

Quantum Graph Neural Network for Resource Management in Wireless Communication

Le Tung Giang, Nguyen Xuan Tung, and Won-Joo Hwang

Abstract—Effective resource management in wireless communication systems is a critical requirement, given the interference challenges and the need for efficient allocation strategies. Graph Neural Networks (GNNs) have emerged as powerful tools for tackling this problem due to their scalability and ability to generalize over complex graph-structured data, like that found in wireless networks. However, the computational complexity of GNNs on large-scale systems limits their real-time deployment. Recent advances in quantum computing and quantum machine learning (QML) offer a promising solution by leveraging the unique properties of quantum systems to reduce computational overhead. This paper proposes a Quantum Graph Neural Network (QGNN) model specifically designed for a wireless communication scenario, implemented as a variational quantum circuit (VQC) to realize the message-passing mechanism integral to GNNs. Applied to a supervised resource management task in a wireless network, the proposed QGNN demonstrates encouraging results, showcasing its potential as a scalable and efficient approach for real-time resource management in future wireless systems.

Index Terms—Quantum Graph Neural Network, Quantum Machine Learning, Resource Management, Wireless Communication

I. INTRODUCTION

Resource management is a central challenge in wireless communication, with demands for efficient frequency and power allocation intensifying as network densities increase [1]. Recent advancements in machine learning (ML) have enabled dynamic and adaptive resource allocation strategies, offering real-time solutions that traditional models could not achieve. Among ML models, Graph Neural Networks (GNNs) stand out for their exceptional scalability and generalization capabilities in managing graph-structured data [2], [3], like the interference relationships among User Equipments (UEs) in cellular networks. GNNs model these relationships by passing messages among neighboring nodes (representing UEs), thus capturing the network's structural dependencies to optimize resource allocation. However, training GNNs often meets a challenge due to the high computational requirements of their iterative message-passing operations, especially as the network scale increases.

Recently quantum computing has made some improvement in compared with classical processor. Quantum machine learning leverages the advantage of both the efficiency of machine learning techniques and the power of quantum computing, showing the potential to realize more powerful artificial intelligence [4]. As a fundamental tool of quantum machine learning, the quantum neural network (QNN)

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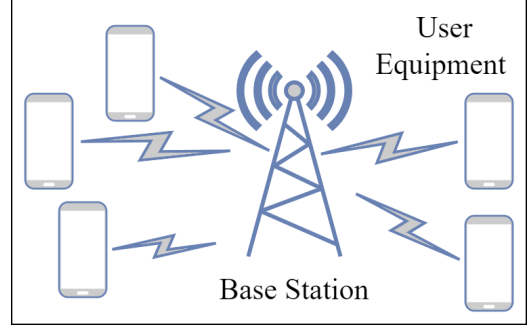


Fig. 1: System Model with 1 BS and 5 UEs.

has been widely researched and applied in various areas, including pattern recognition [5], automatic control [6], signal processing [7], and more. Various QNN models have been proposed in the literature [8], reflecting the diverse approaches in this rapidly evolving field.

In this paper, we propose a Quantum Graph Neural Network (QGNN) model that integrates quantum computation into GNN architectures, allowing efficient message-passing on quantum circuits. Specifically, we design a variational quantum circuit (VQC) capable of implementing the message-passing mechanism of GNNs, using the principles of quantum amplitude encoding and entanglement to capture interactions among network nodes. The proposed QGNN model is applied to a supervised resource management scenario in a wireless network, where simulation results reveal promising accuracy in interference management and resource allocation, highlighting the potential of quantum-enhanced GNNs for wireless communication.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a cellular network where multiple User Equipments (UEs) communicate with a single Base Station (BS). Each UE experiences interference from other UEs in the network due to the shared wireless medium. When each UE connects to the BS, an interference component I_0 is added to the total interference for every active UE. This interference reflects the cumulative effect of other UEs transmitting within the same frequency band, which impacts the Signal-to-Interference-plus-Noise Ratio (SINR) for each user.

The SINR for a given UE n is expressed as:

$$\text{SINR}_n = \frac{p \cdot \alpha_n \cdot h_n}{\sum_{i \neq n} \alpha_i \cdot I_0 + n_0} \quad (1)$$

where p represents the transmit power of each UE, assumed to be constant across all UEs, and α_n is a binary variable indicating whether UE n is actively transmitting ($\alpha_n = 1$) or not ($\alpha_n = 0$). The term h_n denotes the channel gain for UE n , which quantifies the quality of the wireless link between the UE and the BS. The interference factor I_0 represents the contribution of each transmitting UE to the interference experienced by other UEs in the network, while n_0 is the

