Optimal Task Scheduling in 6G Networks: A Variational Quantum Computing Approach

Uman Khalid[1], Junaid ur Rehman[2], Ahmad Farooq[3], Fakhar Zaman[4], and Hyundong Shin[1(✉)]

[1] Department of Electronics and Information Convergence Engineering, Kyung Hee University, Yongin, Republic of Korea
hshin@khu.ac.kr

[2] Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Esch-sur-Alzette, Luxembourg

[3] Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland

[4] Commonwealth Scientific and Industrial Research Organisation (CSIRO), Clayton, Australia

Abstract. Optimal task scheduling in 6G networks plays a crucial role in enabling a wide range of applications such as augmented reality, virtual reality, autonomous vehicles, and the Internet of Things (IoT). With the network landscape becoming a more complex and diverse ecosystem, it is critical to advance conventional scheduling algorithms in order to guarantee the necessary efficiency and performance. In this regard, quantum computing can significantly speed up search for optimal schedules, increase the likelihood of finding optimal solutions, and facilitate the creation of correlations between tasks in a scheduling problem by virtue of parallelism, superposition, and entanglement. In this paper, we explore the variational quantum computing approach to tackle the complex task scheduling problem in cloud radio access network (C-RAN) architecture for 6G networks. By leveraging the quantum approximate optimization algorithm (QAOA) and utilizing IBM Qiskit as a simulation testbed, we aim to optimize task scheduling for enhancing wireless network performance. Herein, the classical quadratic constrained integer optimization (QCIO) problem instance is transformed to an Ising Hamiltonian formulation to implement task scheduling optimization on a quantum computer. We also evaluate the effectiveness and stability of QAOA by analyzing the expected cost and the probability of obtaining an optimal schedule as a function of QAOA circuit layers. Our findings highlight the applicability of variational quantum computing in addressing intricate optimization problems as well as setting the stage for the

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT) (NRF-2019R1A2C2007037, NRF-2022R1A4A3033401) and by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2023–2021-0–02046) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

N.-S. Vo et al. (Eds.): INISCOM 2024, LNICST 595, pp. 61–72, 2024.
https://doi.org/10.1007/978-3-031-67357-3_5

development of more advanced quantum optimization algorithms for 6G networks.

Keywords: Cloud radio access network · Task scheduling · Variational quantum computing · Quantum approximate optimization algorithm

1 Introduction

The evolution of mobile communication networks from 2G to 5G has brought tremendous advancements in terms of higher data rates, lower latency, and improved user experience [20,24]. However, as the communication and computational demands for supporting data-intensive and computation-intensive applications continue to grow, the necessity for further network improvements is becoming increasingly urgent [13]. To this end, the sixth generation (6G) networks have been envisioned to meet these stringent requirements, enabling potential applications ranging from smart cities and autonomous vehicles to virtual reality and telemedicine [13,16,20].

One of the key challenges in 6G networks is the management of the high volume of data traffic generated by a large number of connected devices [8,11,23]. C-RAN architecture has been proposed to address this challenge, where a centralized cloud-based processing unit manages the radio access networks for multiple base stations. Task scheduling is a crucial issue in C-RAN architecture, where efficient scheduling of computational tasks is necessary to maximize resource utilization, reduce network congestion, and ensure the timely delivery of data traffic. The task scheduling problem in C-RAN architecture is known to be an NP-hard problem, and finding an optimal solution is intrinsically challenging for classical computers. Contrarily, quantum computing has the potential to tackle such complex optimization problems by capitalizing its inherent ability to explore large solution spaces more effectively than classical computing [14,19,22].

