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Quantum Deep Unfolding Based Resource Allocation Optimization for Future Wireless Networks

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ABSTRACT

This paper introduces Quantum Deep Unfolding (QDU), a technique for optimizing power allocation and transmit precoding in multiple-input multiple-output non-orthogonal multiple access (MIMO-NOMA) systems. Solving the optimization problem in such systems poses a significant challenge due to its high computational complexity and non-convex nature, which increases the risk of being stuck at a local minimum. In order to address this issue, QDU leverages an iterative algorithm and analytical derivation to enhance the sum rate performance and training processes by optimizing power allocation and transmit precoding. The proposed approach integrates a Quantum Neural Network (QNN) induced by an iterative deep unfolding algorithm with a learning solution inspired by the training process. At each QDU layer, the iterative optimization involving the Projected Gradient Descent (PGD) operator is unfolded to learn the crucial parameters. The objective of QDU is to maximize the achievable sum rate while simultaneously reducing computational complexity.

Key Words : Deep unfolding, non-orthogonal multiple access, quantum neural networks, wireless communications.

Ⅰ. Introduction

The next generation of wireless communication, known as 6G, is expected to experience significant scalability, with a larger number of devices and transmit antennas. Consequently, optimizing the parameters in 6G systems poses substantial challenges[1]. Therefore, conventional methods of optimizing wireless networks through mathematical analysis have become increasingly difficult due to the growing number of optimization variables, such as transmit precoding and power allocation[2].

To address this issue, neural networks (NNs) have gained popularity in recent years for enhancing the physical layer of wireless communication. These parameterized learning models approximate the optimal solutions for optimization[3]. However, these networks often employ general functions, like perceptrons, in each layer, resulting in a high number of trainable parameters, requiring significant amounts of data and time to attain convergence during model training[4].

To mitigate this problem, the concept of mapping the iteration process of conventional iterative

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algorithms onto layer-wise NN structures has been introduced in [5] and [6]. This mapping entails unfolding the iteration process and incorporating trainable parameters to improve training performance with computationally lighter architectures. Deep unfolding networks have emerged as useful alternatives to model-driven NNs and are rapidly gaining popularity in communication systems. In particular, [5] proposed the use of deep unfolding to optimize transmit precoding in MIMO systems. Unlike conventional neural networks, deep unfolding networks involve iterative algorithms in each layer that employ analytical-based functions. For example, an n-step iterative inference algorithm can be unfolded into an l-layered NN structure with trainable parameters determined by the model. Existing studies on deep unfolding-based optimization typically utilize classical computation. However, classical computation has limitations in terms of computational complexity, particularly for large-scale problems.

Furthermore, there is a growing interest in utilizing Quantum Neural Networks (QNNs), which leverage quantum computation to address the high computational complexity associated with classical approaches and reduce dimensionality[4,15]. QNNs can also utilize quantum entanglement and superposition to process information, potentially an offering exponential speedup over classical NNs for specific tasks[11]. Motivated by these factors, this study employs the advantages of QNNs in a deep unfolding architecture called QDU for optimizing MIMO-NOMA systems.

Since optimization is a non-convex problem, the gradient descent algorithm may converge unexpectedly and find a local minimum. In [6], the author presented deep unfolding neural networks based on Projected Gradient Descent (PGD) for MIMO detection, where the objective function is determined by the constraints. Furthermore, PGD incorporates a projection step to ensure that the updated solution remains within the feasible region defined by these constraints. This property of PGD allows for effective optimization of power allocation, transmit precoding, and other parameters while satisfying the necessary constraints.

In this study, the PGD scheme is utilized in each iteration of QDU, enabling faster training and convergence[10].

Additionally, when it comes to the training process of a QDU network, unsupervised learning presents a viable option as it does not require the labeling of data, unlike supervised learning[7].

To explore the potential of the aforementioned methodologies, the main contributions of this study can be summarized as follows: Firstly, QNNs are employed to optimize transmit precoding and power allocation in wireless systems. Secondly, a model-driven deep unfolding network is considered, incorporating analytical-based transmit precoding and power allocation in each layer. Thirdly, the PGD scheme is proposed in each iteration of the QDU scheme to optimize MIMO-NOMA systems.

