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Machine Learning-Based Beamforming in K -User MISO Interference Channels

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ABSTRACT In this paper, we consider a K -user multiple-input and single-output interference channel and propose a machine learning-based beamforming design. To circumvent the difficulties of beamforming design in interference channels, we consider a beamforming scheme that combines two well-known beamforming schemes, which are maximum ratio transmission and zero-forcing, with one of finite combining factors. However, this problem is still NP-hard, which requires brute-force search for optimal beamforming, so we adopt the machine learning to find the optimal beamforming vectors. Our machine learning design exploits a deep neural network structure, whose input nodes take channel vectors with transmit power, while the output nodes return the combining factors for the transmitters' beamforming. Our numerical results show that our proposed machine learning-based beamforming achieves a sum rate more than 99% of that with the best combining factors numerically found with brute-force search.

INDEX TERMS Machine learning, MISO interference channels, beamforming, deep neural network, maximum ratio transmission, zero-forcing.

I. INTRODUCTION

The fourth industrial revolution is expected to change our society and almost all of our daily life. Artificial intelligence (AI) is considered as a key factor of the changes in various fields and is creating new values. Since AI will replace much of the labor now done by human beings, as the core technology of AI, machine learning is attracting a lot of attention. Machine learning improves its own performance through learning from given data, and machine learning became popular with the emergence of deep learning. In general, deep learning allows us to train more complex models, which are capable of solving more difficult problems. The idea was already announced in the 1980s [2], [3], but not widely used in the past due to the limits of computing power and poor learning progress. There are several factors that have allowed deep learning to overcome such problems. First, the development of fast and cheap graphics processing units (GPUs) made the training of models faster. Second, various approaches were proposed that facilitated the training of models such as improved training methods and

model architectures [4]–[8]. Third, the use of the Internet has greatly increased the amount of data available (see [9] for more details about principles, applications, history, and future prospects of deep learning). Thus, deep learning has become a key technology of machine learning because it achieves the performance that surpasses the existing schemes in many areas [7], [10]–[13].

At the same time, the next generation (5G/6G) of wireless communication systems are being studied intensively. The next communication systems will have more devices, so will be far more complex, but will still require higher performance. Therefore, we need more efficient solutions to provide better services in future systems [14]. As one solution, machine learning is being widely investigated to increase the performance of wireless communication systems [15]–[19]. In [15], the authors provided a comprehensive survey of the crossovers between deep learning and wireless communications. In [16], the authors explained several applications of deep learning for the physical layer. They considered the communication between transmitters and receivers as an end-to-end reconstruction task that they addressed using autoencoders. Their results showed that the autoencoder could be learned without any prior knowledge and could achieve

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performance comparable to traditional methods. In [17], the authors worked with deep learning for channel estimation and signal detection in orthogonal frequency-division multiplexing (OFDM) systems. Unlike the existing OFDM receivers, explicit channel state information (CSI) is not required for their system. Their proposed deep learning-based approach estimates CSI implicitly, and outputs the transmitted symbols directly. Their results showed that deep learning is capable of learning the characteristics of wireless channels, and hence it is advantageous when the function of wireless channels are complicated by severe impairments.

As the number of devices and the demand for higher data transmission rates increase, interference management will become more challenging in future wireless communication systems. For interference management, a variety of beamforming schemes in relation to interference channels (ICs) have been widely studied. In K -user multiple-input and single-output (MISO) interference channels, an optimal beamforming vector that maximizes the achievable sum rate is known to have the form of a linear combination of the channels of each transmitter to the users [20]. However, finding the global optimal point is not easy because we need to find the optimal weight for every channel link, so this is impractical in real-time systems, especially when the number of antennas or the number of users is large. Instead, suboptimal solutions are obtained by some iterative algorithms such as weighted minimum mean square error (WMMSE) [21], [22] and the water filling algorithm combined with zero-forcing (ZF) beamforming [23]. However, these algorithms still require high computational complexity due to heavy operations such as matrix inversions and singular value decompositions in each iteration. To reduce computational complexity, deep learning-based approaches are widely investigated [24], [25]. In these papers, the authors trained a deep neural network (DNN) to obtain good beamforming vectors with low complexity. Especially in [25], the authors showed that their proposed scheme can achieve the higher sum rate than the existing algorithms.

In this paper, we consider a beamforming scheme [20], [28] named as N -level balanced MRT-ZF beamforming that linearly combines the maximum ratio transmission (MRT) and the zero-forcing (ZF) beamforming vectors with one an N -level discrete weights, while the MRT and the ZF beamformings are known to be optimal at low and high signal-to-noise-power-ratio (SNR), respectively. Therefore, instead of finding the exact linear beamforming vector, we focus to increase sum rate by properly choosing the combining factors in the balanced MRT-ZF beamforming scheme. However, since this kind of combinatorial optimization is NP-hard [29], it is still hard to find the optimal combining factors of all transmitters. We adopt machine learning to obtain comparable performance with reduced complexity and to explore the applicability of machine learning for beamforming design.

In our initial work [1], we considered a simple beamforming scheme in two-user MISO ICs, where each transmitter only chooses one between the MRT and the ZF beamforming

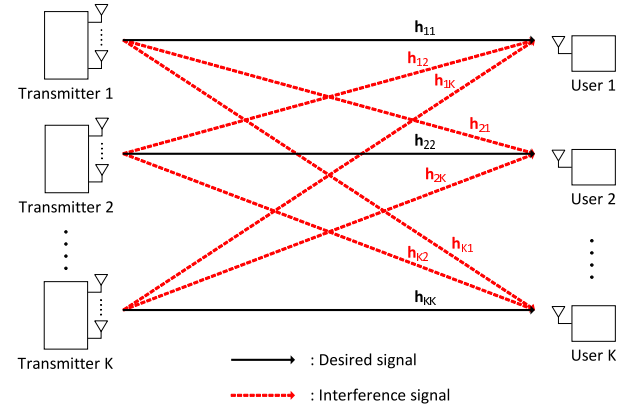


FIGURE 1. Illustration of K -user MISO ICs.

schemes. In this paper, we generalize the system model to K -user MISO ICs and consider a more general beamforming scheme that balances the MRT and the ZF. We propose a deep neural network structure that finds the best one among N -level discrete weights for every transmitter. Furthermore, we discuss the effectiveness of machine learning for beamforming design.