In this paper, we explore the variational quantum computing approach to solve the task scheduling problem in C-RAN architecture [3]. The approach involves modeling the task scheduling problem as a combinatorial optimization problem, where the goal is to find the optimal scheduling solution that minimizes the total completion time of all tasks. We chose to employ variational quantum algorithm (VQA) in the noisy intermediate-scale quantum (NISQ) era due to its resilience to noise and ability to leverage the limited resources of near-term quantum devices, rendering them a promising candidate for efficiently solving complex combinatorial optimization problems such as task scheduling [2,15,17]. We utilize QAOA owing to its efficiency in solving combinatorial optimization problems. We first formulate the task scheduling problem as a QCIO problem and subsequently transform it into a quadratic unconstrained binary optimization (QUBO) problem. The QUBO problem is then tackled using QAOA, which effectively identifies the optimal scheduling solution. We also demonstrate the effectiveness of the proposed approach through simulation experiments and performance analysis.

In short, this paper hints at the prospects of quantum computing and its advantages over classical computing in addressing the challenges of future mobile communication networks. The advantage of this approach lies in the ability of quantum computing to process information in parallel and explore large solution spaces simultaneously, ultimately outperforming classical algorithms [9,10]. Current quantum hardware technologies, such as superconducting and photonic quantum computers, have exhibited substantial computational advantages in solving complex optimization problems [1,4–6,12,21].

The rest of the paper is organized as follows. Section 2 details problem formulation. Section 3 describes the QAOA based variational quantum computing approach for solving the task scheduling optimization problem in C-RAN architecture. Section 4 presents the simulation results and performance analysis of the proposed method. Finally, we conclude in Sect. 5.

2 Problem Formulation

2.1 System Model

We consider a C-RAN system comprising a set of remote radio heads (RRHs) and a baseband unit (BBU), as shown in Fig. 1. The BBU allocates resources such as processing power, energy, and bandwidth to each RRH in the network as per requirement. Herein, we specify the allocation of resources to each RRH by optimizing the task scheduling while considering both task arrival times as well as task deadlines.

Let $k \in K$ represent the RRH index with task arrival time t_k^a, task deadline t_k^d, and T be the total number of available discrete time slots at BBU. We define a vector

$$\vec{p} = (\vec{p}_0[t], \ldots, \vec{p}_{K-1}[t])^{\intercal}, \tag{1}$$

where each constituent vector $\vec{p}_k[t]$ represents the number of processing units allocated to corresponding RRH across the time $t = 0$ to $t = T - 1$, given as

$$\vec{p}_k[t] = (\vec{p}_k[0], \ldots, \vec{p}_k[T-1])^{\intercal}. \tag{2}$$

The values in $\vec{p}_k[t]$ are integers between 0 and $P - 1$, where P is the peak load processing capacity of the BBU at any given time slot t. It is easy to see that the sum of the computational load of all RRHs for each time slot t is given as

$$\vec{p}_{\text{sum}}[t] = \begin{pmatrix} p_0^0 + p_1^0 + \ldots + p_{K-1}^0 \\ \vdots \\ p_0^{T-1} + p_1^{T-1} + \ldots + p_{K-1}^{T-1} \end{pmatrix}. \tag{3}$$

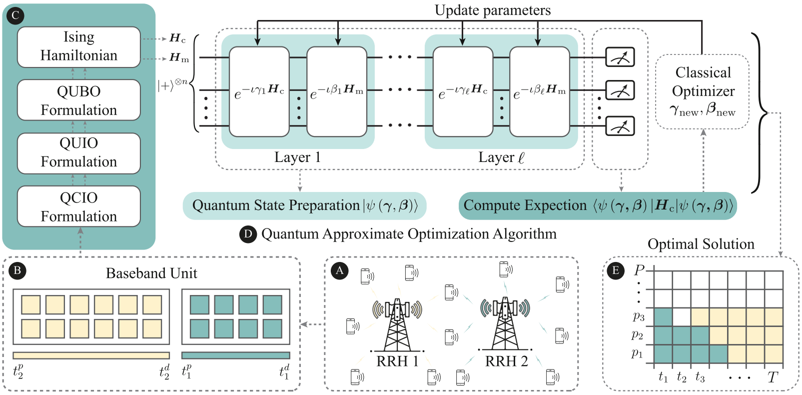

Fig. 1. The illustrative framework for task scheduling optimization in C-RAN with QAOA: Herein, (A) depicts multiple RRHs serving a set of users in a C-RAN architecture. In (B), the BBU receives requests for resource allocation by receiving information about the required processing units along with corresponding arrival and deadline times. (C) represents the transformation of the peak load minimization problem into a formulation that is executable on a quantum computer. (D) shows the quantum circuit implementation of QAOA and its hybrid workflow. Finally, (E) represents the optimal solution obtained through QAOA wherein the processing unit allocation for all time slots is displayed as the filled boxes.