Notations: A complex Gaussian distribution is indicated as $x \sim \mathcal{CN}(\mu\sigma^2)$, where μ and σ denotes the mean and the variance, respectively. Let $|.|$ and $\circ$ indicate element-wise multiplication and absolute value, respectively. Consider $\mathbb{R}$ and $\mathbb{C}$ denote real and complex numbers, respectively. The Kronecker product is represented as $\otimes$. Moreover, H(.), R_y, and M(.) denote the Hadamard gate, rotation on the Y-axis, and quantum measurement operator, respectively.

Ⅱ. System Model

This study considers a single-cell downlink in MIMO-NOMA, as illustrated in Fig. 1. The base station (BS) is equipped with N transmit antennas, while each user has a single antenna. The downlink channel assumes a Rayleigh fading scenario. The user devices are grouped into m-th clusters, with each pair of users receiving a superimposed NOMA signal. This study focuses on power domain NOMA, where the transmit power is divided among the user devices in each group based on predefined power allocation. Successive interference cancellation (SIC) is employed to decode the designated message at each receiving device.

Let N_{Tx} denote the number of transmit antennas at the BS. As shown in Fig. 1, to serve all users within the *m*-th clusters, the BS utilizes a transmit precoding matrix denoted by $\boldsymbol{V}_m \in \mathbb{C}^{N_{\mathrm{Tx}} \times 1}$ as precoding matrix for the NOMA user groups. The NOMA power allocation coefficient is denoted as $\lambda_{m,k}$. Let $d_{m,\mathrm{str}} \leq 1$ and $d_{m,\mathrm{weak}} \leq 1$ be the normalized distance between the strong user and the weak user, respectively. Let $\left|\boldsymbol{h}_{m,k}\right|^2 \in \mathbb{C}^{N_{\mathrm{Tx}} \times 1}$ be the channel gain values for *k*-th user in *m*-th group, respectively[13]. It is assumed, that $\left|\boldsymbol{h}_{m,1}\right|^2 \geq, \ldots, \geq \left|\boldsymbol{h}_{m,k}\right|^2$

The channel coefficient for $u_{m,k}$ can be expressed as $h_{m,k} \sim \mathcal{CN}\left(0, d_{m,\mathrm{str}}^{-\kappa}\right) \in \mathbb{R}$ where κ is the pathloss exponent [8]. Let $\sigma_{\mathrm{noise}}^2$ be the noise variance. The total power transmit is denoted as P_{T}. Thereafter, the received signal model at *k*-th users in *m*-th cluster is given as [18]

$$y_{m,k} = \sum_{k=1}^{N_{user}} \boldsymbol{V}_m \sqrt{\lambda_{m,k} P_{\mathrm{T}}} s_{m,k}, \tag{1}$$

where $\boldsymbol{V} \triangleq [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_m]^T$ is the precoder array for the *k*-th user in *m*-th group. Moreover, $s_{m,k}$ is denoted the information signal of *k*-th user.

2.1 Objective

In the context of optimizing transmit precoding $\boldsymbol{V}_m$ and power allocation $\lambda_{m,k}$ in MIMO-NOMA systems, to objective is to maximize the achievable sum rate, which can be presented as

$$\max_{\mathbf{V}_m, \lambda_{m,\mathrm{str}}} \bar{R}_{\mathrm{sum}}\left(\boldsymbol{V}_m, \lambda_{m,\mathrm{k}}\right), \tag{2a}$$

$$\text{s.t.} \quad 0 < \lambda_{m,\mathrm{str}} \leq 1, \forall_m, \tag{2b}$$

$$\left\|\boldsymbol{V}_m^{[i]}\right\| \leq 1, \forall_m, \forall_i \in \{1, \ldots, N_{\mathrm{Tx}}\}, \tag{2c}$$