The rest of this paper is organized as follows. In Section II, we explain the system model and formulate our problem. In Section III, we propose our machine learning design for beamforming. In Section IV, we evaluate our machine learning-based beamforming scheme. Finally, we conclude our paper in Section V.

Notations: In this paper, boldface capital and boldface lowercase letters refer to matrices and vectors, respectively. The matrix $\mathbf{I}_M$ denotes an $M \times M$ identity matrix, $\|\cdot\|$ denotes the Euclidean norm of a vector, and $|\cdot|$ denotes the magnitude of a scalar value. The superscripts $(\cdot)^T$, $(\cdot)^H$, and $(\cdot)^{-1}$ denote transpose, conjugate transpose, and matrix inversion, respectively. The notations $\text{Re}(\cdot)$ and $\text{Im}(\cdot)$ represent the real and the imaginary parts of a complex number, respectively. Also, $\mathbb{E}[\cdot]$ denotes the expectation, and the notations $\mathbb{R}^{N \times 1}$, $\mathbb{C}^{N \times 1}$, and $\{0, 1\}^{N \times 1}$ represent the sets of a real, a complex, and a binary $N \times 1$ vectors, respectively.

II. PROBLEM FORMULATION

A. SYSTEM MODEL

Figure 1 shows our system model. We consider a K -user MISO IC, where each of K transmitters has N_T ($N_T \geq K$) antennas and serves its own single-antenna user. The received signal at the user i is modelled as follows:

$$y_i = \mathbf{h}_{ii}^H \mathbf{x}_i + \sqrt{\eta} \sum_{j \neq i} \mathbf{h}_{ij}^H \mathbf{x}_j + n_i, \quad (1)$$

where $\mathbf{h}_{ij} \in \mathbb{C}^{N_T \times 1}$ is the channel vector from the transmitter j to the user i represented by

$$\mathbf{h}_{ij} = [h_{ij}^{(1)}, \dots, h_{ij}^{(N_T)}]^T \quad (2)$$

whose elements are independent and identically distributed (i.i.d.) complex Gaussian random variables with zero mean

and unit variance (i.e., Rayleigh fading). Also, $\mathbf{x}_i \in \mathbb{C}^{N_T \times 1}$ is the i th user's desired data. The parameter η represents the interference to signal power ratio (ISR) [26], i.e., $\eta \triangleq \text{INR/SNR}$ to model more general interference channels. The notation $n_i \in \mathbb{C}^{1 \times 1}$ is an additive white Gaussian noise (AWGN) at the user i with zero mean and unit variance. Thus, in (1), the term $\mathbf{h}_{ii}^H \mathbf{x}_i$ becomes the desired signal at the user i , while the term $\sqrt{\eta} \sum_{j \neq i} \mathbf{h}_{ij}^H \mathbf{x}_j$ becomes the interference. In our paper, we assumed that transmitters have perfect CSI, so we can focus on the beamforming design.

With the linear beamforming, the transmitter i 's desired data, i.e., $\mathbf{x}_i$, can be represented by

$$\mathbf{x}_i = \sqrt{P_i} \mathbf{v}_i s_i, \quad (3)$$

where P_i is the transmitter i 's transmit power, i.e., $\mathbb{E}[\|\mathbf{x}_i\|^2] = P_i$, and $\mathbf{v}_i \in \mathbb{C}^{N_T \times 1}$ and $s_i \in \mathbb{C}^{1 \times 1}$ are the transmitter i 's beamforming vector and transmitted symbol such that $\|\mathbf{v}_i\|^2 = 1$ and $|s_i|^2 = 1$, respectively. We assume that each transmitter has the same power budget P and transmits with full power (i.e., $P_1 = \dots = P_K = P$). Thus, with the beamforming vectors $\{\mathbf{v}_1, \dots, \mathbf{v}_K\}$, the transmitter i obtains the achievable rate given by [27]

$$R_i(\mathbf{v}_1, \dots, \mathbf{v}_K) \triangleq \log_2 \left(1 + \frac{P |\mathbf{h}_{ii}^H \mathbf{v}_i|^2}{1 + \eta \cdot P \sum_{j \neq i} |\mathbf{h}_{ij}^H \mathbf{v}_j|^2} \right). \quad (4)$$

B. VARIOUS BEAMFORMING SCHEMES

1) OPTIMAL BEAMFORMING

As we can see in (4), the achievable rate at each transmitter is affected by all transmitters' beamforming vectors. Thus, to increase sum rate, the beamforming vector of each transmitter should be carefully designed considering the effects on its own user and other users. It was shown in [20] that the optimal beamforming vector for each transmitter has the form of linear combination of its own desired channel and the channels to the other users as follows:

$$\mathbf{v}_i(\kappa_{1i}, \dots, \kappa_{Ki}) \triangleq \frac{\sum_{j=1}^K \kappa_{ji} \mathbf{h}_{ji}}{\|\sum_{j=1}^K \kappa_{ji} \mathbf{h}_{ji}\|}, \quad (5)$$

where $\kappa_{ji} \in \mathbb{C}^{1 \times 1}$ is a complex weight for the channel $\mathbf{h}_{ji}$.

Thus, each transmitter's beamforming vector is determined by K complex values, and hence for all transmitters' optimal beamforming vectors, we need to find total K^2 complex values, which is equivalent to find $2K^2$ real values. This problem is extremely hard as it is not a convex problem, so to circumvent this difficulty, many suboptimal solutions have been proposed [21]–[23]. One suboptimal solution is to linearly combine two popular beamforming schemes, which are MRT and ZF beamforming schemes, which we will consider in our machine learning design.