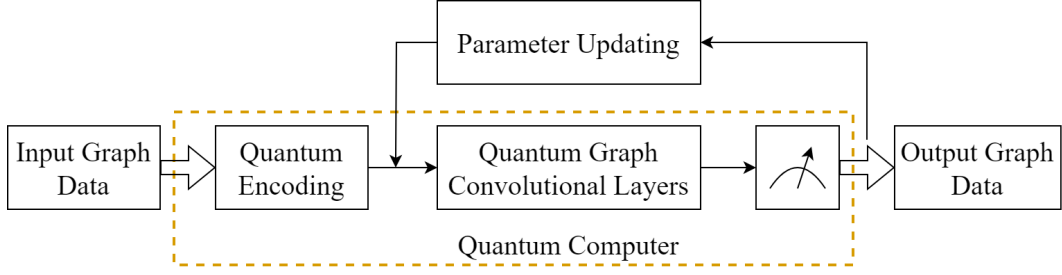


Fig. 2: Architecture of QGNN.

noise power, assumed to be constant and independent across UEs.

The objective of this model is to maximize the total SINR across all UEs by optimizing the binary transmission decisions α . This optimization seeks to enhance network performance by managing interference and maximizing the signal quality for each UE. The problem can be formulated as follows:

$$\max_{\alpha} \sum_{n=1}^N \text{SINR}_n \quad (2a)$$

$$\text{s.t. } \alpha_n \in \{0, 1\}, \quad \forall n = 1, 2, \dots, N. \quad (2b)$$

This optimization problem aims to find the optimal transmission strategy α that maximizes the total SINR across all UEs, thereby improving overall network performance by effectively managing interference.

III. QUANTUM GRAPH NEURAL NETWORK

In this section, we design the Quantum Graph Neural Network (QGNN) architecture, as shown in Fig. 2, which implements message passing within a quantum circuit. The architecture includes quantum encoding, quantum graph convolutional layers, and a measurement step, with iterative parameter updating.

A. Quantum Encoding

Quantum encoding is an essential process for transforming classical data into quantum states that can be processed by a quantum circuit. In this work, we employ amplitude encoding, a technique that embeds classical feature vectors into the amplitude of quantum states. Given a classical feature vector $x = [x_1, x_2, \dots, x_{2^n}]^T$ of dimension 2^n , the corresponding quantum state $|x\rangle$ can be represented as:

$$|x\rangle = \frac{1}{C} \sum_{i=1}^{2^n} x_i |i\rangle, \quad (3)$$

where $C = \sqrt{\sum_{i=1}^{2^n} |x_i|^2}$ is a normalization factor ensuring that the quantum state has unit norm. This approach allows efficient encoding of classical data using fewer qubits, as an n -qubit system can encode 2^n values. We use the AmplitudeEmbedding function from the PennyLane package to implement this encoding in our simulations.

B. Quantum Graph Convolutional Layer

The Quantum Graph Convolutional (QG) layer is inspired by the classical graph convolution operation, where each vertex aggregates information from its neighbors. After amplitude encoding, a graph represented as $G = (V, A)$ with vertices V and adjacency matrix A is transformed into quantum graph data $G_q = (V_q, A)$. Here, $V_q =$

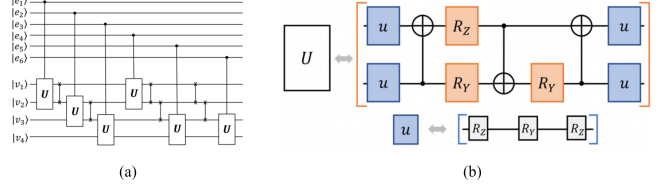


Fig. 3: Quantum Graph Convolutional Layer

$\{|v_1\rangle, |v_2\rangle, \dots, |v_N\rangle\}$ is the set of quantum states representing the vertices' features.

In the QG layer, the adjacency matrix A remains classical, while each quantum state $|v_i\rangle$ encodes a feature vector for vertex i . The layer's implementation follows three steps:

- 1) The topology of the graph, encoded by A , is represented using $N(N-1)/2$ qubits, with each element of A corresponding to a specific qubit in the states $|0\rangle$ or $|1\rangle$.
- 2) A unitary operation U is applied to pairs of quantum states $|v_i\rangle$ and $|v_j\rangle$ connected in the graph, using n two-qubit gates to capture the interaction between features.
- 3) The layer uses controlled-U gates, where each control qubit corresponds to an element of A , to manage connections between vertices.

An example is shown in Fig. 3(a), where a four-vertex graph with 2-dimensional features per vertex is encoded using six qubits for A and four additional qubits for vertex features. This setup captures the graph structure in a quantum-efficient manner, enabling scalable and complex graph operations on quantum hardware.

IV. NUMERICAL RESULTS AND EVALUATION

In this simulation, we employed an exhaustive search technique to determine the optimal SINR values for the given wireless communication scenario. These optimal SINR values were then used as the ground truth in a supervised training framework to train the QGNN. By using the optimal solution as the target, we aimed to guide the QGNN in learning to approximate the best possible resource allocation strategy for maximizing SINR.