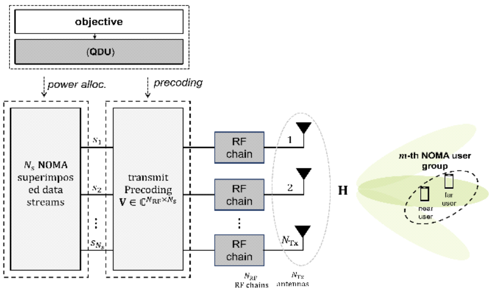

Fig. 1. Utilizing QDU to optimize a MIMO-NOMA systems.

where $\bar{R}_{\mathrm{sum}} = \sum_{k=1}^{N_{\mathrm{group}}} R_{m,k}$ are the average sum rate in *m*-th cluster. Here, Eq. (2b) and Eq. (2c) are the minimum allocated power constraint and minimum data rate, respectively.

2.2 Achievable Rate

In general, the receive signal-to-interference-plus-noise-ratio (SINR) for *k*-th users in *m*-th group can be obtained as [9]

$$\gamma_{m,k} = \frac{\left|\boldsymbol{h}_{m,k}^T \boldsymbol{V}_m\right|^2 \rho \lambda_{m,k}}{\sum_{j=1,\neq k}^{k-1} \left|\boldsymbol{h}_{m,k}^T \boldsymbol{V}_m\right|^2 \rho \lambda_{m,j} + \sigma_{\mathrm{noise}}^2}, \tag{3}$$

where $\rho = \frac{P_T}{\sigma_{\mathrm{noise}}^2}$ indicates the signal-to-noise ratio of the transmitter (SNR)[13,14]. The achievable rates for *k*-th users in *m*-th cluster can be expressed as

$$R_{m,k} = \sum_{k=1}^{N_{\mathrm{user}}} \log_2\left(1 + \gamma_{m,k}\right). \tag{4}$$

Ⅲ. Proposed Scheme

In this section, the general concept of QDU framework is summarized as follows:

3.1 QDU for MIMO-NOMA

The QDU algorithm, which is presented in Fig. 2, is aimed at optimizing the transmit precoding and power allocation, respectively. Set of inputs for deep unfolding layers is the channel vector $\boldsymbol{h}_{m,k}$ and $\Phi^{[l]} = \left(\boldsymbol{V}^{[l]}, \lambda^{[l]}\right)$, where $\boldsymbol{V}^{[l]}$ and $\lambda^{[l]}$ are the transmit precoding and power allocation, which induced the QNN optimization, respectively. Afterwards, $\Phi^{[l]}$ is updated in the *l*-th layer during the training procedure. In each iteration, the optimization $\breve{\Phi}_{l,K}$ is updated through i) performing of ∇ gradient descent step, which involves multiplying it by the negative gradient of the cost function and ii) updating the PGD onto the feasible set determined by constraint (12).

The architecture of the proposed QDU for NOMA-MIMO consisting of cascading parts, which can be described as follows:

