Quantum-Inspired Real-Time Optimization for 6G Networks: Opportunities, Challenges, and the Road Ahead

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ABSTRACT  It is envisioned that 6G, unlike its predecessor 5G, will depart from connected machines and connected people to connected intelligence. The main goal of 6G networks is to support massive connectivity for time-sensitive and computation-sensitive services in mission-critical applications. The creation of real-time optimization (RTO) enabled by the fast growing data analytic and machine learning will seize the opportunities for 6G wireless networks to support such immersive services such as virtual reality (VR), augmented reality (AR), mixed reality (MR), and tactile Internet. Recently, with the rapid development of quantum computers, quantum-inspired optimization and machine learning algorithms have been exploited as efficient solutions for future wireless networks. In this article, we provide a comprehensive view on the new concept of quantum-inspired RTO and its application to the optimal resource allocation for 6G wireless networks. Our main contributions are to introduce some of the initial research results and introduce the potentiality of quantum-inspired RTO on some 6G emerging technologies. Not only do we review the fundamental principles; we also explore the challenges and opportunities of this exciting research direction.

INDEX TERMS  Quantum communications, real-time optimization, resource allocation, 6G networks.

I. INTRODUCTION

HYPER-CONNECTED world is continuously evolving as numerous smart technologies with high data-driven demands and computation complexities are produced daily [1]. Emerging smart technologies such as Internet of Things (IoT), virtual reality, connected vehicles, and smart healthcare systems, are forming the integral part of socio-economic development. There are high demands for network resources and requirements of efficient computation offloading in next generation networks due to the ubiquitous services and applications of massive IoT connectivity and communications [2]. It is projected by 2026, there will be about 3.5 billion 5G subscriptions globally, representing 40 percent of the total mobile subscriptions. In addition, mission-critical applications such as multiplayer interaction games, virtual reality (VR), augmented reality (AR), mixed reality (MR), and tactile Internet, require very low end-to-end transmission latency with ultra reliability and high computation efficiency [3].

Every decade, new generation mobile wireless network is introduced to provide higher data rates and better wireless connectivity. Shortly after 5G started to rollout successfully,
6G has been discussed. Unlike its previous generations, beyond 5G and 6G will depart from the main focus on increasing data rate. Although still in its infancy, key performance indicators (KPIs) for the 6G development are already identified: (i) high-reliability (99.99999%) and ultra-low latency (0.1 ms), (ii) effective energy-efficient communication (1 pJ/bit), (iii) super high data rate (1 Tbps) for both downlinks (DL) and uplinks (UL), (iv) very secure communication, and (v) massive number of served users and heterogeneous users (100 devices/m³) [4], [5], [6].

A. RESEARCH CHALLENGES IN 6G NETWORKS
The move to larger bandwidth of ultra high frequency band such as mmWaves and THz bands is inevitable in beyond 5G and 6G to support higher data-rate communications. However, the transmission in mmWaves/THz band suffer a severe propagation loss, which can be partly compensated by using directional antenna arrays. As a result, it will require more than research on intelligence beamforming design and reconfigurable antenna arrays to launch 6G. Interference is still considered as one of the longest-standing and most pivotal problems in wireless networks. While traditional interference alignment approaches can locally improve user performance, it may fail to handle large-scale networks or higher standard requirements in future 6G networks. Novel interference management schemes and transmit/receive beamforming designs for reducing the interference have to be adopted to exploit the powers and full degree-of-freedoms of their superposed nature. The development and implementation of 6G mmWaves/THz devices will largely depend on short-range connectivity and high data-rate transmission. New signal processing methods and advanced optimization techniques for network performance improvement will be required.

Security is crucial in current wireless network and still an important issue in 6G where the physical layer security can be utilized as an additional level to shield the wireless communications from malicious attacks. Together with traditional cryptography, physical layer security will be leveraged by quantum computing. The achievable secrecy rate of users increases significantly with efficient signalling scheme, but only when the gain of the interference channel surpasses a limit that depends on the rate achieved by the interfered user.

Moreover, 6G will be required to deliver further increases of many folds in data rates compared with 5G networks. The future 6G networks are expected to provide an increase of 100x in volumetric spectral and energy efficiency (in bps/Hz/m³) with highly dynamic networks infrastructure into support massive connectivity with massive number of IoT devices. To this end, optimization, machine learning, data analytic, and signal processing methods can play as game changing technologies to make 6G appealing, as shown in Fig. 1.

Importantly, 6G will support the large-scale deployment of extremely immersive mission-critical services such as VR, AR, and MR. However these applications require extremely immersive human-centric experience that poses formidable challenges on mobile service providers in terms of stringent constraints of high data rates, transmission reliability, and latency. As such, a new optimization solution is urgently needed to unravel highly complex optimal resource allocation problems in 6G networks. In the following, leveraged by recent advances in quantum computing, we will delve in more details regarding the potential application of quantum-inspired real-time optimization (RTO) in 6G networks.

