Beamforming Optimization for MIMO System Based on Graph Neural Networks

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***Abstract*—With the significant increase in demand for future 6G communication networks, higher requirements are being put forward for current communication systems. This paper proposes an unsupervised learning method based on GNN for optimizing the beamforming matrix in multi-user large-scale MIMO systems. By using the channel matrix as input, we aim to maximize the overall system transmit rate under power constraints. This paper constructs graph structure of a multi-user MIMO system and designs the corresponding GNN model. The optimization of the beamforming matrix is achieved by introducing a loss function and penalty terms. Simulation results show that compared with existing algorithms, the proposed GNN optimization method demonstrates superior performance under different conditions of user numbers, BS antenna numbers, and SNR. Especially in large-scale user scenarios, the performance improvement of the GNN optimization method is particularly significant, with a performance ratio up to 131.2% compared to the MMSE method.**

Keywords—beamforming; graph neural networks; MIMO;

I. Introduction

With the noticeable increasing demand for the future 6G communication networks, especially the explosive growth in the number of terminal devices, more demanding requirements are being put forward to current communication system. Combining beamforming technique with the Massive multiple-input multiple-output (MIMO) allows to adjust the amplitude and phase of the transmitted signal, and orient the antenna to radiate towards the target device [1], [2]. As one of the feasible ways to achieve the peak rate, low time delay and high reliability of 6G, beamforming design in multi-user wireless communication networks, researchers have conducted extensive exploration and in-depth discussion on this technique. To meet the demand for Quality of Service (QOS), in [3], authors investigated the optimization algorithms for joint user scheduling and beamforming based on zero-forcing beamforming (ZFBF) and continuous convex approximation respectively. Over recent years, with the deepening of research, deep neural network is considered to be an effective tool for 6G network to realize wireless communication network intelligence [4]. Graph Neural Network (GNN) represent a class of deep learning (DL) techniques that are particularly adept at handling data with graph-like structures. The applicability of GNN to the multi-path routing challenges in satellite networks has been substantiated by researchers [5]. Building on the remarkable success of GNN, they have been employed to enhance the design of multi-antenna beamforming, aiming to optimize the performance of Reconfigurable Intelligent Surfaces (RIS) [6]. In a recent study [7], the authors introduced a GNN-based framework known as the complex residual graph attention network, designed to maximize the total rate in multi-user multi-input single-output (MU-MISO) systems. The efficacy of GNN-based approaches in addressing optimization problems within the realm of multi-user wireless communications has been demonstrated in a series of studies [8] – [11].

In this work, an unsupervised learning method employing GNN to optimize the beamforming matrix based on the channel matrix derived from channel estimation is proposed. To satisfy the QoS requirements, this study leverages historical network data, treats the receiving and transmitting antennas as edge nodes, and employs a neural network to identify the optimal solution for maximizing overall system throughput while adhering to transmit power constraints.

The remainder of the paper is organized as follows. In section II, a brief introduction to the system model is given while the GNN layers and model we propose are presented in section III. Building upon this, the subsequent section will present a demonstration of the simulation results and a brief analysis of the result. Finally, section V elucidates the conclusion of this work.

II. System Model

A multi user massive MIMO downlink system with single base station (BS) and M user equipment (UE) is considered in this research. BS and the UEs have N_t and N_r antennas respectively, each antenna can undertake the task of transmitting and receiving separately. Denote N_i^t and $N_{j,k}^r$ as the *i*-th transmit antenna of BS and *j*-th receive antenna of *k*-th user. Let $H_k \in \mathbb{C}^{N_r \times N_t}$, $k \in \{1, \cdots, M\}$ represent the channel matrix between BS and *k*-th user, $W_k \in \mathbb{C}^{S_k \times N_t}$, $k \in \{1, \cdots, M\}$ represent the beamforming matrix of BS to k-th user. Additionaly, here S_k represents the spatial streams of BS.

Fig. 1 illustrates the schematic diagram of the antenna array within a Multiple-Input Multiple-Output (MIMO)

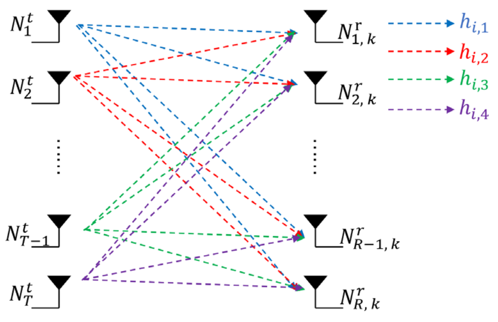

Fig. 1. Antenna framework of MIMO system

system, with $h_{i,j}$ representing the channel coefficient associated with the respective antennas. Account for an Additive White Gaussian Noise (AWGN) channel, assign x_k as signal vector transmitted by BS, then the signal vector received by UEs can be expressed as follows:

$$y_k = U_k^H[H_k W_k x_k + n_k] + \sum_{j\neq k, j\in k} U_k^H[H_k W_j x_j + n_k] \tag{1}$$