1) Precoding part: The analytical-based precoding can be expressed as

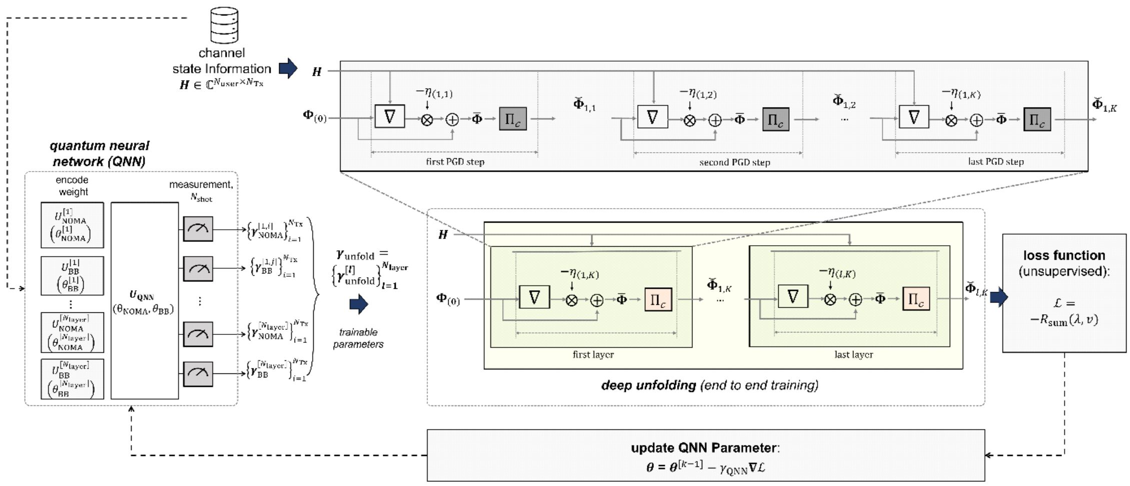

Fig. 2. Proposed QDU framework for MIMO-NOMA.

$$\boldsymbol{V}^{[l]} = \boldsymbol{G}(\boldsymbol{G}^H\boldsymbol{G})^{-1}, \tag{5}$$

where $\mathbf{G} = \boldsymbol{H} \circ \left(\hat{\lambda}^{[l]}\right)^{1/2}$[5]. The resulting equivalent channel is given by $\boldsymbol{H} = [\boldsymbol{h}_1, \dots, \boldsymbol{h}_{m,k}]$, which is equal to the Frobenius norm of the actual MIMO channel matrix $\boldsymbol{H} \in \mathbb{C}^{N_{\text{user}}^{[m,n]} \times N_{\text{Tx}}}$ Afterwards, the optimization vector for the transmit precoding can be calculated as

$$\widehat{\boldsymbol{V}}^{[l]} = \frac{\boldsymbol{V}^{[l]} \circ \gamma_{\text{BB}}^{[l]}}{\left\|\boldsymbol{V}^{[l]} \circ \gamma_{\text{BB}}^{[l]}\right\|}, \tag{6}$$

where $\gamma_{\text{BB}}^{[l]}$ are obtained from QNN the optimization vector for $\boldsymbol{V}^{[l]}$.

2) NOMA Power Allocation: Initially, the analytical-based power allocation can be expressed as

$$\lambda^{[l]} = \left\{\lambda_{\text{str}}^{[l]}, \lambda_{\text{weak}}^{[l]}\right\}, \tag{7}$$

where $\lambda_{\text{str}}^{[l]} = \sqrt{\frac{1+\|\boldsymbol{h}_{m,\text{str}}\|^2 \rho - 1}{\|\boldsymbol{h}_{m,\text{weak}}\|^2 \rho}}$ and $\lambda_{\text{weak}}^{[l]}$ are the NOMA power allocation coefficients for $u_{m,\text{str}}$ and $u_{m,\text{weak}}$, respectively [13]. Let $\gamma_{\text{NOMA}}^{[l]}$, which is obtained from the QNN, be the optimization variable for $\lambda^{[l]}$ Subsequently, $\hat{\lambda}^{[l]}$ can be calculated as follows:

$$\hat{\lambda}^{[l]} = \lambda^{[l]} \circ \gamma_{\text{NOMA}}^{[l]}. \tag{8}$$

In summary, the performance of conventional training in QDU is constrained by the complexity and difficulty of direct handling of limitations, such as the restricted number of iterations relative to the number of layers and neurons. However, QNNs are employed to learn and optimize the step size parameter.

3.2 Quantum Variational Circuit

Figure 3 shows the QNN processes data using the following method, where the encoding and decoding steps are illustrated. Furthermore, the *encoding* operation of the quantum variational circuit for QDU can be expressed as [11]

$$U_{\text{encode}}\left(\theta_{\text{NOMA}}^{[l]}, \theta_{\text{BB}}^{[l]}\right) = \otimes_{n=1}^{N_{\text{wieght}}} \otimes_{i=1}^{N_{\text{data}}} \mathbf{R}_y\left(\tanh\left(x_{\text{input},i}^{[n]}\right)\right)\mathbf{H}, \tag{9}$$

where $\mathbf{R}_y\left(\tanh\left(x_{\text{input},i}^{[n]}\right)\right)$ is the term used for encoding[4,12]. The operation of $tanh(.)$ is used for pre-processing.

