Quantum Machine Intelligence for 6G URLLC

Fakhar Zaman, Ahmad Farooq, Muhammad Asad Ullah, Haejoon Jung, Hyundong Shin, and Moe Z. Win

Abstract

Immersive and mission-critical data-driven applications, such as virtual or augmented reality, tactile Internet, industrial automation, and autonomous mobility, are creating unprecedented challenges for ultra-reliable and low-latency communication (URLLC) in the sixth generation (6G) networks. Machine intelligence approaches deep learning, reinforcement learning, and federated learning (FL), to provide new paradigms to ensure 6G URLLC on the stream of big data training. However, classical limitations of machine learning capabilities make it challenging to achieve stringent 6G URLLC requirements. In this article, we investigate the potential of variational quantum computing and quantum machine learning (QML) for 6G URLLC by utilizing the advantage of quantum resources, such as superposition, entanglement, and quantum parallelism. The underlying idea is to integrate quantum machine intelligence with 6G networks to ensure stringent 6G URLLC requirements. As an example, we demonstrate the quantum approximate optimization algorithm for NP-hard URLLC task offloading optimization problems. The variational quantum computation for QML is also adopted in wireless networks to enhance the learning rate of machine intelligence and ensure the learning optimality for mission-critical applications. Considering the security and privacy issues, as well as computational-resource overheads in FL, distributed quantum computation in blind and remote fashions is further investigated for quantum-assisted FL.

Introduction

Intelligent ultra-reliable and low-latency communication (URLLC) is the crucial objective in applications enabled by the fifth/sixth generation (5G/6G) networks, such as telemedicine, tactile Internet, and virtual/augmented reality. It is envisioned that 6G communication will provide a data rate of up to 1 Terabits per second and fully support mission-critical applications, such as high-precision robot control, which requires stringent end-to-end (E2E) latency and reliability. Although 5G URLLC can ensure E2E delay up to 1 millisecond, the highly dynamic nature of 6G networks presents unprecedented challenges in achieving various stringent requirements [1]. In this scenario, the model-based tools are very useful in analyzing and optimizing the performance of wireless networks. However, due to non-convex optimization problems and simplified assumptions in model-based methods, the required quality of service (QoS) in 6G cannot be assured. In recent years, it has been shown that the near-optimal solutions for complex systems can be obtained by utilizing deep learning (DL) technologies, such as deep neural networks (DNNs), deep reinforcement learning (DRL), and federated learning (FL) [2].

To date, considerable efforts have been devoted to taking the advantage of DL for intelligent wireless networks, such as DRL for open radio access network (O-RAN) slicing and resource allocation to ensure URLLC [3]. Although DL has the potential to learn complex systems, it is not straightforward to deploy DL technologies to ensure URLLC in highly dynamic communication systems. One of the major bottlenecks is the learning rate of DL models, which decreases with system dimensionality and may violate stringent latency requirements of 6G networks. Furthermore, the learning optimality and computation-resource overheads in DRL and FL, respectively, limit the efficiency of classical machine learning (ML) models. These limitations make it challenging to deploy DL for 6G URLLC.

Quantum supremacy — *an experimental demonstration that quantum computers outperform their classical counterpart* — is one of the major milestones of the 21st century in computing science (see Fig. 1 for quantum potentials). The advantages of quantum computers have been shown decades ago in solving factorization problems by utilizing quantum resources, such as superposition and entanglement. Recently, quantum computing has been introduced in QML [5]. The QML integrates quantum computing with ML and gives birth to new ideas, such as the variational quantum eigensolver (VQE) and quantum approximate optimization algorithm (QAOA), which have the potential to outperform classical ML for solving complex optimization problems, called quantum speedup [6]. For instance, Grover's search algorithm and quantum Fourier transform can reduce computational complexity by a factor of $\sqrt{N}$ in comparison with their classical counterparts, where N denotes the number of data points [7].

In this article, we investigate the potential of quantum machine intelligence by utilizing the advantage of quantum speedup to ensure stringent URLLC requirements in intelligent 6G networks. This work aims to outline the challenges and limitations of deploying DL for 6G URLLC and enlist possibilities given by the realm of QML in extremely dynamic wireless networks. In the following section, we briefly overview the requirements of 6G URLLC, followed by the potential of recent advancements in DL, DRL, and FL for 6G URLLC, and we outline the limitations of classical ML in the