2.2 Cost Function

The summation of all components of the vector $\vec{p}_{\text{sum}}[t]$ gives the total number of processing units allocated by the BBU. For optimizing the peak computational load, ℓ_2-norm of $\vec{p}_{\text{sum}}[t]$ should be minimized. Note that $\|\vec{p}_{\text{sum}}\|_2$ is

$$\|\vec{p}_{\text{sum}}\|_2^2 = \vec{p}_{\text{sum}}^{\intercal}\vec{p}_{\text{sum}} = \vec{p}^{\intercal} A \vec{p}, \tag{4}$$

where $A = \mathsf{I}_K^{\intercal}\mathsf{I}_K \otimes I_T$, I_T is the $T \times T$ identity matrix and, $\mathsf{I}_K = (1, 1, \ldots, 1)^{\intercal} \in \mathbb{R}^K$. Thus, the cost function for the minimization of the peak computational load is as follows

$$f_1(\vec{p}) = \|\vec{p}_{\text{sum}}\|_2^2 = \vec{p}^{\intercal} A \vec{p}. \tag{5}$$

From (5), it is trivial that only minimizing function f_1 without any constraints would imply no computation at all. So, we introduce the appropriate constraints in the following subsection to enforce the optimal scheduling for the required number of computations at valid time slots.

2.3 Constraints

Firstly, we define a matrix C as

$$C = \sum_{k=0}^{K-1} C_k \cdot I_T, \tag{6}$$

where

$$C_k = (0 \ldots 0 \underbrace{1}_{t_k^a} 1 \ldots 1 \underbrace{1}_{t_k^d} 0 \ldots 0), \tag{7}$$

for every $k \in \{0, \ldots, K-1\}$. Then, the constraints are given by

$$C\vec{p} = \vec{n}, \quad \vec{n} = (n_0, \ldots, n_{K-1})^\intercal, \tag{8}$$

where n_k is the number of computations allotted to an RRH k . Thus, formulating the QCIO problem as

$$\begin{aligned} \min_{\vec{p} \in \{0,\ldots,P-1\}^{KT}} \quad & f_1(\vec{p}) \\ \text{subject to} \quad & C\vec{p} = \vec{n} \end{aligned} \tag{9}$$

3 Variational Quantum Computing Approach

The VQA is a family of quantum algorithms that aims to find the ground state of a given Hamiltonian using quantum computers [3]. Here, we employ QAOA which is designed to solve combinatorial optimization problems by finding the minimum of a cost function that maps a set of input variables to a real number. To implement QAOA on a quantum computer, the cost function needs to be transformed into a form that can be represented as a Hamiltonian acting on the quantum states. This is typically achieved by mapping the optimization problem to a QUBO form, where the input variables are represented as binary variables and the cost function is expressed as a quadratic polynomial [7]. However, the optimization problem may have constraints that are hard to enforce directly using quantum operations. This can make it difficult or even impossible to find the ground state of the Hamiltonian that represents the optimization problem. One way to overcome this challenge is to convert the hard constraints into soft constraints. Soft constraints are constraints that are not strictly enforced, but rather are penalized in the objective function. By introducing a penalty term in the objective function, we can still find a solution that satisfies the hard constraints to a certain degree while optimizing the objective function.