2) CONVENTIONAL BEAMFORMING SCHEMES: MRT, ZF, AND REGULARIZED ZF

The MRT and the ZF beamforming schemes are ones of the most popular linear beamforming schemes. The MRT beamforming only considers the desired channel and maximizes

the SNR and is optimal when the desired signal power is much stronger than the interference power. For transmitter i , the MRT beamforming vector is [28], [30]

$$\mathbf{v}_i^{\text{MRT}} \triangleq \frac{\mathbf{h}_{ii}}{\|\mathbf{h}_{ii}\|}, \quad (6)$$

and the corresponding SNR becomes $P \|\mathbf{h}_{ii}\|^2$.

On the other hand, the ZF beamforming focuses to suppress the interference power. The ZF beamforming vector forces the interference power to zero by constructing the beamforming vector orthogonal to the interfering channels. Let $\mathbf{H}_i \in \mathbb{C}^{N_T \times K-1}$ be the matrix comprised of all of the interfering channels of the transmitter i such that $\mathbf{H}_i \triangleq [\mathbf{h}_{1i}, \dots, \mathbf{h}_{i-1i}, \mathbf{h}_{i+1i}, \dots, \mathbf{h}_{Ki}]$. Then, the ZF beamforming vector for the i th transmitter becomes the projection of the desired channel onto the null space of $\mathbf{H}_i$ as follows [28], [31]:

$$\mathbf{v}_i^{\text{ZF}} \triangleq \frac{(\mathbf{I}_{N_T} - \mathbf{H}_i \mathbf{H}_i^\dagger) \mathbf{h}_{ii}}{\|(\mathbf{I}_{N_T} - \mathbf{H}_i \mathbf{H}_i^\dagger) \mathbf{h}_{ii}\|}, \quad (7)$$

where $\mathbf{H}_i^\dagger \triangleq (\mathbf{H}_i^H \mathbf{H}_i)^{-1} \mathbf{H}_i^H$ is the Moore-Penrose pseudo-inverse of $\mathbf{H}_i$. Note that the ZF beamforming becomes optimal when the interference power is much stronger than the desired signal power.

Albeit optimal in high SNR region, the performance of ZF beamforming can be improved by regularization in low and moderate SNR regions [32]. With the regularized zero-forcing (RZF), the beamforming vector for the i th transmitter becomes

$$\mathbf{v}_i^{\text{RZF}} \triangleq \frac{(\mathbf{I}_{N_T} - \mathbf{H}_i \mathbf{H}_i^\dagger) \mathbf{h}_{ii}}{\|(\mathbf{I}_{N_T} - \mathbf{H}_i \mathbf{H}_i^\dagger) \mathbf{h}_{ii}\|}, \quad (8)$$

where $\mathbf{H}_i^\dagger$ is the regularized pseudo-inverse of $\mathbf{H}_i$, which has a form of

$$\mathbf{H}_i^\dagger \triangleq (\mathbf{H}_i^H \mathbf{H}_i + c \mathbf{I}_{K-1})^{-1} \mathbf{H}_i^H. \quad (9)$$

In (9), the constant c is a regularization parameter, whose optimal value should be numerically found. We choose a proper regularization parameter $c = 1/P$ from simulation, which make the RZF beamforming vectors converge to the standard ZF beamforming vectors.

3) N -LEVEL BALANCED MRT-ZF BEAMFORMING [20], [28]

In this paper, we consider N -level balanced beamforming, which linearly combines the MRT and the ZF beamforming vectors with one of N -level discrete combining factors. At the transmitter i , the balanced beamforming vector is constructed by

$$\mathbf{v}_i(\alpha_i) \triangleq \frac{\alpha_i \mathbf{v}_i^{\text{MRT}} + (1 - \alpha_i) \mathbf{v}_i^{\text{ZF}}}{\|\alpha_i \mathbf{v}_i^{\text{MRT}} + (1 - \alpha_i) \mathbf{v}_i^{\text{ZF}}\|}, \quad (10)$$

where α_i is the combining factor at the transmitter i ranged in $[0, 1]$ such that

$$\alpha_i \in \left\{ \frac{0}{N-1}, \frac{1}{N-1}, \dots, \frac{N-1}{N-1} \right\}. \quad (11)$$

Thus, each transmitter's beamforming vector is characterized by the combining factor.

C. PROBLEM DESCRIPTION

In this paper, we find the optimal beamforming strategy with N -level balanced MRT-ZF beamforming that maximizes the achievable sum rate. With N -level balanced MRT-ZF beamforming, each user chooses one of N -level discrete combining factors (i.e., weights), so the beamforming vectors of all transmitters can be represented by the sequence of combining factors, i.e., $(\alpha_1, \dots, \alpha_K)$.

We call the sequence of all transmitters' combining factors, i.e., $(\alpha_1, \dots, \alpha_K)$ as a beamforming strategy of the transmitters. Then, with N -level balanced beamforming, the set of all beamforming strategies denoted by $\mathcal{S}_N$ can be defined as follows:

$$\mathcal{S}_N = \left\{ (\alpha_1, \dots, \alpha_K) \mid \alpha_1, \dots, \alpha_K \in \left\{ \frac{0}{N-1}, \dots, \frac{N-1}{N-1} \right\} \right\}. \quad (12)$$

Thus, our problem becomes to find the best one among total N^K beamforming strategies in $\mathcal{S}_N$ as follows:

$$\underset{(\alpha_1, \dots, \alpha_K) \in \mathcal{S}_N}{\text{maximize}} \quad \sum_{i=1}^K R_i(\mathbf{v}_1(\alpha_1), \dots, \mathbf{v}_K(\alpha_K)). \quad (13)$$