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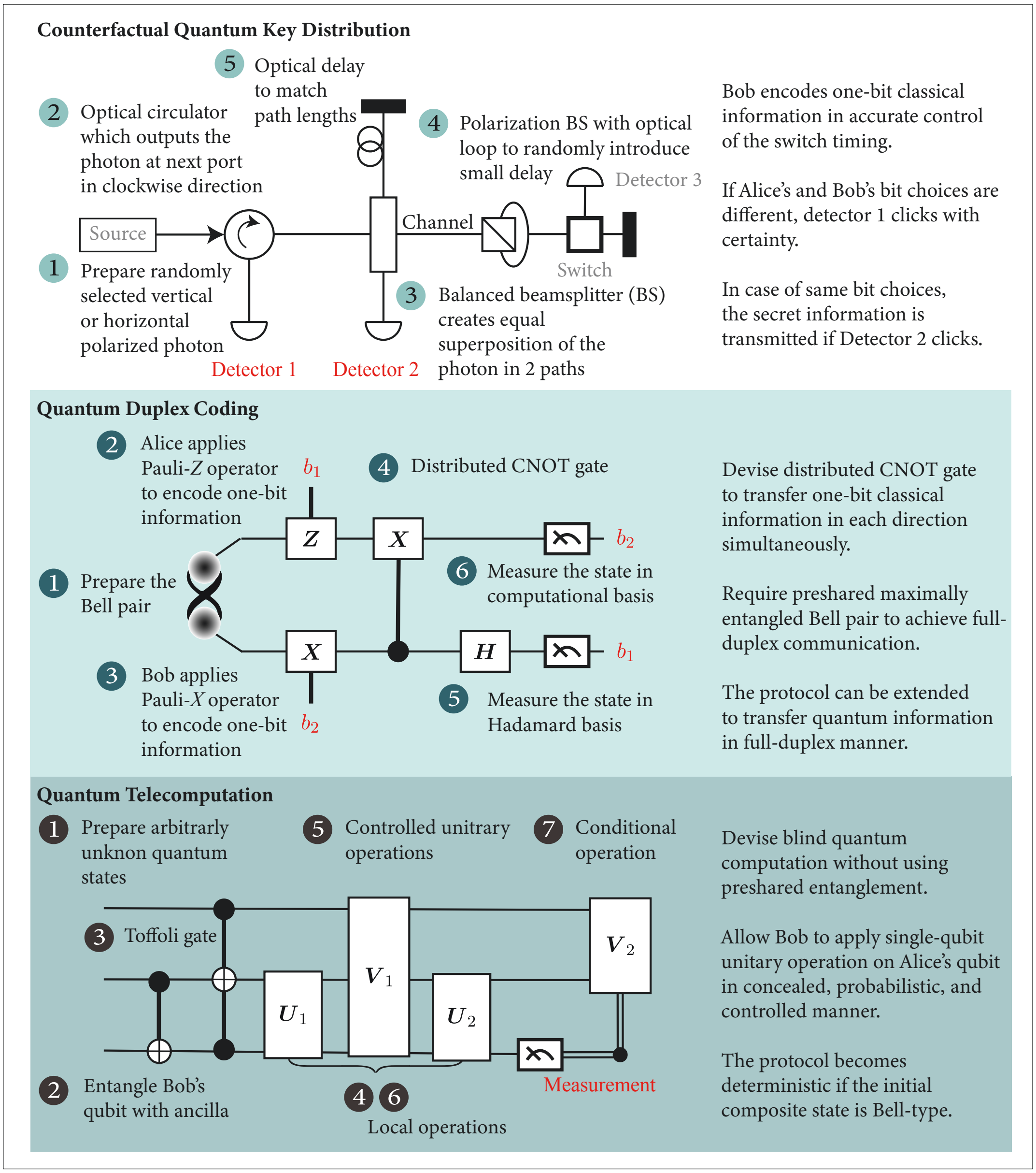

FIGURE 1. Quantum potentials in communication and computation: counterfactual quantum cryptography, full-duplex quantum communication, and distributed quantum computation. Counterfactual quantum key distribution enables particle-free secret sharing to provide absolute randomness, security, and improved transmission quality. Quantum duplex coding allows remote parties to transmit one classical bit in each direction by means of counterfactual disentanglement, while the quantum telexchanging allows the exchange of one-qubit quantum information without using preshared entanglement and without transmitting any physical particle over the quantum channel. In addition, the quantum telecomputation enables Bob to perform quantum remote control (computing) at a distant party (Alice) in a cryptographic manner (see [4] and references therein).

achievability of the stringent requirements. Following that, we present the advantage of QML for 6G URLLC. In particular, we describe the potential of variational quantum algorithms (VQAs), quantum reinforcement learning (QRL), and quantum federated learning (QFL) for 6G applications. Furthermore, we demonstrate the numerical simulation results to show that the VQA and QAOA can significantly reduce the learning time to achieve high throughput in wireless networks and perform optimal decision making, respectively, to ensure stringent E2E latency requirements. Lastly, we describe the challenges in quantum computing and give our concluding remarks.

Intelligent Learning Models for 6G URLLC

For mission-critical applications, URLLC is one of the most challenging features of the next-generation (i.e., 6G) networks. The new technologies and applications for 6G networks have more stringent requirements for E2E delay and reliability.

URLLC in 6G

Ultra-high Reliability: Ultra-high reliability is a system of systems, which aims to enhance the reliability of the network by going beyond traditional approaches. In 5G networks, URLLC aims to meet 99.999% (five-nines) reliability by using a plethora of channel coding, channel estimation, and pack-

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et duplication transmission techniques. Although reliability can be improved by retransmission, it increases the latency and sacrifices network resources. In practice, the reliability requirement varies from 10^{-7} to 10^{-3} based on the applications and services of the network. For instance, the emergence of 6G-based technologies, such as tactile Internet requires at least two folds of improvement as compared to 5G systems. Conventionally, a network provides common configurations of URLLC requirements, which may lead to resource mismanagement. However, customized URLLC requirements increase the design complexity of networks [1].