3.1 Converting Hard to Soft Constraints

For a penalty parameter $\varrho \geq 0$, we define

$$f_2(\vec{p}; \varrho) = f_1(\vec{p}) + \varrho \|C\vec{p} - \vec{n}\|_2^2. \tag{10}$$

Algorithm 1. Quantum Approximate Optimization Algorithm

```
procedure QAOA(ℋ_M, ℋ_C, l)
    Prepare equal superposition of all 2^n computational basis states
    while not converged do
        for i = 1 to l do
            Apply cost Hamiltonian ℋ_C for time γ_j
            Apply mixer Hamiltonian ℋ_M for time β_k
        end for
        Measure the state in the computational basis
        Compute ⟨ψ(γ, β)|ℋ_C|ψ(γ, β)⟩
        Update γ, β using classical optimization routine
    end while
    return Final parameters γ*, β* and energy of cost function E(γ, β)
end procedure
```

Note that f_2 is also a quadratic cost function with

$$f_2(\vec{p};\varrho) = \vec{p}^{\,t}\hat{A}_n\vec{p} + \hat{L}_n\vec{p} + \hat{c}_n, \tag{11}$$

where $\hat{A}_n = A + \varrho C^{\intercal}C, \hat{L}_n = -2\varrho n^{\intercal}C$, and $\hat{c}_n = \varrho\|\vec{n}\|_2^2$. For a fixed penalty parameter ϱ, we have a quadratic unconstrained integer optimization (QUIO) problem as

$$\min_{\vec{p}\in\{0,\dots,P-1\}^{KT}} f_2(\vec{p};\varrho). \tag{12}$$

It is important to note that if ϱ is chosen large enough then the solution of QUIO is also a solution of QCIO. On the other hand, this means that very small values of ϱ may lead to unfeasible solutions, i.e., solutions $\vec{p}$ of QUIO that do not satisfy the constraint $C\vec{p} = \vec{n}$ of QCIO.

3.2 QUBO Formulation

Now, we utilize binary encoding in order to transform the formulated QUIO problem into QUBO form. Binary encoding is executed by a transformation matrix B such that $\vec{p} = B\vec{b}$, where the coefficients b_i of $\vec{b}$ are binary, i.e., $b_i \in \{0,1\}$. By substituting $\vec{p} = B\vec{b}$ in (12), we get the QUBO cost function as

$$\min_{b\in\{0,1\}^N} f_3(\vec{b};\varrho), \tag{13}$$

where $f_3(\vec{b};\varrho) = \vec{b}^t\widetilde{A}_n\vec{b} + \widetilde{L}_n\vec{b} + \widetilde{c}_n, \widetilde{A}_n = B^t\hat{A}_nB, \widetilde{L}_n = \hat{L}_nB$, and $\widetilde{c}_n = \hat{c}_n$. Note that the dimension increases after binary encoding, for instance, $\vec{p}$ has $N = KT$ entries, whereas $\vec{b}$ has $\widetilde{N} = wKT$ entries. Here, w corresponds to the binary precision, i.e., the number of bits used to represent the integer in binary form.

3.3 QUBO to Ising Hamiltonian

To solve QUBO problem with QAOA on a quantum computer, the corresponding Ising Hamiltonian is required beforehand. Alternately, QUBO cost function of

(13) can be represented as

$$f_3(\vec{b}) = \sum_{i=0}^{n-1}\sum_{j>i}^{n-1} a_{ij} b_i b_j + \sum_{i=0}^{n-1} l_i b_i + \widetilde{c}_n, \tag{14}$$

where a_{ij} and l_i are the entries of $\widetilde{A}_n$ and $\widetilde{L}$, respectively. Subsequently, we replace

$$b_i \leftrightarrow \frac{1}{2}\left(I^{\otimes n} - \sigma_Z^{(i)}\right),$$

where

$$I^{\otimes n} = \underbrace{I \otimes \cdots \otimes I}_{n \text{ times}},\ I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix},$$

and

$$\sigma_Z^{(i)} = I \otimes \cdots \otimes I \otimes \underbrace{Z}_{\text{place } i} \otimes I \otimes \cdots \otimes I,\ Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}.$$

