Quantum Machine Learning-based Linear Precoding for Rate-Splitting Multiple Access in LEO Satellite Communication System

Celine Nerima Wafula *, Lia Suci Waliani†, and Soo Young Shin‡
Department of IT Convergence Engineering, Kumoh National Institute of Technology, Gumi, South Korea
e-mail: {*nerimace,†liasuciwaliani,‡wdragon}@kumoh.ac.kr

***Abstract*—This study proposes quantum machine learning (QML) for optimization problems in low earth orbit (LEO) satellite-to-terrestrial communication systems. Specifically, a QML model is applied to maximize the precoders of the common and private streams intended for a ground station (GS) in a down-link LEO satellite-to-terrestrial, rate-splitting multiple access (RSMA) communication system.**

***Index Terms*—Downlink, linear precoding, LEO satellite, optimization, quantum machine learning, RSMA, 6G.**

I. Introduction

As the global shift to 6G networks draws near, low earth orbit (LEO) satellites shine in significance due to their high data rate capacity and low latency. This is because LEO satellites, contrary to other satellite types, e.g. geostationary (GEO) satellites, are situated at a lower altitude with denser constellations [1]. However, they encounter issues with interference control in multiple input multiple outputs (MIMO) based networks, as well as inefficient resource allocation and utilization [2].

To address these limitations, next-generation multiple access (NGMA) has been suggested [3]. Particularly, for MIMO systems, Rate-Splitting Multiple Access (RSMA) uses its versatile interference management techniques, along with fair user resource block allocation, making it a strong alternative to traditional methods like Space Division Multiple Access (SDMA) and Non-Orthogonal Multiple Access (NOMA) [4].

As a result, this study focuses on using the 1-layer rate-splitting (RS) strategy [5] to split ground station (GS) messages, compute transmission precoders, and perform successive interference cancellation (SIC) at the GS. A non-convex optimization problem of maximizing sum rate and optimal power allocation, for satellite-to-terrestrial networks (STN) is realized. This stems from the network's overall dynamic and demanding nature [6].

For that reason, a quantum machine learning (QML) [7] model is integrated aiming to surpass benchmark methods by reducing computational complexity, and offering a promising advancement in satellite communication for 6G readiness.

II. Rate Splitting Multiple Access Model

The system considers an STN comprising an LEO satellite with a base station (BS) having a single antenna, M_t serving N GSs, each having a single antenna such that $(M_t > N)$. The GSs share a frequency channel, hence the BS broadcasts all message streams in a non-orthogonal manner. A BS has a set of messages, $\{W_1, ..., W_N\}$. The message W_n, intended for n-th GS is divided into two parts [8]. A common part W_n^c, and private one W_n^p, $(n = 1, ..., N)$. Each of the common parts is encoded into a common stream $\mathbf{s}_c$, while the private parts are into their respective private streams, solely denoted as $\mathbf{s}_{p,n}$. Taking into account a linear precoding manner [9], the streams $\mathbf{s} = [\mathbf{s}_c, \mathbf{s}_{p,1}, ..., \mathbf{s}_{p,N}]$ are precoded via a matrix $\mathbf{P} = \left[\mathbf{p}_c, \mathbf{p}_{p,1}, ..., \mathbf{p}_{p,N}\right]$, such that the transmitted signal from the BS is as follows:

$$x_n = \mathbf{p}_c \mathbf{s}_c + \sum_{n=1}^{N} \mathbf{p}_{p,n} \mathbf{s}_{p,n}, \tag{1}$$

and at the n-th GS, the received signal should be:

$$\begin{aligned} y_n &= \mathbf{h}_n^H x_n + \omega_n, \\ &= \mathbf{h}_n^H \mathbf{p}_c \mathbf{s}_c + \mathbf{h}_n^H \mathbf{p}_{p,n} \mathbf{s}_{p,n} + \sum_{j \neq n, j \in N} \mathbf{h}_n^H \mathbf{p}_{p,j} \mathbf{s}_{p,j} + \omega_n, \end{aligned} \tag{2}$$

where $\mathbf{h}_n \in \mathbb{C}^{Mt \times 1}$, represents the channel vector between the BS at the LEO satellite and the n-th GS, while ω_n is the additive white Gaussian noise. According to [10], [11], the channel model for the satellite to GS is calculated as:

$$\mathbf{h}_n = \delta_n \sqrt{G_s G_n (\frac{c}{4\pi f_c d_s})^2}, \tag{3}$$

in that c is the speed of light, f_c is the carrier frequency, d_s is the distance between the path of the n-th ground station from the LEO satellite, δ_n represents the small-scale fading with a Rician distribution, and G_s, G_n is the satellite antenna gain and ground station antenna gain respectively.