Low Latency: 5G URLLC can ensure E2E delay up to 1 millisecond (ms). However, 6G-enabled technologies, such as high-precision robot control and autonomous vehicles require 0.1 ms latency but the 5G networks cannot fulfill this gap. The latency in radio access networks can be categorized as user plane latency, control plane latency, and packet retransmission, where user plane latency denotes the total time required for transmit processing, packet transmission, and receive processing, whereas control plane latency denotes transition delay from an inactive state to an active state. In addition, the E2E delay also includes the communication delay between various layers of the network. It is already well known that the cross-layer technologies significantly affect the latency and reliability of the network and require effective approaches for cross-layer optimization to ensure URLLC in 6G.

Deep Learning

Deep Neural Networks: The DNNs are a combination of basic structures, such as feed-forward, convolutional, and recurrent neural networks. In general, DNNs are used to approximate a function $y = \phi(x, \theta)$ where x, y, and θ are input, output, and learning parameters. For example, the input/output in URLLC can be state-decision pairs obtained from the optimization algorithm, historic data of traffic loads, and trajectories of mobile users. In practice, DNNs are composed of many hidden layers where the DNN structure and the number of hidden layers depend on the type of data and required accuracy, respectively. Although model accuracy is enhanced by increasing the number of hidden layers, it significantly increases the learning time, which may violate the low-latency requirement of 6G networks. Despite the long convergence time of DL models, DNNs and recent ML advances have shown the advantages in solving and learning complex communication networks. DNNs can accurately model the communication systems by utilizing E2E optimization. 6G URLLC requires effective signal processing algorithms to deal with massive data and complex problems. In this scenario, DL can efficiently tackle an enormous amount of data due to its parallel processing architecture and provide high accuracy in prediction and estimation problems.

Predictions in URLLC: The major advantage of DL over traditional ML techniques is the ability to tackle an enormous amount of data. Hence, DL plays a crucial role in solving physical and link layer problems. It can predict network topologies, such as channel information, the future behavior of communicating parties, and customized services to meet the high reliability and the stringent network availability requirements in non-stationary 6G networks. DL has been widely used in wireless networks as follows [2]:

- The knowledge of channel state information (CSI) enables the development of efficient transmission, scheduling, and user-association schemes. In dense networks, it is more challenging to accurately estimate CSI. To overcome this challenge, recurrent and convolutional neural networks have been used to estimate CSI accurately and precisely, which can significantly reduce the packet loss probability and enhance the network reliability.
- In 6G URLLC, the E2E delay of 0.1 milliseconds and 1 million terminals/km2 will be crucial in designing future technologies, such as industrial automation. To guarantee these stringent requirements, the O-RAN with artificial intelligence (AI) has been proposed. The goal is achieved by designing DL models for optimized traffic steering and load balancing, which prioritize the quality of experience (QoE) and QoS parameters.
- The analysis and controllability of mobile traffic-flow data to achieve ultra-low latency and ultra-high reliability are other challenging tasks in 6G networks. The traditional traffic prediction, such as Markov chain and autoregressive models mainly focuses on modeling the stationary flow characteristics. Neural networks with long short-term memory have been used to effectively predict peak values of traffic flow in the network.

Deep Reinforcement Learning

Reinforcement learning (RL) is a widely-used ML approach in AI, which learns from real-life experiences. It has the capability to learn optimal policies to ensure URLLC in complex networks. However, the learning rate and exploration-exploitation balance are critical aspects for an RL agent [2].

Key Elements: RL trains an agent by direct interaction with the environment. At each time instant, the agent selects an action based on a policy $\pi(a | s_t = s)$ where s_t denotes the state of the system at time instant t. After taking the action a, the agent observes the reward r and the next state s_{t+1} of the system to update the action value functions that depict the long-term accumulated reward. For instance, the RL framework has been recently deployed to learn the optimal policy for resource allocation to ensure URLLC at a given data rate. In this model:

- The number of packets transmitted to each user and the average packet length for each user denote the state of the system.
- The number of resources assigned to each user represents the action taken by the agent at each time step.
- The data rate of each user denotes the reward observed by taking an action at time instant t.

Optimal Policy Learning: In RL, the main goal is to learn the optimal action-selection policy $\pi^*(a | s)$ to maximize the cumulative reward. In general, RL algorithms can be categorized as model-based and model-free, where the term "model" refers to the dynamics of the communication network. If the dynamics of the communication system are known, optimal policies to ensure URLLC can be learned by dynamic programming. However, as the number of users grows in the network, the state-action space increases exponentially, which significantly reduces the learning rate of the agent and may violate the latency requirement of 6G networks. To overcome this challenge, actor-critic algorithms have been deployed in wireless networks to estimate the state-action values and the policy by using DNNs and the policy gradient theorem. In wireless communication, many network problems can be solved by using RL, such as resource allocation, beamforming, and power control. In 6G networks, the major challenge is the learning rate of the RL agent to meet low-latency and high-rate requirements in massive non-stationary networks.