Here $n_k \in \mathcal{N}(0, \sigma_k^2)$ symbolizes the white gaussian noise, and $U_k \in \mathbb{C}^{N_r \times S_k}$ denotes to the normalized receiver of k-th user. Without taking interference between users into account, y_k could be expressed as (2):

$$y_k = U_k^H[H_k W_k x_k + n_k] \tag{2}$$

Then, the achievable data transmit rate at the k-th user is expressed as (3):

$$R_k(W_k) = \log_2\left(1 + \frac{\left|U_k^H H_k W_k\right|^2}{\left|U_k^H H_k W_k\right|^2 + \sigma_k^2}\right) \tag{3}$$

To streamline the processes, only take the first space stream of user into consideration. The optimization object of this work is transmitting rate. The optimizing task could be described as follows:

$$\max_{\{u_k, w_k\}} \sum_{k\in\mathcal{K}} R_k \ , \tag{4a}$$

$$s.t. \quad r_k \le R_K, \forall k \in \mathcal{K} \ , \tag{4b}$$

$$\sum_{k\in\mathcal{K}} \|W_k\|_2^2 \le P_b \ , \tag{4c}$$

$$\|U_k\|^2 = 1, \forall k \in \mathcal{K}, \tag{4d}$$

Addressing the complexity of rate calculation formulas is inherently challenging due to their non-convex nature, which is further complicated by the non-convex constraints as indicated in term (4b). The presence of a potentially infinite number of local optima within the feasible solution space renders the task of algorithmically determining a global optimum computationally daunting, often with complexity that scales exponentially. Traditional approaches, such as the WMMSE algorithm or the Max-SNR algorithm, are burdened by significant computational demands.

To address the need for low computational latency and to leverage historical network data effectively, this paper introduces a Graph Neural Network (GNN) based beamforming optimization method. By integrating a penalty function into the total loss function and initializing the network with random weight and bias vectors, the proposed GNN method has demonstrated impressive performance in simulations, striking a balance between computational efficiency and optimization accuracy.

III. GNN Model

A. Graph Information Construction

This subsection introduces how the structure of multi-user MIMO system is turned into a graph. Provided with M users, and K Spatial Stream for each user, as previously described, all actual users are converted into $\sum_{i=1}^{M\bullet K} S_i$ virtual users. Each UE is equipped with N_r receiving antennas, while BS is furnished with N_t transmitting antennas. The channel matrix is utilized as the adjacency matrix in our model, where each antenna is represented as a node, and each communication link between the antennas is denoted as an edge. This configuration effectively constructs a graph-based representation of the multi-antenna wireless communication network, as depicted in Fig. 2.

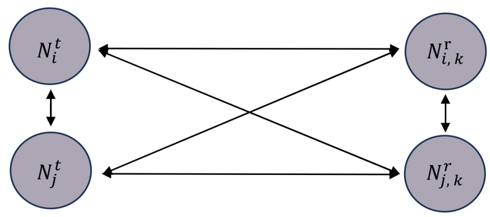

Fig. 2. Graphical representation of a MIMO system

B. GNN Layers and Loss Function

To achieve higher transmission rates and reduce computational complexity, we introduce a beamforming optimization technique leveraging a Graph Neural Network (GNN) algorithm. The process begins by consolidating and reshaping the beamforming matrix W_k, $k \in \{1, \cdots, M\}$ into a vector form v_0. This vector serves as the parameter set that is subject to updates. Concurrently, the input features from the antenna nodes are fed into the GNN model. Subsequently, the GNN model, equipped with L fully connected layers, is trained. We utilize the notation v_l, $l \in \{0, \cdots, L\}$ to represent the input vector for each layer, facilitating a structured and efficient optimization approach. The mapping function is characterized as:

$$f_G^l(v_l) = \mathrm{ReLU}(W_l v_l + bias_l) \tag{5}$$

Here W_l and $bias_l$ refers to the weight and bias vector of the l-th layer, respectively. Nonlinear activation function is set to ReLU, which is widely used in the training of neural network.

