y. Wang, J. Fang, Z. Meng and S. Liang, "Heterogeneous Graph Contrastive Learning with Metapath-Based Augmentations," in IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 8, no. 1, pp. 1003-1014, Feb. 2024, https://doi.org/10.1109/TETCI.2023.3322341

[22] H. Lee, K. Lee, J. P. Yoon, J. Kim and J. -Y. Kim, "Real-Time Self-Supervised Ultrasound Image Enhancement Using Test-Time Adaptation for Sophisticated Rotator Cuff Tear Diagnosis," in IEEE Signal Processing Letters, vol. 32, pp. 1635-1639, 2025, https://doi.org/10.1109/LSP.2025.3557754

[23] R. I. Bendjillali, M. S. Bendelhoum, A. A. Tadjeddine, and M. Kamline, "Enhancing 5G massive MIMO systems with EfficientNet-B7-powered deep learning-driven beam-forming," *Transactions on Emerging Telecommunications Technologies*, vol. 35, no. 11, e5034, Nov. 2024. https://doi.org/10.1002/ett.5034

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