Federated Learning

In traditional learning and communication networks, it requires participating end nodes to transmit data samples to the central node to train the ML model, which may pose security/privacy issues and communication overheads. In this scenario, decentralized learning, such as FL, can be a possible solution [8].

Key Steps: FL is a decentralized learning technique, which enables distributed devices to learn collaboratively without transmitting their data to the central node. The key steps of the FL training model are as follows:

- Each learning node uses its local samples to train the local ML model and transmits parameters of the trained model to the central node.
- The central node integrates local models by performing model averaging and shares the global model with all learning nodes.

From the key steps of the training process, it can be seen that FL achieves privacy by allowing each learner to obtain learning parameters from locally available training data. Unlike centralized DL and DRL schemes, local training data is not shared with the central node. FL, thus, achieves privacy while overcoming the latency issues in the network.

Distributed Learning: FL enables learning nodes to reduce the unnecessary communication overhead, which enables to achieve low latency in the network. The learning nodes learn the tail distribution of network-wide queues locally without sharing actual queue-length samples. Recently, FL has been deployed to achieve accurate learning of network queues by using the Lyapunov-based procedure for transmitting power and resource allocation in distributed nodes. This method shows a considerable reduction in queue lengths, which can grow beyond a predefined threshold in contemporary schemes. In addition, FL has been used in mobility prediction to estimate the future behavior of non-stationary communicating parties to ensure stringent URLLC requirements in 6G networks.

Limitations

Recent advances in ML, DL, and DRL have shown the potential to solve complex problems. However, the learning rate, learning optimality, and communication/computation overheads in classical ML and FL pose limitations to achieve stringent 6G URLLC requirements. This subsection highlights fundamental limitations of DL and DRL for 6G networks.

Learning Rates: Although DNNs have revolutionized learning, prediction, and classification for complex systems, they require the large number of training samples to train the model as the number of hidden layers increases in neural networks. Furthermore, the increase in the number of cross layers to be optimized and the number of users in the network significantly increase the complexity of optimization problems. For instance, in massive networks, resource allocation problems along with cross-layer optimization tend to transform into NP-hard optimization problems, which require long training time and high computation overheads. Although the DL model can be trained offline, due to non-stationary dynamics of the environment, this offline training leads to model mismatch. In this scenario, deep transfer learning can be a possible solution. The basic idea is to divide DNNs into two parts: first, pre-trained and second, post-trained, with fewer hidden layers. Although post-training of the second part may counter model mismatch the fewer hidden layers increase the prediction/estimation error. These limitations of classical ML make it challenging to achieve stringent URLLC requirements in 6G networks. In this scenario, quantum neural networks (QNNs) have the potential to overcome these challenges.

Learning Optimality: In RL, the main goal of the agent is to learn the optimal policy directly from the interaction with the environment where the convergence time depends on the state-action space and the knowledge of the environment. In real-time implementations, the dimensionality of the state action pairs poses the following limitations on classical RL even in the best-case scenario (e.g., the dynamics of the environment are fully known):

- In classical RL, the policies are learned based on the state-action values, which require updating the state-action values for each pair. In communication networks, a high dimensional state-action space limits the learning rate. Although DRL can generalize the estimation of state-action values by using DL, a widely-used deep policy gradient can learn deterministic policies only. It is well known that stochastic policies outperform deterministic policies. In quantum mechanics, the measurement outcomes of a quantum system are stochastic in nature, which can learn the stochastic policies. In addition, the linear combination of two or more quantum states represents a valid quantum state, which can update the state-value functions of multiple pairs in parallel — called quantum parallelism.
- In classical RL, the ε-greedy policy is one of the most widely-used action-selection policies. Although ε-greedy policy may create an exploration-exploitation balance, it dramatically changes the action-selection probabilities even for a fractional change in state-action values. Furthermore, the action-selection probabilities of the secondbest action and the worst action are the same in the e-greedy policy. In this scenario, the Softmax actionselection approach can be used. However, it requires setting a temperature parameter, which may not be easy to adjust with many parameters to be optimized. In contrast, quantum superposition states provide the perfect means to generate random numbers with smooth probability transitioning.

Computation Overheads: Distributed learning is one of the fastest-growing technologies, which can provide distributed storage and on-demand services via cloud computing. The 6G-enabled

