Quantum-Assisted Precoder and Combiner Optimization in Wireless Systems

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***Abstract*—This study utilize quantum-based method for precoder and combiner optimization in multiple-input and multiple-output (MIMO), which can be briefly described as follows. First, optimization variables for precoder and combiner is obtained from the model. Subsequently, the optimization variables are used to increasing the sum rate and to reduce the complexity.**

***Index Terms*—6G, MIMO, quantum computation, wireless optimization**

I. Introduction

The advancements of multiple-input multiple-output (MIMO) in wireless systems promises enhanced wireless performance through the spatial multiplexing. However to maximize the gain, the direction of the beam need to be optimized. Specifically, the transmission and reception need to be optimized leveraging precoder and combiner, respectively. However, due to the growing scale of recent wireless network, obtaining derivations for precoder and combiner can be challenging [1]. Hence, recent works suggest the use of machine-learning-based estimation [2], [3]. To further improve the learning capability, this study suggest the use quantum computation-based learning model. This study employs quantum-assisted optimization using quantum neural network (QNN) for both transmission precoder and receiver combiner to enhance wireless performance.

Notations: Transpose and conjugate transpose are denoted by $(\cdot)^T$ and $(\cdot)^H$, respectively. $(\cdot)^{-1}$ indicates inversion. $\otimes$ indicates Kronecker product. Normal and circular normal distributions are presented as $\mathcal{N}(\mu,\sigma^2)$ and $\mathcal{CN}(\mu,\sigma^2)$, respectively, where μ is the mean and σ^2 is the variance. $|\cdot|$ and $\|\cdot\|$ are indicating the absolute and norm values, respectively. $\mathbb{E}(\cdot)$ indicates expected value. Real and complex numbers are denoted by $\mathbb{R}$ and $\mathbb{C}$, respectively.

II. System Model

This study assumes a single base station (BS) with N_{Tx} transmit antennas, performing down-link NOMA to serve a number of N_{UT} user terminals (UTs); each UT employs N_{Rx} receiving antennas. The total transmit power of the BS is denoted as P_{Tx}. Let $\mathbf{b}$ be the transmit power assignement vector. To serve kth UT, BS employs kth precoding vector $\mathbf{p}_k \in \mathbb{C}^{N_{\text{Tx},k}}$ and a number of $N_{\text{Tx},k}$ transmission antennas; while the kth UT employs receiving combiner $\mathbf{w}_k \in \mathbb{C}^{N_{\text{Rx},k}}$ with $N_{\text{Rx},k}$ receiving antennas. For the sake simplicity, let us assume similar number of $N_{\text{Tx},k}$ and $N_{\text{Rx},k}$ for all kth UTs.

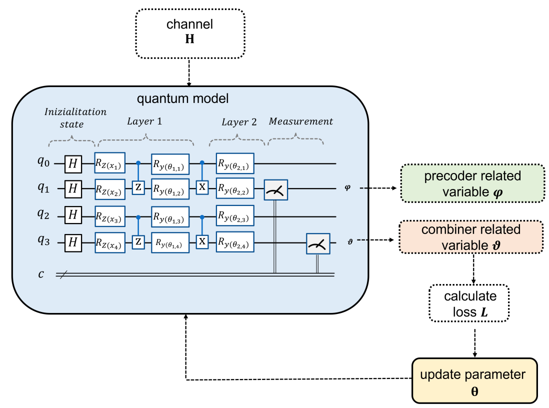

Figure 1. Proposed quantum-assisted scheme.

The reciprocal channel information, which is acquired by the network via pilot signalling, can be expressed as $\mathbf{H} = \{\mathbf{h}_k\}_{k=1}^{N_{\text{UT}}}$. Here, $\mathbf{h}_k$ is the channel of the kth user, modelled as $\mathbf{h}_k = \{g_{i,j}\}_{\forall i,j}$, where $g_{i,j} \sim \mathcal{CN}(0,\sigma_h^2\mathbf{I}_{N_{\text{UT}}})$ is the complex-valued, zero-mean Rayleigh fading coefficient, $i \in \{1,\dots,N_{\text{Tx},k}\}$, $j \in \{1,\dots,N_{\text{Rx},k}\}$; the variance can be assumed as $\sigma_h^2 = d_k^{-\kappa}$, where d_k is the distance between BS and the kth UT.