To realize the optimizing target, we designed a loss function based on penalty method. In this approach, the user's rate requirement constraint is embedded directly into the loss function as a penalty term. The loss function is presented as follows:

$$L_{penal}(\theta) = -\lambda_1 \sum_{k=1}^{K} R_k(W_k \mid \theta) + \lambda_2 \,\mathrm{ReLU}(P_b - \sum_{k\in\mathcal{K}} \|W_k\|_2^2) \quad (6)$$

Here λ_1 and λ_2 indicates the coefficients of each part in the loss function, respectively. Employ bound term P_b as the early stop function, GNN method can traverse the feasible domain of the constraint term and find the global optimal solution.

IV. Simulation Results

In this study, we focus on a multi-user MIMO system, adhering to the parameter configurations outlined in Table 1. The interference range of BS is set to 300 meters, UEs are randomly located in the cell. The channel model is derived from the 3GPP TR 38.901 specification, version 16.1.0 Release 16, with 1000 channel samples generated for each scenario to ensure consistency. These identical channel samples were utilized in both the Max-SNR and MMSE method simulations. Additionally, the sampling rate and carrier frequency employed in our work are set at 100 MHz and 2600 MHz, respectively.

In order to verify the effectiveness and reliability of GNN method we proposed, maximum signal-to-noise ratio (Max-SNR) and minimum mean square error (MMSE) method were introduced as the baseline of the simulation. The simulation result is shown in the next subsection.

TABLE I. System Default Parameters

System Default Parameters	Value
BS Number (B)	1
BS Transmitting Antenna Number (N_t)	16
UE Number (M)	8
UE Receiving Antenna Number (N_r)	16
Maximum Transmit Power of BS (P_b)	20 W
Noise std (σ_0)	1

A. Different UE Numbers

Considering the influence of varying UE numbers within the system interference range on the outcomes, we categorize the UE count into 3 distinct groups: small-scale, medium-scale and large-scale. The UE numbers are set as $\mathrm{M} \in \{4,\ 8,\ 12,\ 16\}$, $\mathrm{M} \in \{32,\ 36,\ 40,\ 44\}$ and $\mathrm{M} \in \{60,\ 64,\ 68,\ 72\}$, other system parameters remain consistent with those detailed in Table 1. The results are shown as Fig. 3 to Fig. 5.

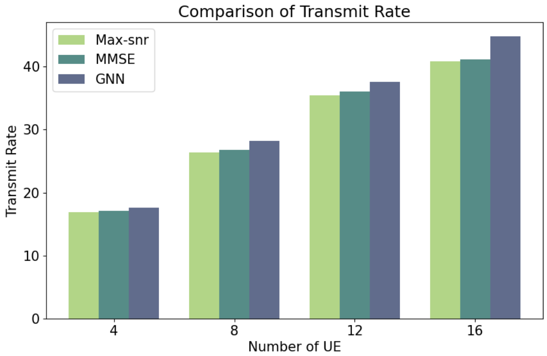

Fig. 3. Comparison of Transmit Rate Under small-scale UE scenario

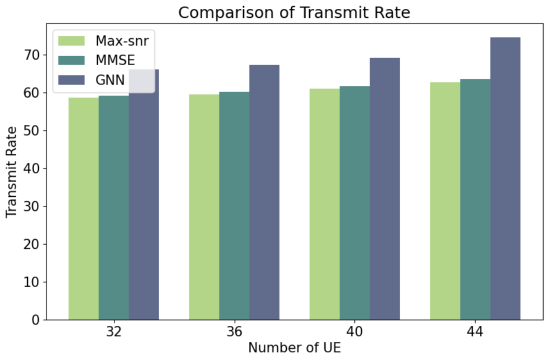

Fig. 4. Comparison of Transmit Rate Under medium-scale UE scenario

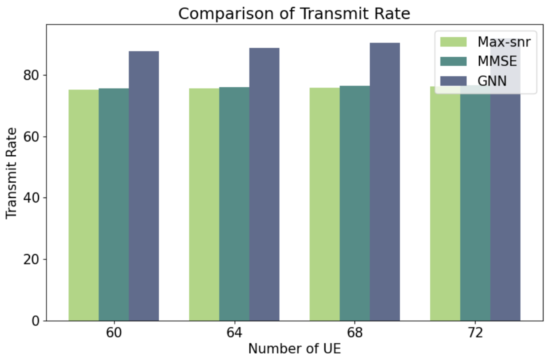

Fig. 5. Comparison of Transmit Rate Under large-scale UE scenario

As illustrated in the figures, the average performance and speed of the three algorithms exhibit an upward trend with the increasing number of users; however, the rate of increase gradually diminishes as UE numbers rise. The Max-SNR and MMSE algorithms yield comparable results, yet the GNN method outperforms them.