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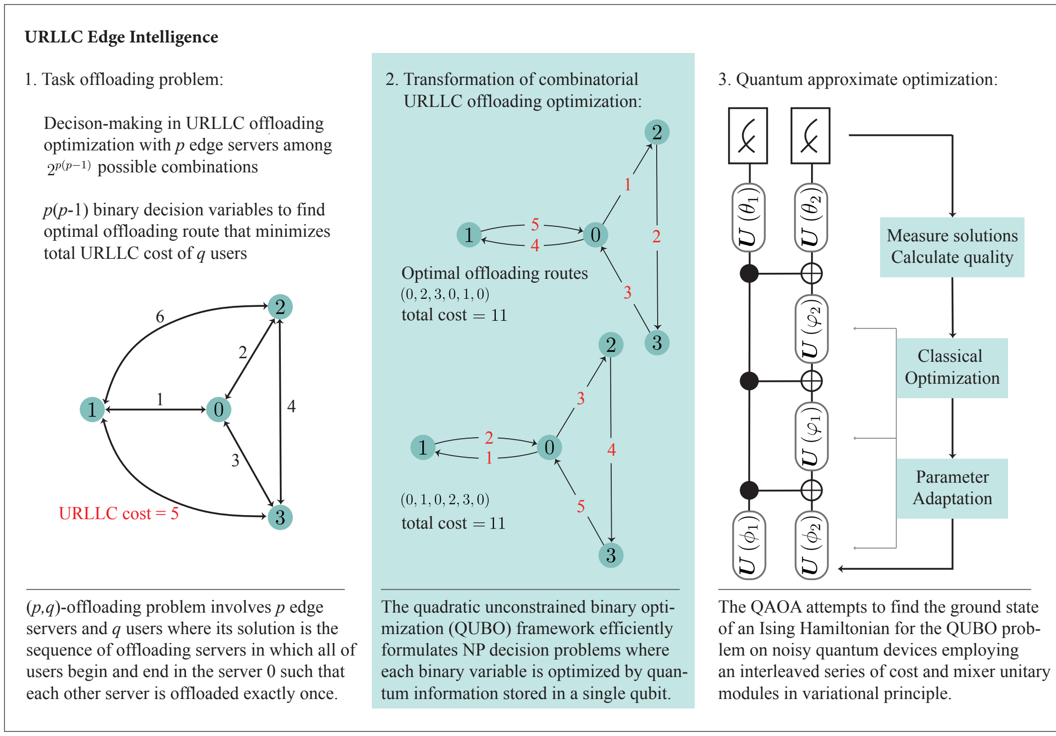


FIGURE 2. Quantum-classical hybrid computing for a small exemplary URLLC task offloading problem. The task offloading optimization is cast as an NP-hard combinatorial optimization problem with a linear URLLC cost function and is simply formulated as the routing problem in [9]. QAOA is a general-purpose algorithm that can solve combinatorial optimization problems, such as max-cut, wireless scheduling, vehicle routing, data analysis, and ML problems on NISQ computers.

technologies, such as augmented or virtual reality, are highly computation-intensive and data-sensitive. In this scenario, long-distance communication in cloud computing may not be able to ensure the stringent 6G URLLC requirements. Mobile edge computing (MEC) is a new paradigm to provide cloud computing at the network edge, which is closer to the mobile user. It can virtualize the cloud beyond the data center to meet latency, data sovereignty, reliability, and interoperability requirements. However, the central problem is optimizing the network performance to achieve a better QoS for cloud computing by designing optimal task offloading and resource allocation. The combinatorial nature of task offloading and coupling of resource management increases the computational overhead. The QAOA has the potential to exponentially reduce the optimal-policy learning rate for task offloading and resource management in MEC (see Fig. 2 for exemplary illustration).

Computational Resources: It is envisioned that 6G will revolutionize communication networks empowered by advances in AI, ML, and cloud computing. The traditional centralized ML technologies pose privacy-risk communication overheads to transmit training data to the central node with its data aggregation problem. In this scenario, FL can provide a decentralized solution, which enables participating nodes to collaboratively train a learning model using their local samples. The participating nodes only update training parameters of the DNN instead of transmitting their local data to the central node. However, each participating node requires enough computational resources to train the DNN corresponding to their own local samples. In quantum information theory, blind computation allows each participating node to use the quantum computational resources of the central node without revealing their training data.

Quantum Learning for 6G URLLC

VQAs are a class of quantum-classical hybrid algorithms that can be implemented on NISQ devices to gain quantum advantages in the near future. To implement the VQA, a quantum computer is initialized with a parametrized quantum state $|\psi(\theta)\rangle$, where θ is a tunable parameter to be optimized on a classical computer. The quantum processor evaluates the expectation value of $\langle\psi(\theta)|\boldsymbol{H}|\psi(\theta)\rangle$, where $\boldsymbol{H}$ is the problem-base Hamiltonian. The function $\langle\boldsymbol{H}\rangle$ determines the expectation of the minimum value of the initial quantum state with respect to the Hamiltonian. The process of measuring on the quantum computer and sending the parameter to be optimized on the classical computer is repeated many times until it converges to the optimal value.

Quantum Approximate Optimization Algorithms

QAOA is a type of VQAs, which can solve combinatorial problems and is one of the most important candidates to achieve quantum advantages in real-world optimization problems. The combinatorial problems require finding an optimal solution from a finite set of possible solutions. In general, as the system dimensionality grows, it increases the problem complexity and difficulty in finding the optimal solution. The quantum algorithms, such as the VQE and QAOA approximate reasonably high-quality solutions [9].