Remark 1 (Optimal Solution): Note that our problem stated in (13) is a combinatorial problem, which is generally NP-hard [29]. To briefly explain the NP-hardness, we consider a simple case, where each transmitter chooses one between MRT and ZF (this is when $N = 2$), so the optimal strategy should be found in

$$\mathcal{S}_2 = \left\{ (\alpha_1, \dots, \alpha_K) \mid \alpha_1, \dots, \alpha_K \in \{0, 1\} \right\}.$$

Then, if every interfering channel is either 0 or ∞ , for sum rate maximization, the transmitter non-interfering the other transmitters should use MRT beamforming, while the transmitter interfering the others should use ZF beamforming. Thus, to find the transmitters with MRT beamforming is equivalent to find the largest subset of transmitters that are mutually non-interfering. This problem is the same with the maximum independent set problem in combinatorial optimization, which is NP-hard [29, Theorem 1]. Therefore, one needs to compare total N^K strategies to find the optimal one, which becomes prohibitive when the number of transmitters (i.e., K) or the number of total levels (i.e., N) increases. This is why we exploit the machine learning to find the best beamforming strategy, which we will explain in the next section.

III. THE PROPOSED MACHINE LEARNING DESIGN FOR N-LEVEL BALANCED MRT-ZF BEAMFORMING

In this section, we explain our machine learning design to solve the problem (13). The structure of our proposed machine learning model is depicted in Figure 2. We consider a deep neural network (DNN) comprised of an input layer, M hidden layers, and an output layer for our machine learning

model. We explain the details on each layer in the next subsections.

A. INPUT LAYER

In our machine learning model, the input layer takes the channel vectors and transmit power (i.e., P). In K -user MISO ICs, we have total K^2 vector channels (K desired channels and $K(K-1)$ interfering channels), each of which is an $N_T \times 1$ complex vector represented by $2N_T$ real values. For example, the channel $\mathbf{h}_{ij}$ given in (2) is comprised of $2N_T$ real values, which are $\{\text{Re}(h_{ij}^{(1)}), \text{Im}(h_{ij}^{(1)}), \dots, \text{Re}(h_{ij}^{(N_T)}), \text{Im}(h_{ij}^{(N_T)})\}$. Thus, for all K^2 channel vectors, we need $2N_T K^2$ real valued features. Also, for the input transmit power, we need one more real valued feature, so our proposed machine learning model takes total $2N_T K^2 + 1$ real-valued features from the same number of input nodes.

B. HIDDEN LAYER

Our machine learning model is comprised of M hidden layers with $(m_1, \dots, m_M)$ hidden nodes and adopts exponential linear unit (ELU) [33] as an activation function. The training performance depends on the number of hidden layers and the number of nodes for each layer. Thus, we repeat experiments to determine the number of hidden layers and the number of nodes in each layer (i.e., the machine learning structure). Note that the numbers of layers and nodes are related to the performance, so should be carefully chosen. In practice, the transmitter can have multiple machine learning models, so can choose one according to the system parameters.

C. OUTPUT LAYER AND TRAINING

The output layer returns K transmitters' beamforming strategies. The output layer is comprised of NK nodes, where every N nodes represent each transmitter's beamforming strategy.

In our problem, each transmitter can have total N beamforming strategies (i.e., $\mathcal{S}_N$ given in (12)), so we can represent each transmitter's strategy with an N -dimensional one-hot encoded vector,¹ which is a popular method to represent the categorical variable with a binary vector in a classification problem. Thus, the target beamforming strategies of K transmitters (the optimal strategies we want to obtain) can be represented by K one-hot encoded vectors $\mathbf{o}_1^*, \dots, \mathbf{o}_K^*$, where $\mathbf{o}_i^* \in \{0, 1\}^N$ is the one-hot encoded vector for the i th transmitter's strategy, and the one's position in $\mathbf{o}_i^*$ indicates the i 'th transmitter's beamforming strategy. For example, when $\mathbf{o}_i^* = [1, 0, \dots, 0]^T$, we can obtain the i th transmitter's beamforming vector $\mathbf{v}_i(\frac{0}{N-1})$.

We use a Sigmoid function as an output function at each node, whose output is ranged in $(0, 1)$. Then, the output values of the NK nodes become the predicted beamforming strategies for K transmitters denoted by $\mathbf{o}_1, \dots, \mathbf{o}_K$, where

¹A one-hot encoded vector has dimensions the total number of categories and is comprised of all zeros with the exception of a single one. In this case, the single one's position represents the belonging category.

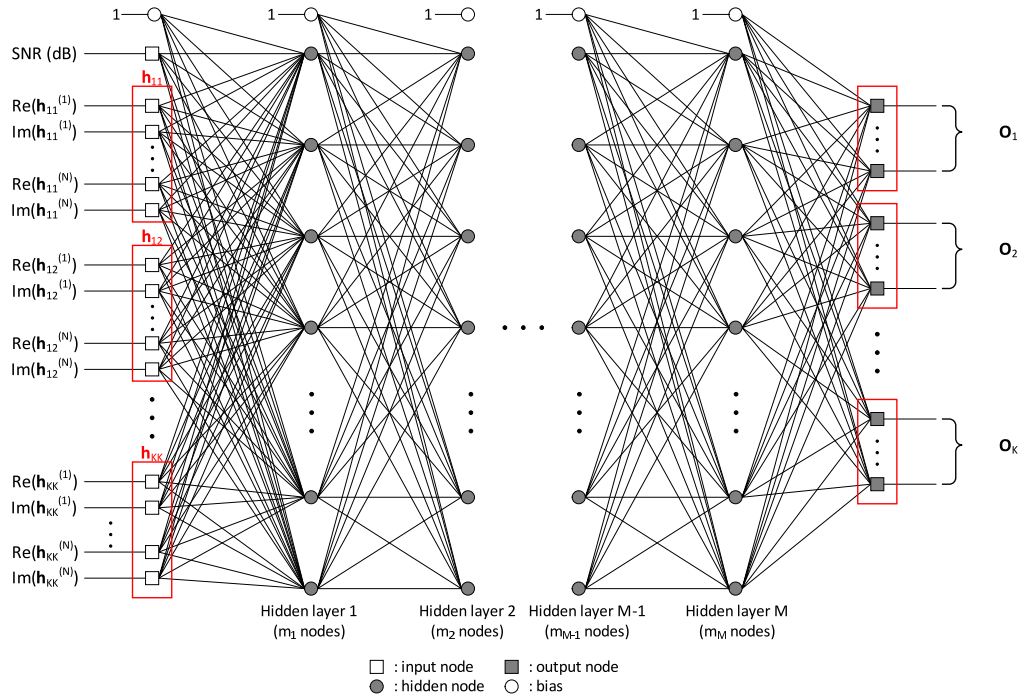


FIGURE 2. The proposed machine learning model.