B. REAL-TIME OPTIMIZATION FRAMEWORK FOR WIRELESS NETWORKS
Optimization is at the heart of any decision-making process, from engineering, business to social, economic, and personal decision. In mission-critical applications, e.g., fire brigades, emergency medical services, very high business value (financial trading systems, on-demand business collaboration platforms), software (automatic vehicle locator app), time is the crucial factor (e.g., with a minimum latency of milliseconds to seconds). A strict real-time deadline is required for such scenarios, particularly under a constantly changing environment. It is in these scenarios that a platform of RTO will see its usefulness and impact the most [7].

A real-time optimization framework as shown in Fig. 2 will attract researchers and practitioners alike because of the uninterrupted need for system improvement, intelligent modeling, resource-saving, profitability maximising, and sustainable development planning. There have been a few studies that investigated optimization problems in real-time scenarios. The RTO solution is a powerful innovation for optimization in real-world applications. This is achieved
by our designing a RTO framework that is capable of analysing input problems, developing suitable and efficient optimization algorithms and proposing a robust programming strategy to solve the problem in real-time. The implementation of RTO is completely feasible and reasonable based on practical research. This disruptive technology will create a new market by setting new goals for solving optimization problems that ultimately revolutionises the current market of optimization applications. While raising the bar in terms of quality and execution time, the RTO will at the same time cut the costs of decision making process.

C. INTRODUCTION OF FUNDAMENTAL QUANTUM COMPUTING

1) FROM CLASSICAL TO QUANTUM COMPUTING

Classical computers function by converting series of computer information into bits and use integrated circuits with billions of transistors. It utilizes the binary elements that are serially processed [8], [9]. Its computation power increases in direct proportion to the number of transistors. To perform any task on a classical computer, it employs combinations of bits, either ‘0’ or ‘1’ to bring forth the desired output. Similarly, quantum computers use quantum bits, simply “qubits”, to perform high multi-dimensional computational tasks. Specifically, qubits are defined in three different states, namely either ‘0’, ‘1’, or ‘0 and 1’ combined. The third state ‘0 and 1’ makes quantum computing fundamentally different from the classical one. The capacity of quantum computers grows exponentially with the number of qubits [10]. Quantum computing aids researchers, engineers, and scientists in solving high computational complexity problems exponentially faster than classical computers. Quantum computers use quantum mechanics concepts, which rely heavily on unique characteristics of superposition and quantum entanglement.

2) QUANTUM COMPUTING—A NEW PARADIGM

Quantum computing constitutes the subdivision of quantum information science that is rapidly advancing in recent years [11]. A quantum computer is a device that utilises quantum mechanics properties to perform computation. Quantum computing leverages quantum communication properties to transmit information in a mode that no eavesdropper can access.

Several researchers have contributed to the successful growth and implementations of quantum computing [12], [13]. It began in 1980 when the a quantum mechanical framework of the Turing machine was examined [14]. Then, quantum computer was modelled to potentially simulate computations that classical computer is unfeasible to do [15]. A quantum algorithm was designed to determine the prime factors to decrypt Rivest–Shamir–Adleman (RSA)-encrypted communications. The first two quantum bits (qubit) quantum computer was produced to perform computations [16]. Recently, institutions, governments, and industry (e.g., Google, Microsoft and Intel) globally are investing hugely into quantum research and development, racing to reach quantum supremacy [17], [18]. The stakes are high, and with countless key players, the arrival of full-scale quantum computers are anticipated soon. Moreover, a quantum system enhances quantum algorithms to provide quadratic or exponential computation speedup as compared with classical computers [19]. Since learning problems are computationally intensive calculations, having an efficient quantum computers are good enough to accelerate optimization.

3) WHY QUANTUM COMPUTERS?

Quantum computing uses the concept of quantum mechanics to offer a massive leap forward in relations to solving complex computation problems [20]. Quantum computers have qubits, which are presented by a superposition between 0 and 1. Each qubit has an amplitude with corresponding complex number probability. This makes a quantum computer more distinct from classical computers. Quantum computing, according to researchers, has the potency to revolutionise the high-tech environment by taking artificial intelligence (AI) to a new level [2], [11]. Quantum computing can significantly perform any task faster than a standard computer. For this benefit, quantum computing is more efficient than classical computing. In quantum computing, the qubit is considered to be in a superposition state, to undertake exponentially faster computations and handle a large number of calculations. Quantum computing is indispensable in the modern days of big data since efficient computers to process the huge volume of data are needed daily [21]. Despite its computational efficiency, quantum computers can minimize the total power consumption drastically and deliver incredibly high speedup for specific problems.