The QAOA is a quantum-classical hybrid model that utilizes NISQ devices to evaluate the

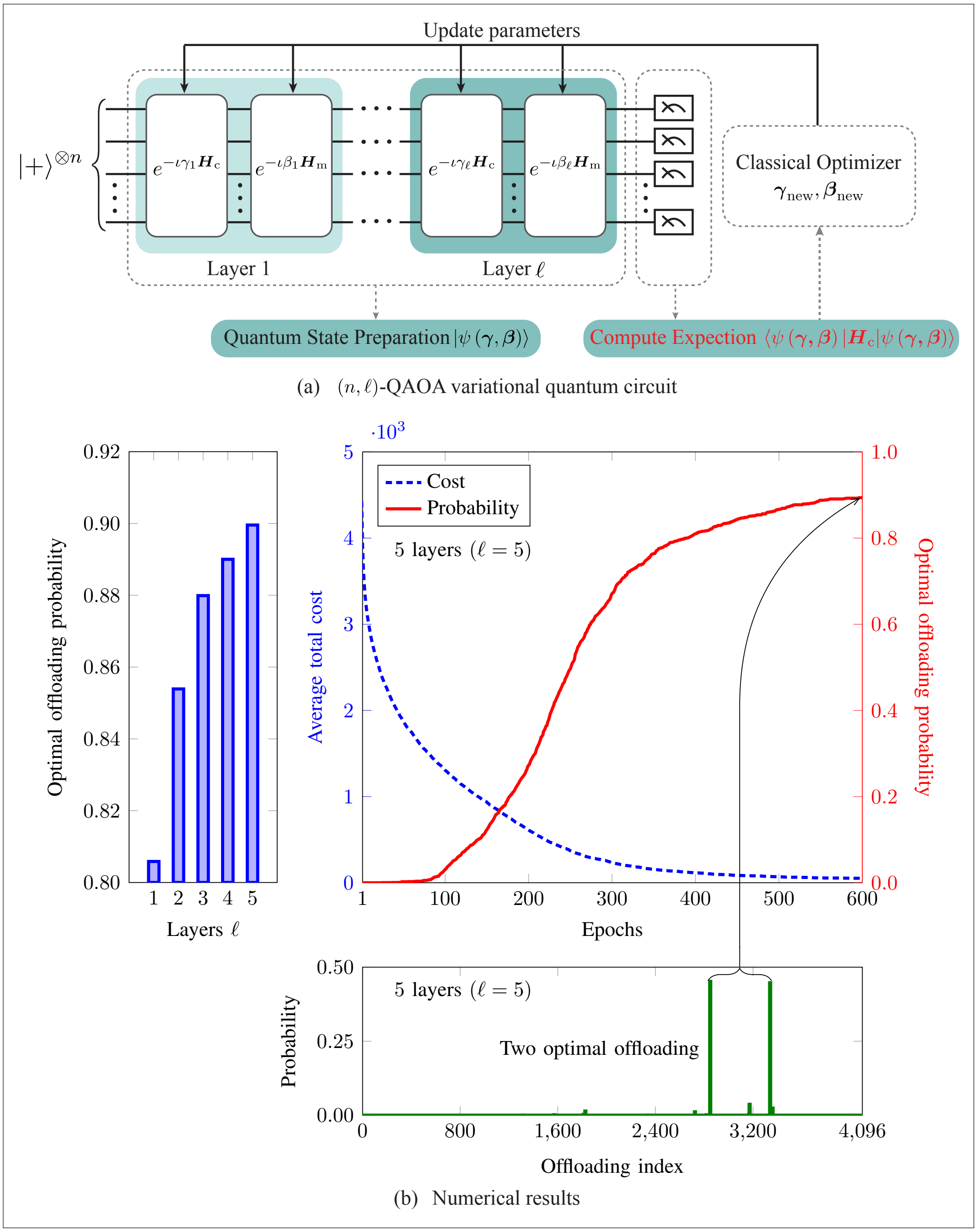
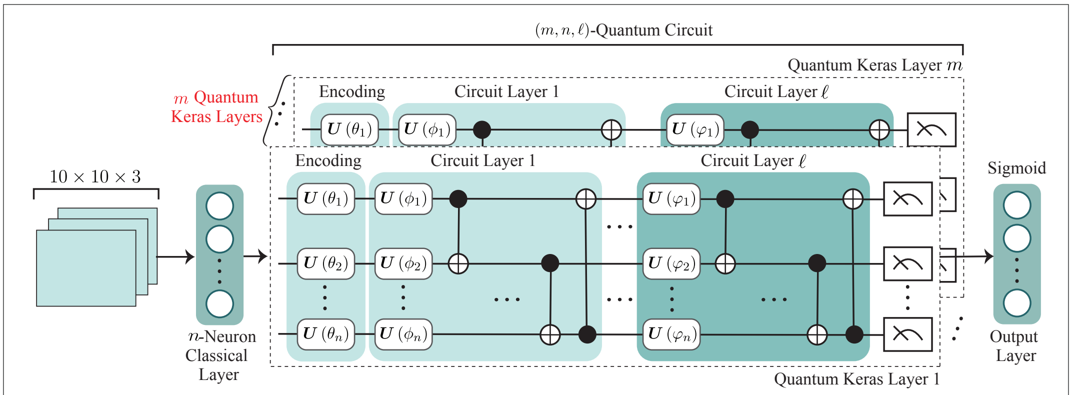