$\mathbf{o}_i \in \mathbb{R}^N$ is the predicted one of the i th transmitter's target beamforming strategy $\mathbf{o}_i^*$.

When training, to minimize the loss between the predicted and the target beamforming strategies, we use mean squared error (MSE) L_{MSE} given by

$$L_{\text{MSE}} = \frac{1}{N_{\text{bat}}} \sum_{j=1}^{N_{\text{bat}}} \sum_{i=1}^K \|\mathbf{o}_i^{*(j)} - \mathbf{o}_i^{(j)}\|^2, \quad (14)$$

where N_{bat} is the batch-size of the training samples, and $\mathbf{o}_i^{*(j)}$ and $\mathbf{o}_i^{(j)}$ are the j th target and the j th output from a mini-batch, respectively.

We use He initialization [34], which is an efficient method for initializing weights when using the ReLU type of activation functions. We use the adaptive moment (Adam) [8] algorithm as a training algorithm and set an initial learning rate of 0.001. To prevent over-fitting, we stop the training when the performance improvement is absent more than 30 consecutive iterations where the maximum number of epochs is limited to 500.

Note that our machine learning model is trained *offline* with a database. Once it is trained, our machine learning model only takes channel coefficients with an SNR value, and returns the beamforming strategy found. As the optimal beamforming vector in our system model is extremely hard to find, which requires the exhaustive search, so the calculation will take long. Thus, our machine learning model is suitable especially when the channel is changing very fast. In practical, the number of interfering transmitters (i.e., K) may vary. In this case, we can train several machine learning

models offline for possible K , and the transmitters can use the appropriate one among them according to interfering scenarios.

D. GENERATION OF THE TRAINING SAMPLES

In machine learning, a good database is prerequisite for training to obtain high performance. Therefore, we collect a large number of samples, each of which consists of CSI, the best beamforming strategy, and transmit power. The CSI of the sample is comprised of randomly generated K^2 channel vectors. For each transmit power and each channel vector set, we numerically found the best one among total N^K strategies with brute-force search as the optimal solution of problem (13).

From the given transmit power and the channel vector set, we find the best beamforming strategy by iteratively solving the non-convex problem in (13). The generation of the samples is executed by stacking on the previous ones, which means that the larger samples are built up of smaller ones. Note that we need to consider the appropriate value of η in (1) for practical environment.

The computational complexity and the training overhead increase as the number of users, i.e., K , increases; for large K , we need more training samples with more complex machine learning structure. However, the machine learning structure is trained *offline*, so the large number of training samples and the optimization of machine learning structure are rather minor issues compared to beam calculation for each channel realization in fast fading channels.

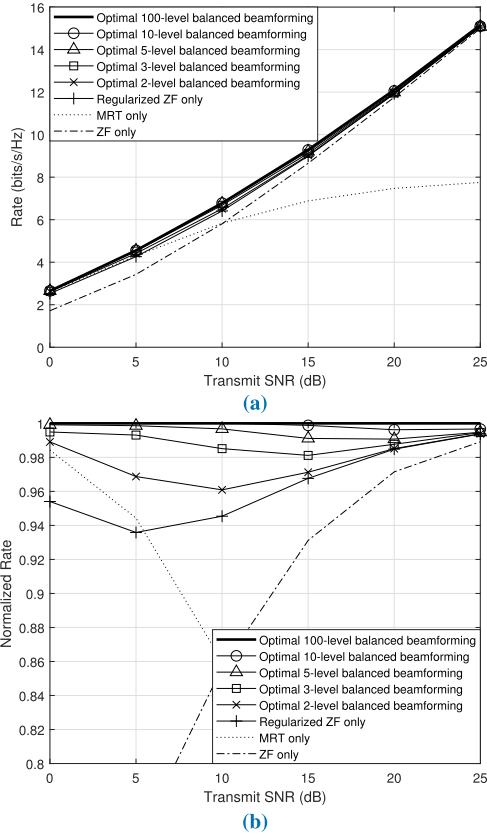


FIGURE 3. The performance of the optimal balanced beamforming in two-user MISO ICs for various level sizes (i.e., N): (a) the achievable sum rate and (b) the achievable sum rate normalized by the optimal 100-level balanced beamforming.

IV. EVALUATION OF OUR PROPOSED MACHINE LEARNING MODEL

A. NUMERICAL RESULTS

In this section, we evaluate our machine learning model. For the simulation, we consider two and three MISO IC cases, i.e., $K = 2$ and $K = 3$ cases, and various total level sizes N . For simulation environment, we fix ISR to 0.2 (i.e., $\eta = 0.2$), where the balanced MRT-ZF beamforming can have various optimal strategies at 10 dB SNR. We also set the number of transmit antennas equal to the number of receivers (i.e., $N_T = K$).

