A Hybrid Autoencoder Quantum Neural Networks for Optimized Wireless Communication

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***Abstract*—This study aims to employ a model of hybrid autoencoder quantum neural network (HAQNN) is purposed to optimize the precoding in multiple-input and multiple-output (MIMO) in wireless communication. Furthermore, the autoencoder is developed to mitigate the limitation of the experimental preparation instance as the quantum state. Moreover, performing the gradient descent by applying the stochastic parameter-shift rule to achieve optimal performance for training is considered. The presented scheme is then employed to optimize MIMO.**

***Index Terms*—Quantum neural network, autoencoder, wireless optimization, wireless communications.**

I. Introduction

The next generation in wireless communication such as 5G and beyond is an important technological revolution and become more challenging to optimize the networks. However, the performance of the future wireless communications systems are significantly affected by optimization, in particular, in precoding MIMO [1]. Moroever, the number of variables to be optimized grows with the number of network and wireless elements (e.g., number of users and transmit antennas) [2].

Recent studies shows the quantum neural network (QNN), which taking advantage of quantum mechanics such as quantum superposition and entanglement, has potential to have increased training capability and reduced training time [3]. Unfortunately, existing and near-term quantum computing with the number of qubits will not have the capacity to utilize the number of variables in which case the large number of networks and wireless elements, due with a long circuit depth or a large number of qubit is limited [4].

However, to cope with this issue, HAQNN [3], which employs encoder, decoder and parameterized quantum rotation gates, which can reduce the number of input elements. Specifically, for future of wireless optimization.

Similar to classical neural networks (NNs), HAQNN parameter vector also needs to be optimized, usually done stochastically with a number of data samples. This study explores the possibilities of training a particular of HAQNN model with parameter-shift rule to estimate gradients and optimize variational parameters [5].

Notations let $\otimes$ Kronecker product, $\mathbb{C}$ indicate the complex numbers. $(\cdot)^T$ indicates conjugate transpose. The notation of R_x, refers to x-axis rotation operation in quantum circuit and the notation $\odot$ indicate as multiplication.

II. Autoencoder QNN architecture

The closeness between the techniques used in classical machine learning. Autoencoder in QNN is use to combat problem in early quantum device, the first stage to employs classical neural network, which can reduced the number of dimension input element significantly. Specifically, the output of lth dense layer which generally can be presented as $\hat{\mathbf{x}} = \mathcal{F}(\mathbf{x}_l \odot \mathbf{w}_l + b_l)$, where $\mathcal{F}(.)$ indicates the activation function, $\mathbf{x}_l$ is the input of the lth layer, $\mathbf{w}_l$ is the weight vector, b_l are the bias vector.

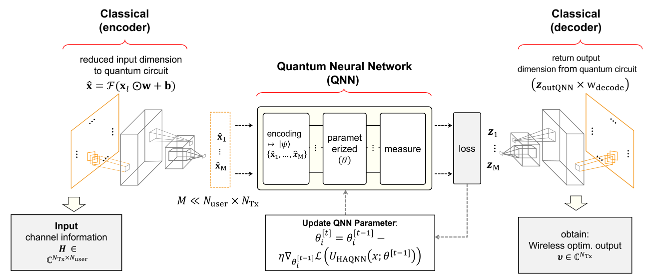

Figure 1: Schematic representation of hybrid autoencoder quantum neural network.

In this case, the first stage is an encoder to the classical neural network as shown in fig. 1, which can reduce the number of input elements for the quantum state significantly. The original dimension of input state is a vector of $\mathbf{x} = \boldsymbol{H} \in \mathbb{C}^{N_{Tx} \times N_{\text{user}}}$, which are then decoded into classical part to obtain into state of $\hat{\mathbf{x}}$ as qubit preparation.

Since, the input stage to the encoder can reduce the input dimension to the quantum circuit. The decoder serves as a decompressor and builds back the dimension of the element vector from it is latent attributes. Considering the decoder model as in fig. 1, the output decoder can be presented as $\mathbf{v} \leftarrow \mathcal{F}(\theta; \mathbf{z})$, where, θ is the vector of the decoder, $\mathbf{z}$ is the output from QNN.