FIGURE 3. Case Study I: (n, ℓ)-QAOA variational quantum computation for the (4, 2)-offloading problem to minimize total URLLC cost in Fig. 2, where n and ℓ are the numbers of qubits and circuit layers, respectively. The POWELL optimizer is used for classical optimization to update the variational parameters γ and β for cost Hamiltonian $\boldsymbol{H}_c$ and mixer Hamiltonian $\boldsymbol{H}_m$, respectively. The decision probability of optimal offloading is obtained by using 2,000 experiments (runs) when the number (depth) of circuit layers is equal to ℓ = 1, 2, 3, 4, 5 (top left). For 5 layers (ℓ = 5), the QAOA finds two optimal offloading routes (total URLLC cost of 11) among 2^{12} options with the probability of 0.9. By using again 2,000 experiments for ℓ = 5, the average total URLLC cost and optimal offloading probability are depicted as a function of epochs (top right) along with the decision probability for all 2^{12} offloading indices (bottom plot).

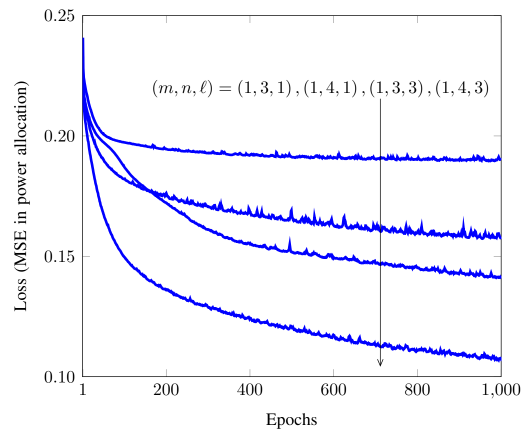
objective function and utilizes a classical optimizer to update its trial solution. The solution quality depends on variational parameters obtained by the classical optimizer and circuit depth (Fig. 3). In wireless networks, efficient and intelligent scheduling is required to meet the stringent URLLC requirements. However, it requires NP-hard heuristics to design an efficient scheduler. To take advantage of quantum algorithms, scheduling can be formulated as combinational problems and the QAOA can be used to ensure URLLC in 6G networks, which has the potential to reduce the computational overhead in task offloading and resource management problems in MEC [10].

Quantum Neural Networks

The QNNs are a subclass of VQAs comprising quantum circuits that contain parameterized



(a) (m, n, ℓ)-QNN variational quantum circuit



Qubits n	Circuit Layers ℓ	Sum Rate [bits/s]
2	1	1.262
	2	1.351
	3	1.408
	4	1.410
3	1	1.392
	2	1.442
	3	1.479
	4	1.589
4	1	1.404
	2	1.530
	3	1.559
	4	1.737

(b) Numerical results

FIGURE 4. Case Study II: (m, n, ℓ)-QNN variational quantum computation for power allocation in wireless networks with a setup as in [12] for 10 users where m denotes the number of quantum Keras layers, whereas n and ℓ denote the numbers of qubits and circuit layers in each quantum Keras layer, respectively. We use a quantum-classical hybrid model with a learning rate of 0.0005 and a batch size of 30 to optimize the sum rate by learning the optimal policy for power allocation in the network. A data set of channel matrices, along with optimal power sets, are generated to train our hybrid model. The training data is inputted to convolutional dense layers to formulate our input for the (m, n, ℓ)-quantum circuit. As the qubit number n and the circuit layers ℓ increase, the mean square error (MSE) in power allocation decreases significantly with the enhanced learning rate, which increases the sum rate due to this quantum speedup. For training the hybrid model, we have implemented the quantum circuit on a quantum simulator, which utilizes classical resources to simulate quantum computing. Due to this limitation, we have set the number of quantum Keras layers to $m = 1$ for simplicity.

gate operations [11]. QNNs utilize quantum bits instead of the classical bits and benefit from unique properties of quantum mechanics, such as quantum superposition and entanglement. The 6G networks become highly heterogeneous with different terminal users and base stations. This heterogeneity tends to complicate network design and ultra-reliable communication protocols. Furthermore, due to the low-latency constraint in 6G URLLC, the base station may not have enough time to acquire CSI of the corresponding devices and transmit high-priority data packets without CSI. QNNs have the potential to reduce the computational complexity of dynamical channel allocation and solve the complex network design to achieve low latency and ultra-reliability (Fig. 4).