The performance of the QGNN model, as shown in Fig. 4, highlights its effective supervised training and generalization capabilities. The training SINR steadily increases across epochs, reflecting the model's ability to capture interference dynamics and optimize resource allocation effectively. The small gap between training and testing SINR indicates strong generalizability to unseen data, a critical attribute for real-world applications. While the model does not fully reach the optimal SINR benchmark due to the inherent limitations of supervised learning, it achieves values very close to the benchmark, particularly in later epochs. This

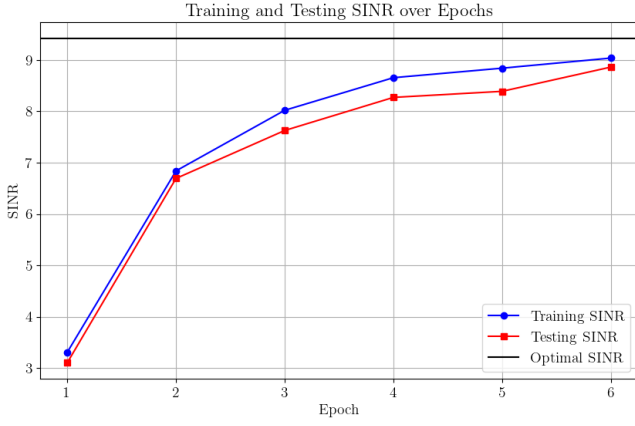


Fig. 4: Training result of the QGNN under supervised setting.

demonstrates the QGNN’s potential as a practical and efficient approach for resource management in wireless networks.

To assess the performance of the QGNN model, we conducted evaluations across 1000 realizations of system localization and channel conditions. This extensive testing allowed us to gauge the robustness and generalization ability of the model under diverse scenarios. Remarkably, the QGNN achieved an accuracy rate of 98% in approximating the optimal SINR values. This high accuracy demonstrates the model’s effectiveness in adapting to variations in network conditions, highlighting its potential for real-world applications in wireless communication resource management.

A. Scalability Evaluation

In this scalability evaluation, we consider a system consisting of 5 UEs. For a fully connected network of 5 UEs, each pair of UEs requires an edge connection, resulting in a total of $\frac{5 \times (5-1)}{2} = 10$ edges. In our QGNN implementation, each edge requires a dedicated qubit to represent the adjacency relationship. Additionally, each node feature requires a separate qubit, adding 5 more qubits for the 5 UEs. Consequently, the total number of qubits required becomes 15 for this setup, with the number increasing rapidly as the network size grows.

Furthermore, as shown in Fig. 5, the number of quantum gates required also increases as the system size scales. Notably, this increase is not linear due to the additional SWAP gates needed to cover interactions between adjacent nodes. These SWAP gates are necessary to manage qubit connectivity, especially in physical quantum devices with limited qubit interconnections. The non-linear growth in gate count further underscores the scalability challenges inherent in this approach, as larger networks would require an exponentially greater number of gates and qubits to represent both node features and edge connections efficiently.

This scalability issue highlights the computational challenges associated with applying QGNNs to larger networks. Future work may need to explore alternative strategies, such as sub-graph decomposition or optimized quantum circuit designs, to make QGNNs more feasible for larger-scale wireless communication systems.

V. CONCLUSION

In this work, we presented a simple implementation of a Quantum Graph Neural Network (QGNN) for wireless

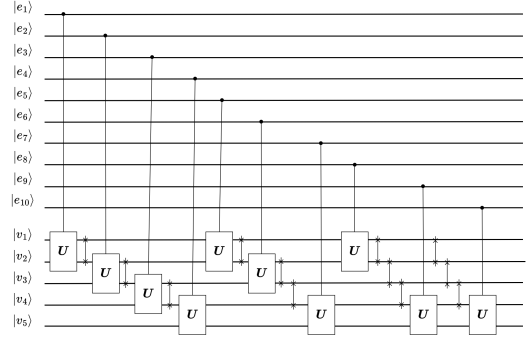


Fig. 5: Number of quantum gates required with increasing UEs, illustrating the non-linear growth due to SWAP gates for adjacency management.

communication resource management. The QGNN model demonstrated promising results, effectively learning to approximate the optimal SINR through supervised training. By leveraging quantum computation, the QGNN offers an alternative approach to traditional machine learning models, potentially reducing the computational burden associated with large-scale graph data.

However, the scalability of the QGNN remains a significant challenge. As the size of the network and the number of UEs increase, the computational resources required for the quantum encoding and graph convolutional layers grow rapidly. This limitation restricts the practical deployment of QGNNs in large-scale wireless networks and highlights the need for scalable quantum algorithms that can manage the complexity of vast communication graphs.

To address these scalability issues, future work may explore sub-graph decomposition techniques, where the overall network is divided into smaller, more manageable sub-graphs. Each sub-graph can then be processed individually, potentially reducing the computational requirements of the quantum circuits. This approach could facilitate the practical application of QGNNs to large-scale wireless communication systems, making quantum-enhanced resource management a feasible option in real-world scenarios.

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