The channel of the kth user can be expressed as $\mathbf{h}_k = \sqrt{\frac{N_{\text{Tx}}N_{\text{Rx}}}{N_{\text{path}}}}\sum_{l=1}^{N_{\text{path}}}\mathbf{g}_l\mathbf{a}_{\text{Rx}}(\phi_i^{\text{Rx}})\mathbf{a}_{\text{Tx}}(\phi_i^{\text{Tx}})^H$, where $\mathbf{g}_l \sim \mathcal{CN}(0,1)$, $\phi_i^{\text{Rx}} \sim \mathcal{U}(-\frac{1}{2},\frac{1}{2})$, and $\phi_i^{\text{Tx}} \sim \mathcal{U}(-\frac{1}{2},\frac{1}{2})$ denotes the complex path gain, angle of arrival (AoA), and angle of departure (AoD), respectively. The distance between antennas can be assumed as $d = \lambda/2$. Besides, the response vector for the receiving and transmitting antennas can be expressed as $\mathbf{a}_{\text{Rx}}(\phi_i^{\text{Rx}}) = \frac{1}{\sqrt{N_{\text{Rx},k}}}\left[1, e^{-j\frac{2\pi}{\lambda}d\cos\left(\phi_i^{\text{Rx}}\right)},\dots,e^{-j\frac{2\pi}{\lambda}d(N_{\text{Rx},k}-1)\cos\left(\phi_i^{\text{Rx}}\right)}\right]^T$, $\mathbf{a}_{\text{Tx}}(\phi^{\text{Tx}}) = \frac{1}{\sqrt{N_{\text{Tx},k}}}[1, e^{-j\frac{2\pi}{\lambda}d\cos\left(\phi_i^{\text{Tx}}\right)},\dots,e^{-j\frac{2\pi}{\lambda}(N_{\text{Rx},k}-1)d\cos\left(\phi_i^{\text{Tx}}\right)}]^T$ respectively. Considering NOMA, let us sort the user index based on the channel gain, so that $|\mathbf{h}_1|^2 \geq \ldots \geq |\mathbf{h}_{\text{UT}}|^2$ Let $\mathbf{x}$ be the superimposed signal where $\mathbb{E}\{\mathbf{x}\mathbf{x}^H\} \geq 1$.

Accordingly, the received signal by the kth user can be expressed as $\mathbf{y}_k = \underbrace{\sqrt{\mathbf{b}_k}\mathbf{w}_k\mathbf{h}_k^H\mathbf{p}_k\mathbf{x}}_{\text{desired signal}} + \underbrace{\sum_{l=1,l\neq k}^{N_{\text{UT}}}\sqrt{\mathbf{b}_l}\mathbf{w}_l\mathbf{h}_k^H\mathbf{p}_l\mathbf{x}}_{\text{inter-NOMA interference}} + n_k$, where $n_k \sim \mathcal{CN}(0,\sigma_k^2)$ is the additive noise and σ_k^2 is the noise variance.

Using NOMA, the received signal-to-interference-plus-noise ratio (SINR) of the kth user can be expressed as [4] $\gamma_k = \frac{\mathbf{b}_k|\mathbf{w}_k\mathbf{h}_k^H\mathbf{p}_k|^2}{\sum_{l=1}^{k-1}\mathbf{b}_l|\mathbf{w}_l\mathbf{h}_k^H\mathbf{p}_l|^2+\sigma_k^2}$, where σ_k^2 indicates the noise variance.

The objective is to maximize the sum rate given precoder $\mathbf{p}$ and combiner $\mathbf{w}$, as follows:

$$\max_{\mathbf{p},\mathbf{w}} \quad R_{\text{sum}} = \sum_{k=1}^{N_{\text{UT}}} \log_2(1+\gamma_k) \tag{1a}$$

$$\text{s.t.} \quad \sum_{k=1}^{N_{\text{UT}}} \mathbf{p}_k^H\mathbf{p}_k \le P_{\text{Tx}}, \tag{1b}$$

$$\|\mathbf{w}_k\|^2 \le 1, \forall k \in \{1,\ldots,N_{\text{UT}}\} \tag{1c}$$

The constraint of Eq. (1b) satisfies the power constraints of the transmit antennas while the constraint of Eq. (1b) related to the combiner.

III. Proposed Scheme

In this section, the proposed scheme is presented. First, the precoder and combiner are described. Eventually, the considered quantum operation is exhibited.