II. QUANTUM-INSPIRED REAL-TIME OPTIMIZATION FOR 6G NETWORKS

In this section, we study the shift in approach from traditional optimization platform to quantum inspired real-time optimization platform.
A. FROM TRADITIONAL OPTIMIZATION TO QUANTUM INSPIRED REAL-TIME OPTIMIZATION

Firstly, we consider quantum optimization algorithms (QOAs) by exploiting the quantum mechanics rules in order to perform superior efficient computation for optimization algorithms with their amplitude amplification. In contrast to conventional optimization algorithms, many classical algorithms need a complete background on step-by-step local optimum points that leads to a heavy shift amplitude toward high-cost operational states. Hence, there is an improvement in searching computational cost and solution performance by implemented QOAs.

Secondly, we investigate a combination of quantum computing and evolutionary algorithms (EAs). This scheme utilises both advantages of quantum mechanics and heuristic search by using natural selections for cutting down the processing time of problem-solving to achieve real-time contexts. In classical methods, the implementation of GAs is induced to NP-hard problems when the population of individuals and the natural selections of the model is large-scale. By using quantum computing-inspired optimization algorithms, means of qubits can represent the population and a single quantum form can easily perform the fitness evaluation and selection procedures.

Finally, another advantage of quantum inspired real-time optimization is to deploy high-performance computing–enabled quantum computer for an effective amalgamation of machine learning and optimization. Quantum-based learning employs quantum operations for its inference by using qubit-based computation. They can speed up the learning-based rates for fast reaching the convergence of optimal results under huge datasets in the training stage. Meanwhile, this step requires a lot of time and resource in training stage with the traditional methods.

B. CONVENTIONAL APPROACHES FOR REAL-TIME OPTIMIZATION

Gradient techniques (e.g., first-order, second-order) in optimization concept are simple and efficient by using the derivative of functions to design the optimization algorithms for finding the optimum of the problems. This approach is efficient for convex and nonconvex optimization problems, linear and nonlinear programming [22], [23], [24]. The classic first-order methods and their significant improvement was proposed by its variants, accelerated first-order, proximal approaches, stochastic gradient methods [7]. However, it is not suitable for large-scale and complex optimization problems, especially, it has not been considered a good direction for designing RTO algorithms. The second approach is parallel and distributed computing for modern wireless communication problems, e.g., large-scale problems, big-data transfers, real-time signal processing control, hybrid resource allocation with multi-objective problems [25], [26], [27], [28]. Third approach relies on the assistance of machine learning models in RTO applications in modern wireless communication [29], [30], [31], [32], [33]. In light of the challenges of 6G networks and beyond, machine learning-inspired optimization process is an efficient way to approach real-time contexts. As provided in Fig. 3 and [7], more novel ideas of efficient optimization methods can be introduced for solving problems arising in realistic systems.

C. QUANTUM-INSPIRED REAL-TIME OPTIMIZATION (RTO)

Quantum computing [34], [35] operates on superpositions and entanglement by using quantum-mechanical phenomena (qubit). Thus, a quantum computer is to perform quantum computing. Both academia and industry are funding for quantum computing research and trying to design quantum computers for widely research and commercial purposes.

Compared with a standard computer, a proof-of-concept quantum computer can achieve a 100 millions-fold speed-up. Therefore, this has been shown that the RTO contexts require efficient and superior fast quantum approaches [36], [37], [38], [39], [40], [41]. As discussed, machine learning and optimization will bring many benefits for real-time applications when the testing stage is implemented in super fast after the learning-based optimization in the training stage. However, to achieve a good solution as the real optimization algorithm could provide, the training stage must learn or train a large dataset with sufficient finite number of training samples, which still requires a very long time for training. High-performance computing (HPC)–enabled quantum computer has also been considered a promising approach for machine learning [42], [43], [44], [45], [46], and then machine learning-inspired RTO.

Quantum optimization algorithms (QOAs) exploit the quantum mechanics rules in order to perform superior efficient computation for optimization algorithms with their amplitude amplification [47]. Presently, in the context of optimization, almost quantum research focuses on combinatorial problems. Similar to classical optimization algorithms, many kinds of quantum algorithms are heuristic, indicating many doubts about the finding of a desired optimal
solution and even if an optimum is found [37]. In heuristic approaches, these methods evaluate the specific behavior on classes of optimization problems rather than determining worst-case bounds. A QOA may not need the background of the optimum cost while shift amplitude toward low-cost effective states in combinatorial optimization problems [47]. Hence, there is a trade-off between searching computational cost and solution performance.