This gives the cost Hamiltonian $\mathcal{H}_C$, which is of the form

$$\mathcal{H}_C = \sum_{i=0}^{n-1}\sum_{j>i}^{n-1} h_{ij}\sigma_Z^{(i)}\sigma_Z^{(j)} + \sum_{i=0}^{n-1} h_i'\sigma_Z^{(i)} + h'' I^{\otimes n}, \tag{15}$$

where the coefficients h_{ij}, h_i' and h'' can be computed from a_{ij}, l_i and $\widetilde{c}_n$. Similarly, the mixer Hamiltonian $\mathcal{H}_M$ is defined by

$$\mathcal{H}_M = \sum_{i=0}^{n-1} \sigma_X^{(i)},$$

where

$$\sigma_X^{(i)} = I \otimes \cdots \otimes I \otimes \underbrace{X}_{\text{place } i} \otimes I \otimes \cdots \otimes I,\ X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

The connection between the QUBO cost function f_3 and the cost Hamiltonian $\mathcal{H}_C$ is established by

$$\langle \psi | \mathcal{H}_C | \psi \rangle = \sum_{\vec{b} \in \{0,1\}^n} |\lambda_b|^2 f_3(\vec{b}), \tag{16}$$

where quantum state $|\psi\rangle$ with amplitudes λ_b is

$$|\psi\rangle = \sum_{\vec{b} \in \{0,1\}^n} \lambda_b |b\rangle, \quad \lambda_b \in \mathbb{C}, \sum_{\vec{b} \in \{0,1\}^n} |\lambda_b|^2 = 1.$$

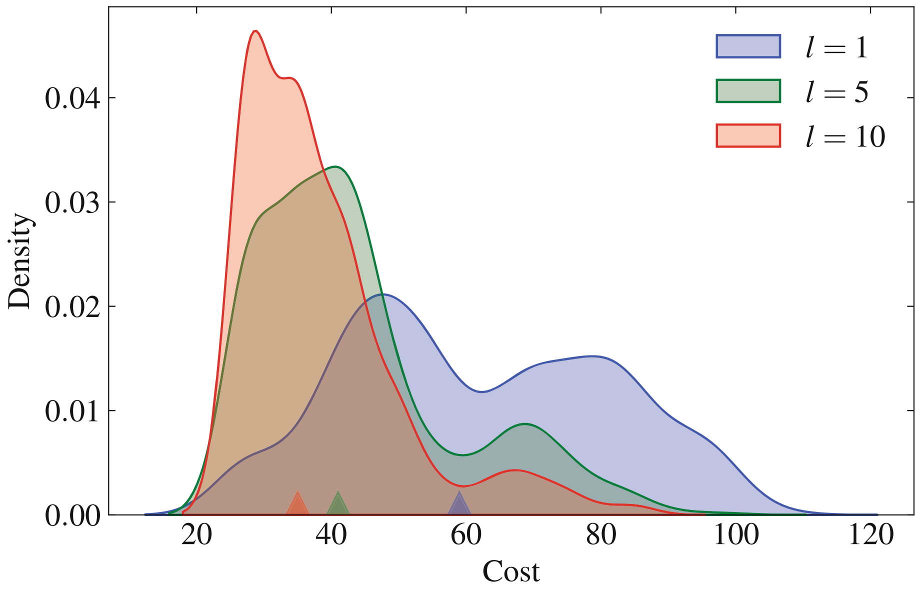

Fig. 2. Cost density of solutions obtained through 1000 trials is plotted for layer counts $l = 1, 5$, and 10.

3.4 Quantum Approximate Optimization Algorithm

QAOA utilizes a parameterized quantum circuit to generate a trial state that is measured to obtain an expectation value (see Algorithm 1). The expectation value is used as an objective function to be optimized by a classical optimization algorithm.