The trainable parameter resulting from the aforementioned decoding operation function can be expressed as:

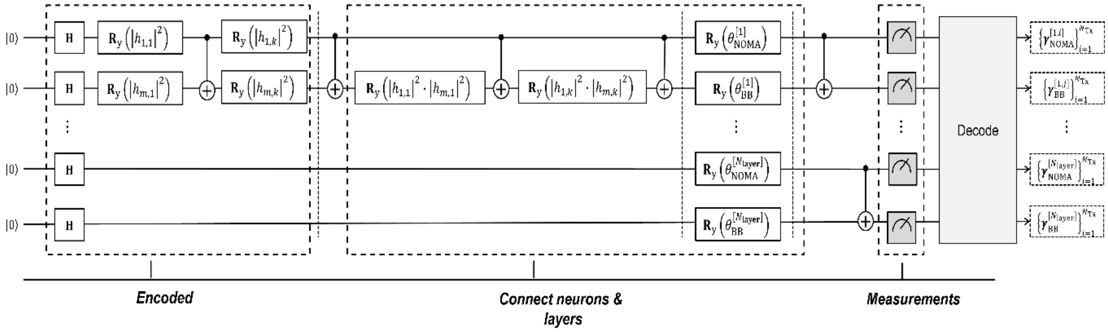

Fig. 3. Utilize quantum circuit based on the QNN operation.

$$\gamma^{[l]}_{\text{unfold}} \leftarrow U_{\text{decode}} = \left(|\psi\rangle^{[l]}_{\text{unfold}}\right) = \frac{1}{N_{\text{shot}}}\sum_{j=1}^{N_{\text{shot}}} \mathbf{M}\left(|\psi\rangle^{[l]}_{j,\text{unfold}}\right), \quad (10)$$

where N_{shot} denotes the number of shots taken in the quantum measurement process. Let $|\psi\rangle^{[l]}_{j,\text{unfold}}$ be the measurement output state of QNN for $\gamma^{[l]}_{\text{BB}}$ and $\gamma^{[l]}_{\text{NOMA}}$, respectively.

3.3 Training Model

1) *Projected gradient descent*: To improve the training convergence and satisfy the power constraint in Eq. (2c), a PGD operator is included in each *l*-th layer of QDU algorithm, as specified in the formula[6,19]:

$$\Pi^{[l]}_{c} = \begin{cases} \boldsymbol{V}, & \text{if } \ \mathbf{Tr}\|\boldsymbol{V}_m\| \le 1 \\ \frac{\boldsymbol{V}}{\|\boldsymbol{V}\|_F}\sqrt{P_{T}}, & \text{otherwise} \end{cases} \quad (11)$$

where $\boldsymbol{V} \triangleq [\boldsymbol{v}_1, \boldsymbol{v}_2, \dots, \boldsymbol{v}_m]^T$. Let $c = \{\|\boldsymbol{V}_m\| \le 1\}$ be the power constraint set, which solves the problem in Eq. (3c). Subsequently, the *k*-th PGD update can be expressed as

$$\bar{\Phi}^{(k)}_i = \Phi^{(k-1)}_i - \eta^{(k)}_l \nabla f\left(\Phi^{(k)}_i\right). \quad (12)$$

Afterwards, the update is projected as $\check{\Phi}_{l,K} = \Pi^{[l]}_{c}\left\{\bar{\Phi}^{(k)}_i\right\}$.