III. Sytem Model

A. Wireless Optimization

For the optimization of the single-cell downlink MIMO, transmitting antenna precoding can be optimized. The base station (BS) with N_{Tx} be the number of transmitter arrays serving the N_{user} receiving user. Each user have a single receiving antenna. Let P be the transmit power of the BS. As an input for the HAQNN, the Rayleigh fading channel information of $\boldsymbol{H} \in \mathbb{C}^{N_{\text{Tx}} \times N_{\text{user}}}$ are considered. Hence, $\boldsymbol{H} \mapsto \mathbf{x}$. The channel coefficient for the kth user denotes as $\boldsymbol{H} \sim \mathcal{CN}(0, d_k^{-\kappa}) \in \mathbb{C}^{N_{\mathrm{Tx}}}$, where $d_k \in (0,1)$ and κ indicates the normalized distance values and channel coefficient, respectively. Moreover, the precoding vector of the transmit antenna is denoted as $\mathbf{v}$. The signal-to-interference-plus-noise-ratio (SINR) for kth user terminal can be defined as $\Gamma_k = \frac{|\boldsymbol{H}_{k,m}^T \mathbf{v}_m|^2 P}{a\sum_{j=k+1}^{N_{\mathrm{Tx}}} |\boldsymbol{H}_{k,m}^T \mathbf{v}_m|^2 P + \sigma^2}$, where a and σ are the inter-beam interference constant and additive white Gaussian noise (AWGN) with variance, respectively. The user rate of kth user is calculated as $R_k = \log_2\left(1 + \frac{|\boldsymbol{H}_{k,m}^T \mathbf{v}_m|^2 P}{a\sum_{j=k+1}^{N_{\mathrm{Tx}}} |\boldsymbol{H}_{k,m}^T \mathbf{v}_m|^2 P + \sigma^2}\right)$. The sum rate of the users is given as $R_{\mathrm{sum}} = \sum_{k=1}^{N_{\mathrm{user}}} R_k$ [1].

The objective is an optimize the sum-rate, which can be presented as:

$$\max_{\mathbf{v}_k} \quad R_{\mathrm{sum}} \tag{1a}$$

$$\text{s.t.} \quad \|v\|_F^2 \leq N_{\mathrm{Tx}} \tag{1b}$$

Accordingly, the objective can be estimated as non-fractional programming [6].

B. Quantum Variational Circuits

As shown in fig. 1, the constructions of quantum neural network can be implemented as variational quantum circuits. These encoding operation of the quantum operational circuits can be expressed as $U_{\mathrm{encode}}(\theta_x^{[i]}) = \bigotimes_{n=1}^{N_{\mathrm{weight}}} \bigotimes_{i=1}^{N_{\mathrm{data}}} \mathbf{R}_{\mathrm{x}}(\tanh\left(x_{\mathrm{input},i}^{[n]}\right))\mathbf{H}$, where $\mathbf{R}_{\mathrm{x}}(\tanh\left(x_{\mathrm{input},i}^{[n]}\right))$ is encoding part [7].

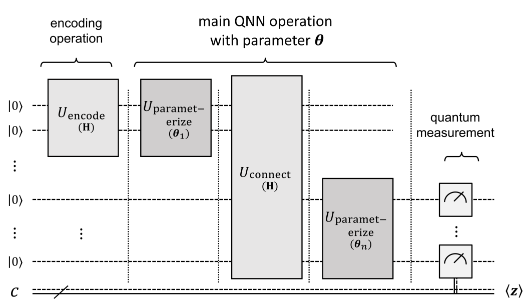

Figure 2: Utilized quantum circuit for simulation QNN.

C. Training Model Based Parameter-Shift Rule

The partial gradient of the quantum node f with respect to the θ_i can be expressed as [5]

$$\nabla_{\theta_i} f_{\mathrm{HAQNN}}(x;\theta^{[t-1]}) = \frac{1}{2}\left(f_{\mathrm{HAQNN}}(x;\theta^{[t-1]} + \mathfrak{s}) - f_{\mathrm{HAQNN}}(x;\theta^{[t-1]} - \mathfrak{s})\right), \tag{2}$$

where $\mathfrak{s}$ is the shifting parameter. To update the ith parameter $\theta_i^{[t]}$, the following expression is considered:

$$\theta_i^{[t]} = \theta_i^{[t-1]} - \eta \nabla_{\theta_i^{[t-1]}} \mathcal{L}\left(U_{\mathrm{HAQNN}}(x;\boldsymbol{\theta}^{[t-1]})\right), \tag{3}$$

where η is the learning rate. Subsequently, the loss function can be expressed as $\mathcal{L} = -\bar{R}_{\mathrm{sum}}$, which considers unsupervised learning.

IV. Simulation Result

The simulation scenario operations were performed in IBM Q using IBM qiskit. During the numerical simulation, $N_{\mathrm{user}} = 3$, $N_{\mathrm{tx}} = 8$, $P/\sigma^2 = 10$ dB, and $\eta = 0.01$, $N_{\mathrm{qubits}} = 4$ $N_{\mathrm{layer}}^{[n]} = 3$, where $N_{\mathrm{neuron}}^{[n]} = 2$, was considered. Employing Monte-Carlo simulation of 1000 trials. The performance of the MIMO by using the presented HAQNN is shown in Fig. 3.

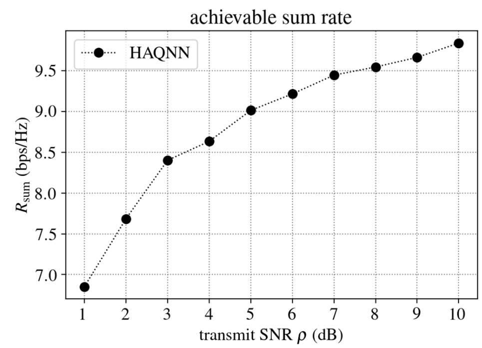

Figure 3: Achievable rate by using HAQNN.

V. Conclusion

This study explores the opportunity of optimizing wireless communication using a hybrid autoencoder-based QNN. A particular numerical training result was shown. For future work, integration with massive MIMO can be considered.

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