In scenarios with a small number of users, the performance of the proposed algorithm is comparable to that of the other two algorithms. However, in large-scale user scenarios, our proposed algorithm demonstrates a significant improvement in performance. It is particularly noteworthy that as the number of UEs increases, the performance gap between the GNN method and the other two algorithms expands, culminating in a 35-bit/s/Hz advantage. Specifically, when M = 4, the performance ratio of the GNN_BO algorithm to the MMSE algorithm is 103.8%. This ratio further increases to 131.2% when M = 72, highlighting the scalability and robustness of the GNN method in handling larger user populations. Based on the discussion above, it can be inferred that the performance of GNN method exhibits greater advantages. This phenomenon is likely to be caused by the increase of number of iterations. With the increase of iterations, the chance GNN method gets closer to the optimal solution raises.

B. Different BS Transmitting Antenna Numbers

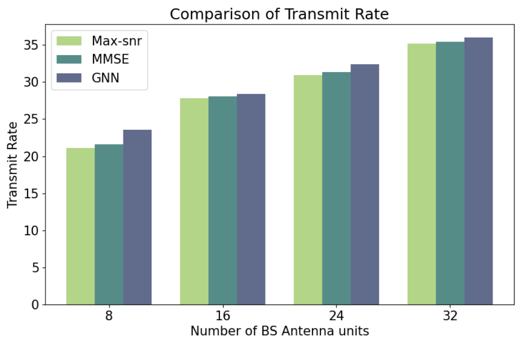

Fig. 7: Comparison of Transmit Rate Under Different Antenna Numbers

Given that the number of UE remains constant, this subsection compares the impact of varying the number of antennas on transmission rates. With other parameters remain as Tab.1, set antennas' number $N_r = N_t \in \{8,\ 16,\ 24,\ 32\}$, the result is illustrated in the Fig. 6.

As demonstrated in figure 6, the performance of the three algorithms rises with the increase of antenna numbers. Similar to the preceding outcome, GNN method performed better in each set of antenna number. is important to note that with the increase of antenna number, the benefits of GNN method start to diminish. This phenomenon may be attributed to the increased dimensions of the beamforming matrix, and the complexity of object function. With the increase of the solution space of the optimization problem, it becomes harder for GNN method to meet the optimal solution.

C. Different BS Transmit SNR

In this subsection, we simulate the transmit rate across varying BS transmit SNR. The BS transmit power is set to a constant 20W, and the noise power levels are examined at $\sigma^2 \in \{1,\ 1.33,\ 2,\ 4\}$. The findings are graphically depicted in Fig. 7.

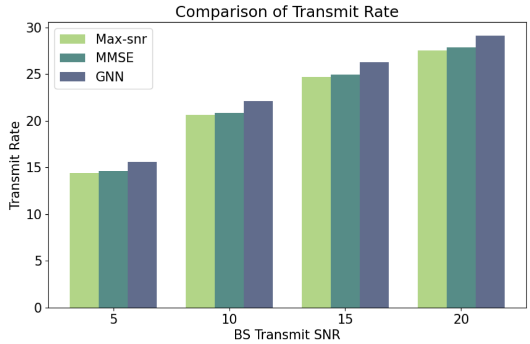

Fig. 6: Comparison of Transmit Rate Under Different BS Transmit SNR

As it depicted in the graphic, GNN method demonstrates the most superior performance of all the algorithms. Different SNR settings had few effects on the rate gap between the algorithms. When SNR is set to 20dB, the ratio between GNN method and MMSE method is 95.8% and the ratio goes down to 93.6% when SNR drops to 5dB. Without losing generality, the channel conditions become better with the increase of SNR, and the results of both algorithms increase with the increase of SNR.

Conclusion

In this paper, an unsupervised learning method based on graph neural networks (GNN) is proposed for optimizing beamforming matrices in multi-user MIMO systems. By constructing the graph structure of multi-user MIMO system and designing the corresponding GNN model, this research successfully transforms the multi-antenna wireless communication network into the graph representation. On this basis, the optimization of beamforming matrix is realized by introducing loss function and penalty term. The simulation results show that compared with the existing Max-SNR and MMSE methods, the proposed GNN optimization method shows better performance under different conditions of the number of users, the number of BS antennas and the SNR. Especially in large-scale user scenarios, the performance improvement of GNN optimization method is particularly significant, compared with MMSE method, the performance ratio is up to 131.2%. The results validated the effectiveness and reliability of GNN in solving multi-user wireless communication optimization problems. In the future work, we will explore the application of GNN in more complex communication scenarios and further investigate how to improve the scalability and adaptability of the algorithm.

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