2) *Parameter shift rule*: The partial gradient update of the quantum node *f* with respect to the θ_i can be expressed as

$$\nabla_{\theta_i} f_{\text{qnn}}\left(x;\theta^{[t-1]}\right) = \frac{1}{2\sinh(\mathfrak{s})}\left(f_{\text{QNN}}\left(x;\theta^{[t-1]}+\mathfrak{s}\right) - x f_{\text{QNN}}\left(x;\theta^{[t-1]}-\mathfrak{s}\right)\right), \quad (13)$$

where $\mathfrak{s}$ denotes the parameter-shift coefficient. However, focusing on θ_i, the gradient update can be described as

$$\nabla_{\theta_i} f_{\text{qnn}}\left(x;\theta^{[t-1]}\right) = \langle\psi_{i-1}|_{\theta_i} U^{\dagger}_i(\theta_i) B_{i+1} U_i(\theta_i)|\psi_{i-1}\rangle. \quad (14)$$

Moreover, the loss calculation can be denoted by $\mathcal{L}\left(U_{\text{QNN}}\left(x;\boldsymbol{\theta}^{[t-1]}\right)\right)$, while the gradient of the loss can be calculated as

$$\nabla_{\theta^{[t-1]}_i}\mathcal{L}\left(U_{\text{QNN}}\left(x;\boldsymbol{\theta}^{[t-1]}\right)\right) = \frac{1}{2\sinh(\mathfrak{s})}\mathcal{L}\left(U_{\text{QNN}}\left(x;\boldsymbol{\theta}^{[t-1]}\middle|\theta^{[t-1]}+\mathfrak{s}\right)\right) - \mathcal{L}\left(U_{\text{QNN}}\left(x;\boldsymbol{\theta}^{[t-1]}\middle|\theta^{[t-1]}-\mathfrak{s}\right)\right). \quad (15)$$

To update the *i*-th parameter of QDU network, denoted as $\theta^{[t-1]}_i$, the following gradient descent formula can be used[11]:

$$\theta^{[t]}_i = \theta^{[t-1]}_i - \eta\nabla_{\theta^{[t-1]}_i}\mathcal{L}\left(U_{\text{QNN}}\left(x;\boldsymbol{\theta}^{[t-1]}\right)\right), \quad (16)$$

where η is denoted as the learning rate $\{1, \ldots, N_{\text{weight}}\}$

3) Loss Function: By adopting an unsupervised learning methodology, the computation of the loss function for QDU can be expressed as:

$$\mathcal{L} = -\sum_{n=1}^{N_{\text{data,test}}^{[m]}} \bar{R}_{\text{sum}}(\boldsymbol{V}_m, \lambda_{m,k})|_i, \tag{17}$$

where $\bar{R}_{\text{sum}}(\boldsymbol{V}_m, \lambda_{m,k})|_i$ is the achievable rate from the i-th training iteration, describe in Eq. (2a). Moreover, minimizing the loss function will lead to a higher sum rate and better overall system performance.

Ⅳ. Simulation and Result

Iterative training method is used in this simulation. The following simulation scenario is considered. The QNN operations ($U_{\text{encode}}, U_{\text{decode}}$) were performed in IBM Qiskit[17]. Consider the number of shot N_{shot} = 1024, number of dataset N_{dataset} = 100 and number of train N_{train} = 1000. The user distance and channel gain values are assumed as follows. Let us considers two users for each NOMA group as denoted by $N_{\text{user}}^{[m]}$ = 2. The normalized distance of both users as $d_{m,\text{str}}$ = 0.5, respectively. Moreover, the number of layers for the QDU is set to be $N_{\text{layer}}^{[n]}$ = 4, where the learning rate is denoted as η = 0.01, was considered. Employing Monte-Carlo simulation of 1000 trials, the training result of the QDU achieved a similar result compared to the conventional method based on gradient descent.

Moreover, as shown in Fig. 4, the QDU achieved sum rate was observed to be significantly increased with respect to the SINR. The QDU achieved a similar result to the conventional training model. However, the QDU enforces the constraint after each iteration, when the projection of QDU step is excessively aggressive, causing the solution to be significantly altered to satisfy the constraints. As a result, the achieved sum rate could be lower compared to the conventional training based gradient-descent method, which does not directly enforce constraints during optimization.