We first show the performance of N -level balanced beamforming with respect to the number of the total level sizes, i.e., N , which we will compare with our machine learning design. For two-user MIMO ICs, Figure 3(a) shows the performance of optimal N -level balanced beamforming with respect to the transmit SNR when $N \in \{2, 3, 5, 10, 100\}$, while Figure 3(b) shows the achievable rate normalized with the achievable rate of 100-level balanced beamforming. On the other hand, for three-user MIMO ICs, Figure 4(a) shows the performance of N -level balanced beamforming with respect to the transmit SNR when $N \in \{2, 3, 5, 10, 100\}$, while Figure 4(b) shows the achievable rate normalized with the achievable rate of 100-level balanced beamforming. As we can see in Figure 3

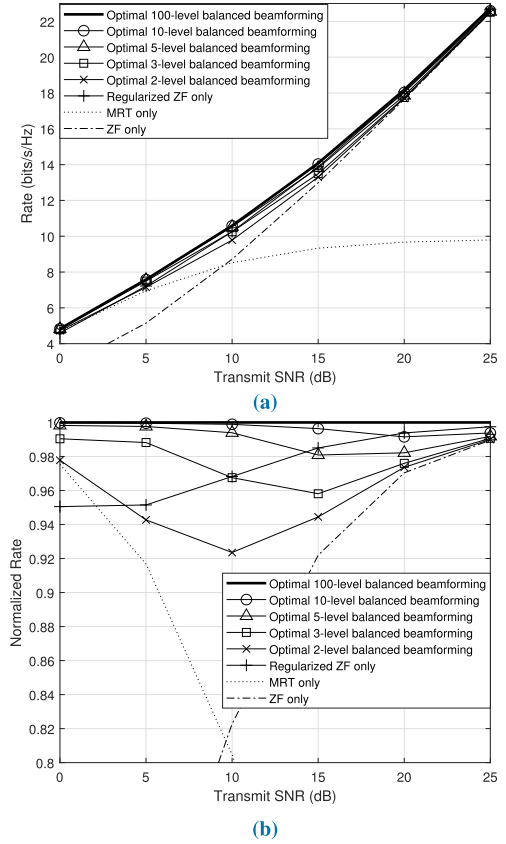


FIGURE 4. The performance of the optimal balanced beamforming in three-user MISO ICs for various level sizes (i.e., N): (a) the achievable sum rate (a) and (b) the achievable sum rate normalized by the optimal 100-level balanced beamforming.

and Figure 4, the performance of optimal N -level balanced beamforming increases as the level size N increases. Also, we can observe that the performance increment is not significant when the number of total levels, i.e., N , is larger than 10; we can check that 10-level balanced beamforming can achieve more than 99% performance of 100-level balanced beamforming. For N -level balanced beamforming, one need to compare all of N^K strategies to find the optimal one. Thus, there is a trade-off between the performance and the computational complexity.

Next, we show the performance of our proposed machine learning-based beamforming with respect to the transmit SNR. As we explained in Section III, our machine learning model is comprised of an input layer with $2NK^2 + 1$ nodes, 5 hidden layers with 500 nodes each, and an output layer with NK nodes. The optimal machine learning structure is not easy to find as the accuracy of the machine learning structure varies with many factors such as the number of layers, the number of nodes in each layer, the number of training samples, and the training method. Thus, we chose the appropriate structure from the simulations.

For two-user MIMO ICs, Figure 5(a) shows the performance of machine learning-based N -level balanced beamforming with respect to the transmit SNR when

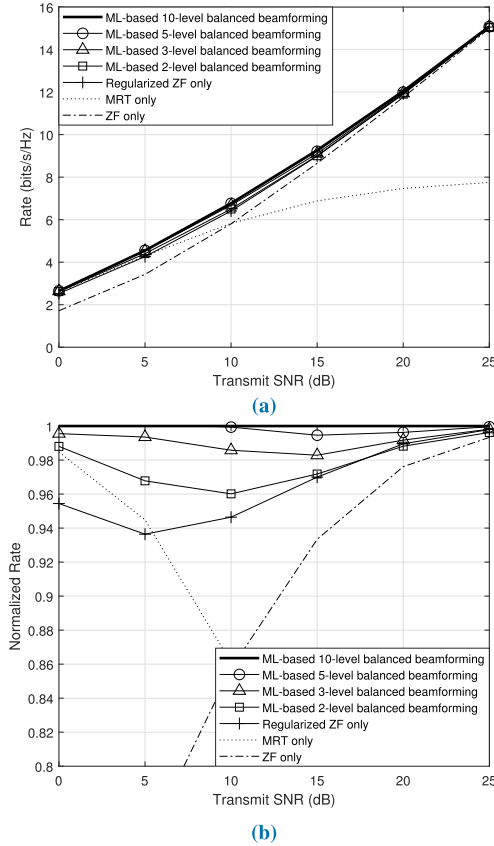


FIGURE 5. The performance of the machine learning-based balanced beamforming in two-user MISO ICs for various level sizes (i.e., N): (a) the achievable sum rate and (b) the achievable sum rate normalized by the machine learning-based 10-level balanced beamforming.

$N \in \{2, 3, 5, 10\}$, while Figure 5(b) shows the achievable rate with our machine learning-based beamforming normalized by the machine learning-based 10-level balanced beamforming. Also, for three-user MIMO ICs, Figure 6(a) shows the performance of machine learning-based N -level balanced beamforming with respect to the transmit SNR when $N \in \{2, 3, 5, 10\}$, while Figure 6(b) shows the achievable rate with our machine learning-based beamforming normalized by the machine learning-based 10-level balanced beamforming. As we can see in Figure 5(b) and Figure 6(b), the performance of machine learning-based beamforming increases as the number of total levels, i.e., N , increases.

In Figure 7, we compare our machine learning-based beamforming with the optimal balanced beamforming. In Figure 7(a) and Figure 7(b), we show the achievable rate of our machine learning-based balanced beamforming normalized by the corresponding optimal balanced beamforming for two-user cases and three-user cases, respectively. As we can see in Figure 7, our proposed machine learning design can achieve more than 99% of the optimal scheme numerically found. Note that our machine learning design can be further improved with various ways including more delicate training and adjusting structure.