QAOA starts by preparing the qubits in uniform superposition as

$$|+\rangle^{\otimes n} = \underbrace{|+\rangle \otimes \cdots \otimes |+\rangle}_{n \text{ times}}, \quad |+\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle),$$

and then applies the following unitary transformation

$$U(\boldsymbol{\gamma}, \boldsymbol{\beta}) = e^{-i\beta_l \mathcal{H}_M} e^{-i\gamma_l \mathcal{H}_C} \cdots e^{-i\beta_1 \mathcal{H}_M} e^{-i\gamma_1 \mathcal{H}_C},$$

where $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_l)$ and $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_l)$ are the parameters of the algorithm, and l is the number of layers of the circuit. This prepares the following state

$$|\psi(\boldsymbol{\gamma}, \boldsymbol{\beta})\rangle = U(\boldsymbol{\gamma}, \boldsymbol{\beta})\, |+\rangle^{\otimes n}. \tag{17}$$

The parameters γ_i and β_i are then optimized using classical optimization algorithms such that the expectation value

$$E(\boldsymbol{\gamma}, \boldsymbol{\beta}) = \langle \boldsymbol{\psi}(\boldsymbol{\gamma}, \boldsymbol{\beta}) | \mathcal{H}_C | \boldsymbol{\psi}(\boldsymbol{\gamma}, \boldsymbol{\beta}) \rangle, \tag{18}$$

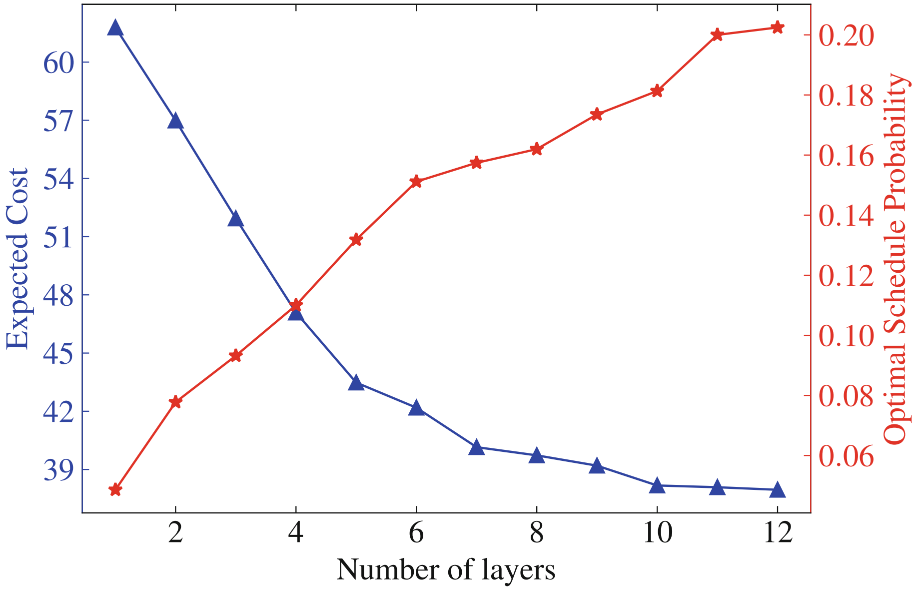

Fig. 3. Expected cost and optimal schedule probability for 1000 trials plotted as a function of the number of circuit layers.

is minimized as

$$(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*) = \underset{\boldsymbol{\gamma},\boldsymbol{\beta}}{\operatorname{argmin}} \;\; E(\boldsymbol{\gamma}, \boldsymbol{\beta})). \tag{19}$$

Now, measuring the $|\psi\left(\boldsymbol{\gamma}^*, \boldsymbol{\beta}^*\right)\rangle$ should result in a bitstring $\vec{b}^*$ with high probability that is a good approximation of the minimum of f_3, given as

$$f_3\left(\vec{b}^*\right) \approx \min_{\vec{b}\in\{0,1\}^n} f_3(\vec{b}).$$

In other words, this is a hybrid workflow wherein the quantum state in (17) is constructed on a quantum computer for a given set of parameters, and the expectation value (18) is computed by performing measurements on this quantum state. Based on this expectation value, a classical optimizer (19) proposes the next set of parameters and the process starts from the beginning. In this way, a near-optimal solution is iteratively approximated.