Quantum Reinforcement Learning

Quantum Simulation for Model-Based RL: It is well known that knowledge of the environment can significantly speed up the learning rate of the agent, which plays an important role in meeting URLLC requirements in RL-assisted 6G technologies. In this context, quantum simulation has the potential to exponentially enhance the learning rate by taking advantage of quantum superposition and entanglement. Due to high computational capabilities of quantum computers, QRL has the potential to ensure stringent URLLC requirements in real-time learning. To take the quantum advantage in RL, an agent can deploy quantum simulation to enhance the learning rate subject to high reliability, low latency, and efficient power consumption [13] as follows:

- In QRL, an agent can simulate the dynamics of a communication network on a quantum computer. In contrast to classical RL, an agent can take advantage of quantum superposition. It allows an agent to take all possible actions $a \in \mathcal{A}(s)$ in parallel, which enable the agent to update state-action values $Q(s, a)$ for all a simultaneously, where $\mathcal{A}(s)$ denotes the set of all possible actions for a given state s. The agent stores the policy $\pi(a\,|\,s)$ in qubits $|a_s\rangle =$

$\Sigma b_a|a\rangle$ and simulate the dynamics of a communication network with action $|a_s\rangle$ and state $|s\rangle$.

- As the agent knows the dynamics of a communication network, it can design the oracle function $\boldsymbol{U}_e$ such that it transforms $|a\rangle$ to $-|a\rangle$ for all a with the reward $r > 0$, where e denotes the environment. Now the agent iterates the policy by performing Grover's iteration $\boldsymbol{U}_{a_s}$ to amplify the selection probabilities of good actions.

Note that in both approaches, the policy is represented by a quantum state, which is stochastic in nature and enables the agent to learn optimal stochastic policies. To take action in real-time applications, the agent measures the learned policy $|a_s\rangle$ for given s in computational basis $|a\rangle$, observes the measurement outcome a with probability $|b_a|^2$, and takes action a. As the policy is perfectly known at each time step, it can be cloned such that the learned policy is not destroyed.

QRL for Resource Management: Resource allocation is one of the most important tasks in wireless networks, which requires RL techniques to efficiently learn optimal policies. The QRL has the potential to enhance the learning rate. However, the quantum-assisted RL techniques require knowledge of the environment. Furthermore, 6G networks are non-stationary due to the high mobility of participating parties. To encounter the model mismatch problem, we can divide the QRL system into two parts. In the first part, QNN can be used to update the dynamics of the communication network at each step. In the second part, the quantum simulator can be used to simulate the learned dynamics and find the optimal policies to ensure URLLC. Due to the known dynamics of the communication, the learned optimal policies can be validated by using quantum benchmarking to ensure QoE and QoS subject to stringent URLLC requirements.

Recently, QRL has been used to learn a real-time optimal resource management policy [14]. It has been shown that the QRL can reduce the computational complexity of the optimal-policy learning problems. As optimal-policy learning can be formulated as a search problem in state-action space, Grover's policy iteration approach reduces the computational complexity of an RL agent by a factor of

$$\sqrt{N_s N_a}$$

where N_s and N_a denote the number of possible states and actions, respectively [14].

Quantum Federated Learning

Quantum-enabled FL provides a possible solution to the problem of distributed processing power required for conventional FL. By taking advantage of quantum resources, such as quantum entanglement, QFL allows a client to perform quantum computation on a remote server without revealing input and output data to the server — called blind quantum computation [15]. This allows QFL to learn from distributed data by using computational resources of the central node only under quantum-safe security and privacy. Recently, blind quantum computation has been proposed to allow a client node to execute quantum computation using one or more remote quantum servers while keeping the structure of the computation hidden along with input and output data.

Although the primary task of FL is to ensure the privacy of the data, blind quantum computation protocols allow the client node to verify the operations being performed by the central node or its data. In addition, blind quantum computation allows unconditional security against any adversary on the channel between two nodes by utilizing principles of quantum mechanics, such as quantum non-locality and quantum non-cloning theorem. Therefore, the blind quantum computation technology takes the advantage of both conventional centralized learning and FL without compromising the security and privacy of data. In FL-assisted 6G URLLC applications, due to data sensitivity, QFL provides a key resource to address limitations of classical FL in the following manners:

- QFL mimics conventional central learning systems, which enhance the learning rate due to a single processing node. In contrast, QFL significantly reduces communication overhead as it does not require transmission of training samples to the central node.
- In QFL, the server takes advantage of QNNs to further enhance the learning rate to ensure stringent URLLC in 6G networks.

Challenges and Research Directions

Quantum machine intelligence provides unprecedented tools, such as VQAs, QRL, and QFL to enhance the learning rate and ensure stringent URLLC as well as quantum-safe security in 6G networks. However, quantum technologies are still in their infancy. For instance, state-of-the-art quantum computers have a limited number of qubits and require strictly controlled environments. The ongoing research is developing a pathway toward NISQ devices, which can play an important role in edge quantum learning.

Quantum Noise and Error Mitigation

Quantum error correction (QEC) is one of the key elements in achieving fault-tolerant quantum computing. Classical error correction schemes can achieve unprecedented levels of reliability in classical computing, whereas QEC codes, such as stabilizer coders are fairly limited. Quantum error mitigation provides alternate means to counter quantum noises by designing hardware-aware qubit control and pulse reshaping methodologies.

Distributed Quantum Learning and Communication

In FL, communication architecture plays an important role in enhancing the learning capability of the system. Recently, quantum communication has been attempted at the terahertz band. However, the limited performance of optical-to-terahertz converters may significantly affect the QFL efficiency. Dedicated optical fiber links are required between server and client nodes to exchange quantum information.

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