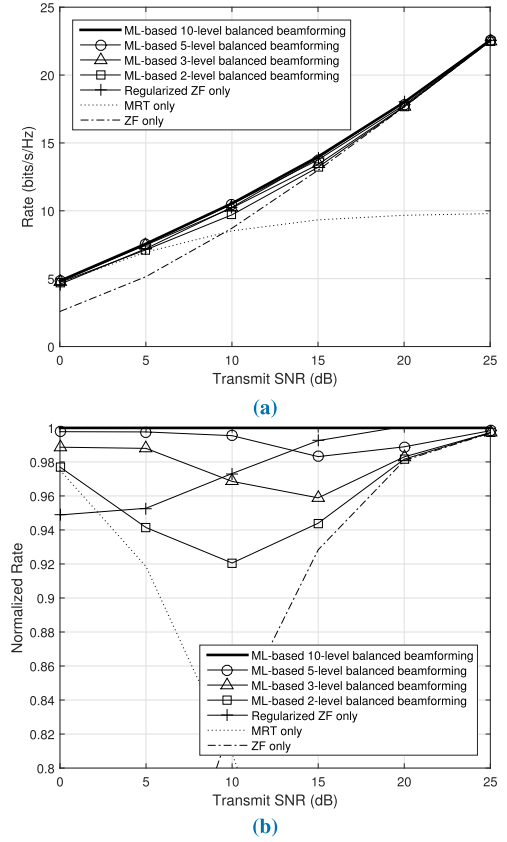


FIGURE 6. The performance of the machine learning-based balanced beamforming in three-user MISO ICs for various level sizes (i.e., N): (a) the achievable sum rate and (b) the achievable sum rate normalized by the machine learning-based 10-level balanced beamforming.

B. COMPLEXITY COMPARISON

As we mentioned earlier, N -level balanced beamforming in K -user MISO interference channels can have N^K strategies, so the optimal beamforming strategy can be found by comparing all of the N^K strategies. Thus, in K -user MISO interference channels, the optimal N -level balanced beamforming needs to calculate N^K sum rates corresponding to all strategies and finds the best one among them. Thus, the computational complexity roughly becomes

$$\mathcal{O}(N^K), \quad (15)$$

where $\mathcal{O}(\cdot)$ is big-O notation [35].² Thus, the computational complexity for the optimal N -level balanced beamforming becomes prohibitive as the number of users (i.e., K) or the number of total levels (i.e., N) increases.

On the other hand, our machine learning model does not require to find the performances of all beamforming strategies. The computational complexity of our machine learning model will be related with the number of nodes. In our machine learning model, the number of input nodes is $2NK^2 + 1$, and the number of output nodes is NK . When

²For two functions $f(x)$ and $g(x)$, we say $f(x) = \mathcal{O}(g(x))$ if and only if there exist constants $c > 0$ such that $|f(x)| \leq c|g(x)|$ when x is sufficiently large.

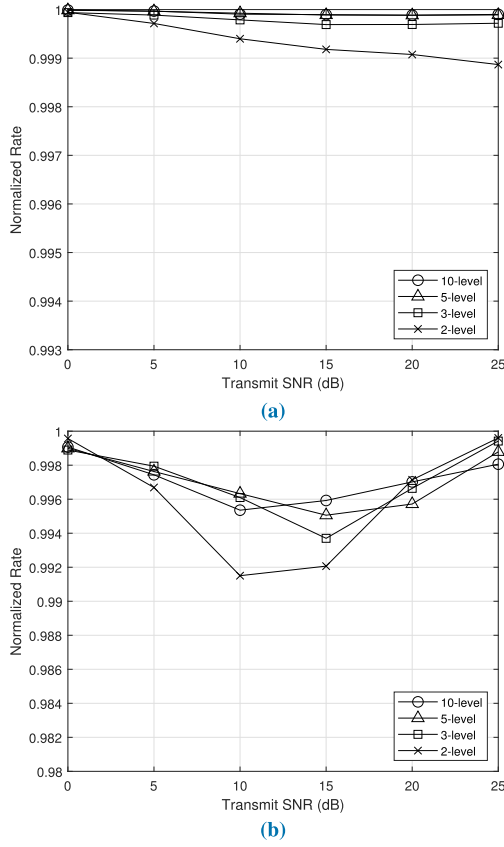


FIGURE 7. The performance ratio of our machine learning-based balanced beamforming to the optimal balanced beamforming for various level sizes (i.e., N): (a) two-user cases and (b) three-user cases.

there are total M hidden layers, where the i th layer has m_i nodes, the computational complexity can be approximated as the number of total paths among the nodes. Thus, the computational complexity of our machine learning model becomes

$$\mathcal{O}\left((2NK^2 + 1)m_1 + m_1m_2 + \dots + m_{M-1}m_M + m_MNK\right) \approx \mathcal{O}(NK^2). \quad (16)$$

Thus, our machine learning model can reduce the computational complexity of the optimal balanced beamforming given in (15), i.e., $\mathcal{O}(N^K)$, into $\mathcal{O}(NK^2)$, while achieving more than 99% of the performance.

Note that, even with the complex machine learning structure, once it is optimized, we expect that the beamforming vector computation will be done in a few system clocks because our machine learning model has a parallel computing structure between the layers.

C. EFFECTS OF IMPERFECT CSI

In our paper, we mainly consider the perfect CSI, but the perfect CSI is almost impossible in practical scenarios. In this subsection, we evaluate our proposed machine learning model when the transmitters have imperfect CSI.