4 Simulation Results

Here, we utilize IBM Qiskit to implement QAOA [18]. In this approach, the problem instance is encoded using $n = KT\log_2(P)$ qubits. The state vector $|b_{n-1}, \ldots, b_1, b_0\rangle$ corresponds to an integer solution array where each w qubits

Table 1. Experiment settings and optimal results

Parameter	**Value**
Number of qubits	12
Shots per experiment	2^{14}
Trials per layer	1000
Optimizer	MinEigenOptimizer
Backend	Aer statevector
w, K, T, P	$2, 2, 3, 4$
$t_1^a, t_1^d, p_1[t]$	$0, 1, 4$
$t_2^a, t_2^d, p_2[t]$	$1, 2, 5$
Penalty (ϱ)	5.6
Optimal cost	27.0
Optimal solution statevector	$\|111000000111\rangle$
Optimal solution integer array	$[3, 1, 0, 0, 2, 3]$

encode an entry. Among the 2^n possible solutions derived from the QAOA routine for a specific problem instance, only those solutions are considered feasible that satisfy all constraints. To simulate the algorithm, we carefully selected a complex instance and execute experiments using 2^{14} shots (maximum available). The reliability of experiments increases by increasing the number of shots per experiment. The parameters used for the simulation are provided in Table 1.

We assessed the QAOA's effectiveness by conducting 1000 trial runs for each circuit layer count l and selecting the feasible solution with the highest probability from these trials. Herein, the maximum number of iterations were set to 1000. Figure 2 depicts that the stability of QAOA increases by increasing the number of circuit layers. The results show that increasing the number of circuit layers leads to a decrease in the expected cost and improves the stability of the results by reducing the variance. Therefore, QAOA implemented with higher circuit depth can capture more complex patterns and dependencies, ultimately leading to better performance in solving complex optimization problems. Then, the expected cost is calculated as the mean of the costs of these solutions over all trials, as shown in Fig. 3. We analyzed the algorithm's performance by plotting the expected cost as a function of the number of layers l. Additionally, we calculated the probability of obtaining an optimal schedule by using the ratio N^*/N_T, where N^* represents the number of times we obtain an optimal schedule with high probability and N_T is the total number of trials. The results demonstrate that increasing the number of layers leads to a decrease in the expected cost and an increase in the probability of obtaining an optimal schedule. By measuring the frequency of optimal solutions, we assessed the effectiveness of the QAOA in finding the best possible schedule. This metric provides valuable insights into the QAOA performance and enables fine-tuning of hyper-parameters to achieve better results.

5 Conclusion

In this paper, we explored the variational quantum computing approach in effectively optimizing task scheduling in C-RAN architecture for 6G networks. Multiple trial runs have validated the effectiveness and robustness of the employed method. The results demonstrate the applicability of quantum computing algorithms in addressing complex optimization problems regarding wireless networks. QAOA is theoretically promising for exponentially speeding up combinatorial optimization problems compared to classical methods. However, significant practical advantages depend on factors like problem characteristics, instance size, and NISQ hardware constraints. Quantum computers, due to NISQ era limitations such as gate errors, may not consistently outperform classical algorithms, especially for certain problem sizes. A hybrid approach, combining the benefits of both quantum and classical methods, might be employed to address these challenges. Therefore, by further improving variational quantum computing capabilities, the research direction contributes to the development of next-generation hybrid quantum-classical networks that can meet the perpetual computational requirements of emerging 6G applications.