A. Training Framework

To facilitate higher rate of training convergence, the optimization objective can be reformulated as $\max_{\mathbf{p},\mathbf{w}} \Omega = \frac{\sum_{k=1}^{N_{\text{UT}}}\gamma_k}{\|\mathbf{h}_k\|}$ The main point is to normalize the achieved received SINR γ_k with UTs' given channel information. The loss can simply be expressed as $\text{Loss} = -\Omega$.

Toward obtaining model that can minimize loss, the gradient descent method is used: $\theta_t = \theta_{t-1} - \nabla_{\theta_t}\mathcal{L}(-\Omega)$.

B. Transmit Precoder

Given transmission $\mathbf{p}$, we can divide it as different sub-vector designated for the kth user, as $\mathbf{p} = \{\mathbf{p}_k\}_{k=1}^{N_{\text{Tx},k}}$, where $\mathbf{p}_k$ is assigned to the k-th user and $N_{\text{Tx},k}$ is the number of transmit antennas assigned to the kth user. The precoder for the k-th user is given by [4]

$$\mathbf{p}_k(\mathbf{P}_{tx},\varphi_k) = \sqrt{\mathbf{P}_{tx}}\frac{(I_{N_{\text{UT}}}+\varphi_k\sum_{k=1}^{N_{\text{UT}}}\mathbf{h}_k\mathbf{h}_k^H)^{-1}\mathbf{h}_k}{\|(I_{N_{\text{UT}}}+\varphi_k\sum_{k=1}^{N_{\text{UT}}}\mathbf{h}_k\mathbf{h}_k^H)^{-1}\mathbf{h}_k\|},$$

where $\mathbf{b}_k$ and φ_k are the power assignment and steering variables for kth user, respectively. Precisely, the vector $\{\varphi_k\}_{k=1}^{N_{\text{UT},k}}$ is obtained from QNN.

C. Power Vector

The power assignment vector is given by $\mathbf{b} = \{\tilde{\mathbf{b}}_k\lambda_k\}_{k=1}^{N_{\text{UT},k}}$, where $\tilde{\mathbf{b}}_k$ is the power assigned to the k-th user and λ_k is the NOMA power coefficient. Based on [5], the power can be obtained as follows. The power vector can be obtained as follows. Firstly, the following variables can be calculated:

$$\begin{aligned} &\mathbf{D} = \text{diag}\{1/|\mathbf{p}_1^H\mathbf{h}_1|^2,\ldots,1/|\mathbf{p}_{N_{\text{UT}}}^H\mathbf{h}_{N_{\text{UT}}}|^2\}, \\ &\mathbf{c} = [\sigma_1^2,\ldots,\sigma_{N_{\text{UT}}}^2]^T, \\ &[\mathbf{A}]_{k,l} = \begin{cases} |\mathbf{p}_l^H\mathbf{h}_k|^2, & k=l, \\ 0, & k \ne l, \end{cases} \end{aligned} \tag{2}$$

Subsequently, the following matrix is calculated: $\Gamma = \begin{bmatrix} \mathbf{DA} & \mathbf{Dc} \\ 1/P_{\text{Tx}}\mathbf{I}^T\mathbf{DA} & 1/P_{\text{Tx}}\mathbf{I}^T\mathbf{Dc} \end{bmatrix}$. Next, by taking the first N_{UT} element of the inverse of Γ, the vector of $\tilde{\mathbf{b}} = \{\tilde{\mathbf{b}}_k\}_{k=1}^{N_{\text{UT}}}$ can be obtained.

D. Receiver Combiner

The combiner for the kth user is denoted by $\mathbf{w}_k$, where the combiner for all users can be expressed collectively as $\mathbf{w} = \{\mathbf{w}_k\}_{k=1}^{N_{\text{Rx},k}}$. Based on minimum mean square error (MMSE) approach that has been proposed in [6], the combiner for the kth user can be expressed as $\mathbf{w}_k = \vartheta_k(\mathbf{h_k}^H(\mathbf{h_k}\mathbf{h_k}^H + \gamma_k^{-1}I)^{-1}), = \vartheta_k((\mathbf{h_k}^H\mathbf{h_k}+\gamma_k^{-1}I)^{-1}\mathbf{h_k}^H)$, where ϑ_k is the steering coefficient for combiner. Accordingly, $\{\vartheta_k\}_{k=1}^{N_{\text{UT},k}}$ is obtained from QNN.

IV. Conclusion

This study employs quantum-assisted to optimize precoding and combiner. In the future, quantum neural network in massive MIMO can be studied.

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