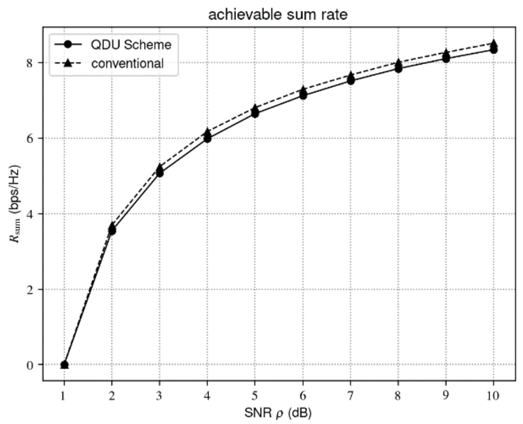

Fig. 4. Achieved sum rate by employing QDU scheme, compared to that conventional training method. During training ρ_{train} = 10 dB is considered.

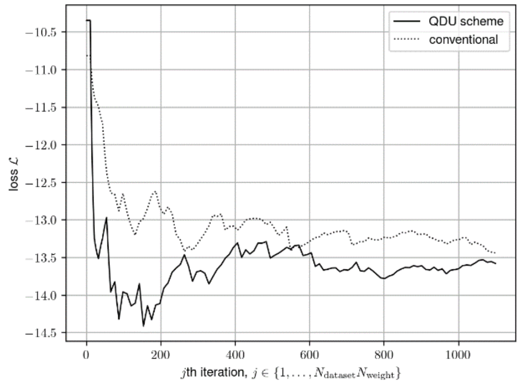

Fig. 5. Convergence performance of the loss function compared to that of conventional training (based on gradient-descent method). During training ρ_{train} = 10 dB is considered. Here, both of the methods converge at approximately $\mathcal{L}$ = -13.5.

Ⅴ. Conclusion

This study proposed QDU framework to optimize the power allocation and transmit precoding in MIMO-NOMA systems, with steps summarized as follows: *Firstly*, the statistical parameters of the dataset are obtained as inputs. *Secondly*, the QNN feedforward process involves obtaining trainable parameter values from the measurement output of QNN. *Thirdly*, the unfolded QDU algorithm is presented, as shown in Fig 2, where each QDU layer includes multiple sub-routines towards power allocation and transmit precoding optimization. Additionally, to prevent gradient exploitation and satisfy the power constraint, each layer of the QDU scheme utilizes the PGD operator. The simulation results demonstrate that QDU outperforms the existing iterative algorithms with reduced computational complexity of the training process. Future work may involve investigating other optimization factors, such as massive MIMO-NOMA.

References

[1] A. Jagannath, J. Jagannath, and T. Melodia, "Redefining wireless communication for 6G: Signal processing meets deep learning with deep unfolding," *IEEE Trans. Artif. Intell.*, vol. 2, no. 6, pp. 528-536, Dec. 2021. (https://doi.org/10.1109/TAI.2021.3108129)

[2] H. Huang, Y. Yang, Z. Ding, H. Wang, H. Sari, and F. Adachi, "Deep learning-based sum data rate and energy efficiency optimization for MIMO-NOMA systems," *IEEE Trans. Wirel. Commun.*, vol. 19, no. 8, pp. 5373-5388, Aug. 2020. (https://doi.org/10.1109/TWC.2020.2992786)

[3] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?," *IEEE Trans. Commun.*, vol. 67, no. 10, pp. 7331-7376, Oct. 2019. (https://doi.org/10.1109/TCOMM.2019.2924010)

[4] B. Narottama and S. Y. Shin, "Quantum neural networks for resource allocation in wireless communications," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 2, pp. 1103-1116, Feb. 2022. (https://doi.org/10.1109/TWC.2021.3102139)

[5] Q. Hu, Y. Cai, Q. Shi, K. Xu, G. Yu, and Z. Ding, "Iterative algorithm induced deep-unfolding neural networks: Precoding design for multiuser MIMO systems," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 2, pp. 1394-1410, Feb. 2021. (https://doi.org/10.1109/TWC.2020.3033334)

[6] L. Pellaco, M. Bengtsson, and J. Jalden, "Matrix-inverse-free deep unfolding of the weighted MMSE beamforming algorithm," *IEEE Open J. Commun. Soc.*, vol. 8, pp. 48088-48100, 2020. (https://doi.org/10.1109/OJCOMS.2021.3139858)