References

1. Arute, F., et al.: Quantum supremacy using a programmable superconducting processor. Nature **574**(7779), 505–510 (2019)
2. Bittel, L., Kliesch, M.: Training variational quantum algorithms is NP-hard. Phys. Rev. Lett. **127**(12), 120502 (2021)
3. Cerezo, M., et al.: Variational quantum algorithms. Nat. Rev. Phys. **3**(9), 625–644 (2021)
4. Duong, T.Q., Ansere, J.A., Narottama, B., Sharma, V., Dobre, O.A., Shin, H.: Quantum-inspired machine learning for 6G: fundamentals, security, resource allocations, challenges, and future research directions. IEEE Open J. Veh. Technol. **3**, 375–387 (2022)
5. Duong, T.Q., Nguyen, L.D., Narottama, B., Ansere, J.A., Huynh, D.V., Shin, H.: Quantum-inspired real-time optimization for 6G networks: opportunities, challenges, and the road ahead. IEEE Open J. Commun. Soc. **3**, 1347–1359 (2022)
6. Fu, Y., Hong, Y., Quek, T.Q.S., Wang, H., Shi, Z.: Scheduling policies for quantum key distribution enabled communication networks. IEEE Commun. Lett. **9**(12), 2126–2129 (2020)
7. Glover, F., Kochenberger, G., Hennig, R., Du, Y.: Quantum bridge analytics I: a tutorial on formulating and using QUBO models. Ann. Oper. Res. **314**(1), 141–183 (2022)
8. Hou, Z., She, C., Li, Y., Niyato, D., Dohler, M., Vucetic, B.: Intelligent communications for tactile internet in 6G: requirements, technologies, and challenges. IEEE Commun. Mag. **59**(12), 82–88 (2021)
9. Huang, H.Y., et al.: Quantum advantage in learning from experiments. Science **376**(6598), 1182–1186 (2022)
10. Khalid, U., Rehman, J.u., Paing, S.N., Jung, H., Duong, T.Q., Shin, H.: Quantum network engineering in the NISQ age: principles, missions, and challenges . IEEE Netw. (2023). https://doi.org/10.1109/MNET.2023.3328892

11. Khalid, U., Ulum, M.S., Farooq, A., Duong, T.Q., Dobre, O.A., Shin, H.: Quantum semantic communications for metaverse: principles and challenges. IEEE Wirel. Commun. **30**(4), 26–36 (2023)
12. Madsen, L.S., et al.: Quantum computational advantage with a programmable photonic processor. Nature **606**(7912), 75–81 (2022)
13. Park, J., et al.: Extreme ultra-reliable and low-latency communication. Nat. Electron. **5**(3), 133–141 (2022)
14. Preskill, J.: Quantum computing in the NISQ era and beyond. Quantum **2**, 79 (2018)
15. Romero, J., Babbush, R., McClean, J.R., Hempel, C., Love, P.J., Aspuru-Guzik, A.: Strategies for quantum computing molecular energies using the unitary coupled cluster ansatz. Quantum Sci. Technol. **4**(1), 014008 (2018)
16. She, C., et al.: A tutorial on ultrareliable and low-latency communications in 6G: integrating domain knowledge into deep learning. Proc. IEEE**109**(3), 204–246 (2021)
17. Sweke, R., et al.: Stochastic gradient descent for hybrid quantum-classical optimization. Quantum **4**, 314 (2020)
18. Team, Q.D.: Qiskit: an open-source framework for quantum computing. https://qiskit.org (2019), accessed: 2024/07/13 19:46:13
19. Terhal, B.M.: Quantum Supremacy, here we come. Nat. Phys. **14**(6), 530–531 (2018)
20. Tomkos, I., Klonidis, D., Pikasis, E., Theodoridis, S.: Toward the 6G network era: opportunities and challenges. IT Prof. **22**(1), 34–38 (2020)
21. Wang, C., Rahman, A.: Quantum-enabled 6G wireless networks: opportunities and challenges. IEEE Wirel. Commun. **29**(1), 58–69 (2022)
22. Zaman, F., Farooq, A., Ullah, M.A., Jung, H., Shin, H., Win, M.Z.: Quantum machine intelligence for 6G URLLC. IEEE Wirel. Commun. **30**(2), 22–30 (Apr 2023)
23. Zaman, F., Khalid, U., Duong, T.Q., Shin, H., Win, M.Z.: Quantum full-duplex communication. IEEE J. Sel. Areas Commun. **41**(9), 2966–2980 (2023)
24. Zaman, F., Paing, S.N., Farooq, A., Shin, H., Win, M.Z.: Concealed quantum telecomputation for anonymous 6G URLLC networks. IEEE J. Sel. Areas Commun. **41**(7), 2278–2296 (2023)