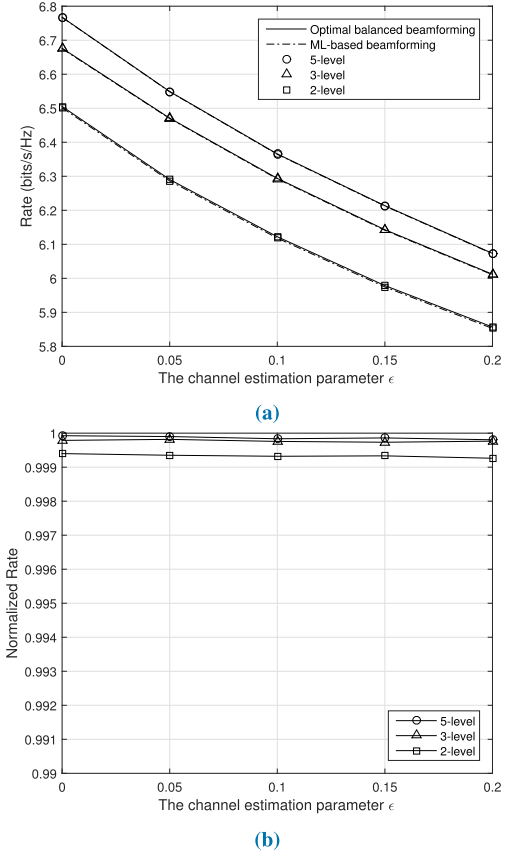


FIGURE 8. The performances of the optimal balanced beamforming and our machine learning-based beamforming with respect to the estimation parameter ϵ in two-user cases: (a) the achievable sum rate and (b) the normalized achievable rate.

We denote by $\hat{\mathbf{h}}_{ij} \in \mathbb{C}^{N_T \times 1}$ the estimated version of $\mathbf{h}_{ij}$ for $i, j \in \{1, \dots, K\}$ and model the imperfect CSI as follows:

$$\hat{\mathbf{h}}_{ij} = \sqrt{1 - \epsilon} \cdot \mathbf{h}_{ij} + \sqrt{\epsilon} \cdot \mathbf{e}_{ij}, \quad (17)$$

where $\mathbf{e}_{ij} \in \mathbb{C}^{N_T \times 1}$ is the channel estimation error vector, whose elements are i.i.d. complex Gaussian random variables with zero mean and unit variance, so becomes isotropic random (i.e., uniformly distributed) in the channel space. Also, $\epsilon \in [0, 1]$ is the channel estimation parameter that represents the imperfectness of the CSI, where $\epsilon = 0$ corresponds to the perfect estimation, and $\epsilon = 1$ corresponds to no association between the estimated and the genuine ones. Thus, the channel estimation model given in (17) maintains the channel gain in the average sense, i.e., $\mathbb{E}_{\mathbf{e}_{ij}}[\|\hat{\mathbf{h}}_{ij}\|^2] = \|\mathbf{h}_{ij}\|^2$.

In Figure 8 and Figure 9, we compare the performances of the optimal balanced beamforming and our machine learning-based beamforming with respect to the estimation parameter ϵ in two-user and three-user cases, respectively, where SNR is fixed to 10 dB with the level size $N \in \{2, 3, 5\}$. Figure 8(a) and Figure 9(a) compare the achievable sum rates of the optimal balanced beamforming and our machine learning-based beamforming, and in both figures, we can observe that the performance of each scheme decreases as the estimation parameter increases because the CSI at the

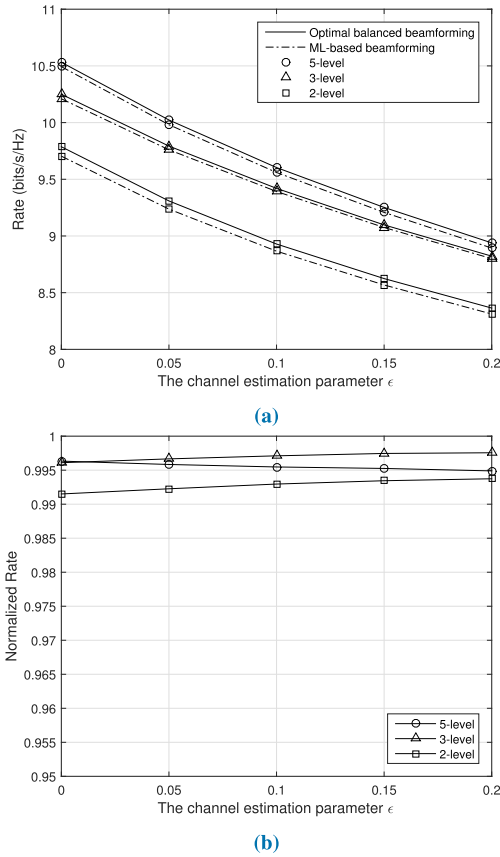


FIGURE 9. The performances of the optimal balanced beamforming and our machine learning-based beamforming with respect to the estimation parameter ϵ in three-user cases: (a) the achievable sum rate and (b) the normalized achievable rate.

transmitters become more inaccurate. Also, Figure 8(b) and Figure 9(b) show the achievable sum rate of our machine learning design normalized by the corresponding optimal balanced beamforming, and we can observe that our machine learning-based beamforming achieves more than 99.9% of the optimal balanced beamforming in two-user cases and more than 99% in three user cases, respectively, regardless of the estimation parameter ϵ .

V. CONCLUSION AND FUTURE WORK

In this paper, we designed machine learning-based beamforming for K -user MISO ICs, where each transmitter uses the balanced MRT-ZF beamforming with finite combining factors. Our machine learning-based beamforming considered a deep neural network structure, which finds the best combining factor for each transmitter. Our proposed machine learning model is based on DNN and takes the channel vectors and transmit power from $2NK^2 + 1$ input nodes, and then returns the best beamforming strategy. We showed that the performance of our proposed machine learning model is comparable to the best beamforming strategy numerically found. Our main purpose is to emulate the existing balanced MRT-ZF beamforming with reduced computational complexity with the aid of machine learning, while achieving comparable

performance. The various machine learning-based beamforming designs that overwhelm the performances of the existing schemes are our on-going research topics.

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