Next, the signal-to-interference plus noise ratio (SINR) of both the common and private streams are obtained from:

$$\gamma_n^c = \frac{\left|\mathbf{h}_n^H \mathbf{p}_c\right|^2}{\sum_{n=1}^{N} \left|\mathbf{h}_n^H \mathbf{p}_{p,n}\right|^2 + \sigma^2}, \tag{4}$$

$$\gamma_n^p = \frac{\left|\mathbf{h}_n^H \mathbf{p}_{p,n}\right|^2}{\sum_{j \neq n, j \in N} \left|\mathbf{h}_n^H \mathbf{p}_{p,j}\right|^2 + \sigma^2}, \tag{5}$$

so that $\left\|\mathbf{p}_{(.)}\right\|^2 = \mathrm{P}^{(.)}$ is the power allocated to that stream, and σ^2 is the noise power [10]. Consequently, the common stream's achievable rate on the n-th GS is given by the output of $\mathbf{R}_n^c = \min_{n=1,\ldots,N} \{\log_2(1+\gamma_n^c)\}$ considering each GS has a corresponding data in the common stream it must successfully retrieve after the SIC operation. The private stream achievable rate is $\mathbf{R}_n^p = \{\log_2(1+\gamma_n^p)\}$, so, the total achievable rate for the n-th GS is $\mathbf{R}_n^{\text{tot}} = \mathbf{R}_n^c/(N+\mathbf{R}_n^p)$.The sum rate for all the GSs will be obtained from $\mathbf{R}_{\text{sum}} = \mathbf{R}^c + \sum_{n=1}^{N} \mathbf{R}_n^p$.

With the aforementioned RSMA system in mind [10], [11], the goal is for the LEO satellite BS to be able to distribute the entire transmit power P^{tot}, among the GS common and private streams, following the QML model's output measurements under constraints $\mathrm{P}^c + \sum_{n=1}^{N} \mathrm{P}^{p,n} \leq \mathrm{P}^{\text{tot}}$, thereby achieving maximum sum rate. Therefore, the optimization problem definition is:

$$\max_{\mathrm{P}^c, \mathrm{P}^{p,1}, \ldots, \mathrm{P}^{p,N}} \mathbf{R}_{\text{sum}}, \tag{6a}$$

$$\text{s.t. } \mathrm{P}^c + \sum_{n=1}^{N} \mathrm{P}^{p,n} \leq \mathrm{P}^{\text{tot}}, \tag{6b}$$

$$\mathbf{R}_n^{\text{tot}} \geq \mathbf{R}_n^{\text{th}},\ n = 1, \ldots, N, \tag{6c}$$

$$\mathrm{P}^c > 0, \mathrm{P}^{p,n} > 0,\ n = 1, \ldots, N, \tag{6d}$$

such that $\mathbf{R}_n^{th}$ expresses the least acceptable rate for the n-th GS to decode their intended message. Noting that the BS has partial channel state information (CSI), deriving suitable conditions for the task in 6 is considerably hideous [12]. Thus, a QML solution is adopted to optimize the linear precoders of each data stream to find a suitable power allocation strategy.

III. QML For Linear Precoding Optimization

This study proposes quantum machine learning (QML) for linear precoder optimization in LEO satellite networks. Let $\mathbf{h} = \{\mathbf{h}_1, \ldots, \mathbf{h}_K\}$ represent the set of channel matrices that serve as input for QML. Herein, the channel matrices are mapped to quantum states through superposition states, expressed as $\mathbb{U}_{\text{p}} \triangleq \bigotimes_{n=1}^{N_{\text{qubit}}} \mathbf{H}(|\mathbf{h}_n\rangle)$. Subsequently, let $\mathbb{U}_{\text{t}}$ denote the feedforward training in QML, represented by $\mathbb{U}_{\text{t}} \triangleq \big(\bigotimes n = 1^{N\text{qubit}} \mathbf{R}_z(\theta_n)\big(\prod_{n=1}^{N_{\text{qubit}}} \mathbf{C}_x(q_n|q_{n-1}) \otimes \ldots \otimes \mathbf{C}_x(q_{N_{\text{qubit}}}|q_{N_{\text{qubit}}-1})\big)\mathbf{R}_z(\mathbf{h}_n)\big)$, where N_{qubit} and θ_n denote the total number of qubits and initial weights, respectively. Lastly, in the final step of the process, the measurement is obtained to derive the classical value which expressed as $\mathbb{M} = \langle 0| \mathbb{U}_{\text{t}}(\theta)^{\dagger} \mathbf{H} \mathbb{U}_{\text{t}}(\theta) |0\rangle$. Due to the development of NISQ, the measurement is iterated N_{shot} times, resulting in $\mathbb{U}_{\text{d}} = \frac{1}{N\text{shot}} \sum_{n=1}^{N_{\text{shot}}} \mathbb{M}$. Owing to the unsupervised learning manner, the loss function can be expressed as $\mathcal{L} = -R_{\text{sum}}$. Hereafter, the gradients in quantum computing employing the parameter shift rule can be expressed as $\nabla\mathcal{L}(\theta) = \frac{\mathcal{L}(\theta+\xi) - \mathcal{L}(\theta-\xi)}{2\sinh(\xi)}$, where $\xi \in (0, \pi)$ denotes the shifting phase. Finally, the parameter update can be expressed as $\vartheta' = \vartheta - \beta\nabla\mathcal{L}(\theta)$, where β denotes learning rate.

IV. Conclusion

This paper presents a quantum machine learning (QML) approach to optimize linear precoding in LEO satellite communications. The methodology tackles complex optimization

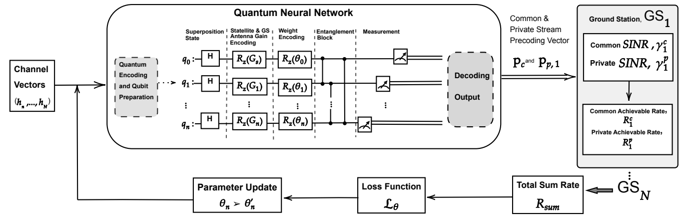

Figure 1. Proposed model for QML linear precoder optimization.

problems in power allocation and aims to demonstrate significant improvements in resource optimization. Future work will focus on expanding the QML applicability to broader RSMA network optimization.

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