[7] H. Hojatian, J. Nadal, J. -F. Frigon, and F. Leduc-Primeau, "Unsupervised deep learning for massive MIMO hybrid beamforming," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 11, pp. 7086-7099, Nov. 2021. (https://doi.org/10.1109/TWC.2021.3080672)

[8] J. Zhao, X. Yue, S. Kang, and W. Tang, "Joint effects of imperfect CSI and SIC on NOMA based satellite-terrestrial systems," *IEEE Access*, vol. 9, pp. 12545-12554, Jan. 2021. (https://doi.org/10.1109/ACCESS.2021.3051306)

[9] H. Zhu, Q. Wu, X. -J. Wu, Q. Fan, P. Fan, and J. Wang, "Decentralized power allocation for MIMO-NOMA vehicular edge computing based on deep reinforcement learning," *IEEE Internet Things J.,* vol. 9, no. 14, pp. 12770-12782, Jul. 2022. (https://doi.org/10.1109/JIOT.2021.3138434)

[10] A. Balatsoukas-Stimming and C. Studer, "Deep unfolding for communications systems: A survey and some new directions," in *Proc. IEEE Int. Wkshp. Sign. Process. Sys. (SiPS)*, pp. 266-271, Nanjing, China, Oct. 2019. (https://doi.org/10.1109/SiPS47522.2019.9020494)

[11] N. H. Nguyen, E. C. Behrman, M. A. Moustafa, and J. E. Steck, "Benchmarking neural networks for quantum computations," *IEEE Trans. Neural Net. Learn. Syst.*, vol. 31, no. 7, pp. 2522-2531, Jul. 2020. (https://doi.org/10.1109/TNNLS.2019.2933394)

[12] C. Zoufal, A. Lucchi, and S. Woerner, "Quantum generative adversarial networks for learning and loading random distributions," *npj Quantum Inf.*, vol. 5, no. 103, Nov. 2019. (https://doi.org/10.1038/s41534-019-0223-2)

[13] M. B. Shahab, M. F. Kader, and S. Y. Shin, "A virtual user pairing scheme to optimally

utilize the spectrum of unpaired users in non-orthogonal multiple access," *IEEE Sig. Process. Lett.*, vol. 23, no. 12, pp. 1766-1770, Dec. 2016. (https://doi.org/10.1109/LSP.2016.2619371)

[14] L. Zhu, J. Zhang, Z. Xiao, X. Cao, and D. O. Wu, "Optimal user pairing for downlink non-orthogonal multiple access (NOMA)," *IEEE Wirel. Commun. Lett.*, vol. 8, no. 2, pp. 328-331, Apr. 2019. (https://doi.org/10.1109/LWC.2018.2853741)

[15] T. Jamalauddin, B. Narottama, and S. Y. Shin, "Quantum deep unfolding for power allocation and precoding optimization," in *Proc. 2020 KICS Summer Conf.*, pp. 83-84, Korea 2022.

[16] R. LaRose and B. Coyle, "Robust data encodings for quantum classifiers," *Phy. Rev. Lett.*, vol. 102, no. 3, p. 032420, Sep. 2020. (https://doi.org/10.1103/PhysRevA.102.032420)

[17] H. Abraham, et al., "Qiskit: An open-source framework for quantum computing," 2019. (https://doi.org/10.5281/zenodo.2562111)

[18] Y. Li and G. A. Aruma Baduge, "NOMA-Aided Cell-Free Massive MIMO Systems," *IEEE Wirel. Commun. Lett.*, vol. 7, no. 6, pp. 950-953, Dec. 2018. (https://doi.org/10.1109/LWC.2018.2841375)

[19] Q. Hu, Y. Liu, Y. Cai, G. Yu, and Z. Ding, "Joint deep reinforcement learning and unfolding: Beam selection and precoding for mmwave multiuser mimo with lens arrays," in *IEEE J. Sel. Areas Commun.*, vol. 39, no. 8, pp. 2289-2304, Aug. 2021. (https://doi.org/10.1109/JSAC.2021.3087233)

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