Obviously, modern heuristic approaches in stochastic optimization, e.g., local search, simulated annealing, tabu search, genetic algorithms, particle swarm optimization (PSO) and ant colony optimization (ACO) provide too many ways to handle the problems that will be too difficult to know whether the selected algorithm is appropriate [40]. The stochastic optimization approaches will frequently appear in widely engineering areas including the modern wireless communication systems [48], [49], [50], [51], [52]. The appropriate association between quantum computing (e.g., quantum annealer) and heuristical techniques (e.g., evolutionary algorithms) is necessary for real-time application.

There are some applications of quantum computing applied to stochastic optimization, e.g., PSO, genetic optimization algorithms. In the first application, a quantum particle swarm optimization (QPSO) is used to improve the classic PSO [53]. In fact, PSO is a swarm intelligent method that can be expanded to solve combinatorial problems. Hence, the discrete QPSO method is proposed based on qubits and characteristic of qubit chromosomes used to approach the optimum. Similarly, the quantum genetic optimization algorithm (QGOA) has been considered and exploited to increase the processing of genetic procedures by reducing the complexity of the selection procedure of a genetic algorithm [47] using the power of quantum computing.

Before having an in-depth discussion on the exploitation of quantum computing for RTO, let us review some basic knowledge of quantum computation.

D. QUANTUM BASICS

1) QUBIT

Qubit is a general notation of quantum computing. A qubit of a quantum system is the q-dimensional complex plane \( \mathbb{C}^q \) in the Hilbert space of its quantum state. Unlike the traditional bit in the normal computers taking the values 0 and 1, a qubit is represented as the form below

\[
|\psi\rangle = \alpha|0\rangle + \beta|1\rangle
\]  

(1)

where \( \alpha, \beta \in \mathbb{C} \) with \( |\alpha|^2 + |\beta|^2 = 1 \), \( |0\rangle \) and \( |1\rangle \) is orthonormal complex vectors representing numerical values for the physical properties of the spinning particle. The qubit \( |\psi\rangle \) can collapses into either 0 and 1 with the probability \( P(0) = |\alpha|^2 \) and \( P(1) = |\beta|^2 \), respectively. Thus, the value 0 with \( \alpha = 1, \beta = 0 \) and 1 are with \( \alpha = 0, \beta = 1 \).

A basic qubit form based on \( q \) vectors is as

\[
|0\rangle = \begin{bmatrix} 1 \\ 0 \\ \vdots \end{bmatrix}, \quad |1\rangle = \begin{bmatrix} 0 \\ 1 \\ \vdots \end{bmatrix}, \quad |q - 1\rangle = \begin{bmatrix} 0 \\ 0 \\ \vdots \end{bmatrix}.
\]  

(2)

An arbitrary vector can be decomposed as

\[
v = v_0|0\rangle + v_1|1\rangle + \cdots + v_{q-1}|q - 1\rangle.
\]  

(3)

In general, we can represent a \( q \)-qubit system by \( q \) copies of \( \mathbb{C}^2 \) tensored together. Particularly, the \( q \)-qubit system is expressed as a tensor product \( (\otimes) \) of \( q \) qubits

\[
a = a_0 \otimes a_1 \otimes \cdots \otimes a_{q-1} \in (\mathbb{C}^2)^{\otimes q},
\]  

(4)

where \( (\mathbb{C}^2)^{\otimes q} \) is open written as \( (\mathbb{C}^2)^{\otimes q} = \mathbb{C}^{2q} \).

2) QUANTUM STATES

A normalised complex vector \( v \in \mathbb{C}^q \) is defined as a quantum state of a qubit

\[
v = \begin{bmatrix} v_0 \\ \vdots \\ v_q \end{bmatrix}, \quad \|v\| = |v_0|^2 + \cdots + |v_{q-1}|^2 = 1.
\]  

(5)

3) QUANTUM GATES

**Hadamard gate (H-gate):** The 1-qubit H-gate is defined as

\[
H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}.
\]  

(6)

Then, the action of H-gate is as

\[
|x\rangle \xrightarrow{H} \frac{1}{\sqrt{2}}((-1)^x)|x\rangle + |1 - x\rangle.
\]  

(7)

**Phase gate (P-gate):** The 2-qubit P-gate is defined as

\[
\Phi = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & e^{i\Phi} \end{bmatrix}.
\]  

(8)

Then, the action of P-gate is as

\[
|x\rangle \xrightarrow{P} \frac{1}{\sqrt{2}} e^{i\Phi}|x\rangle.
\]  

(9)

**CNOT(XOR) gate:** The 2-qubit XOR-gate is defined as

\[
C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.
\]  

(10)

Then, the action of XOR-gate is as

\[
\begin{align*}
|x\rangle & \rightarrow |x\rangle \\
|y\rangle & \rightarrow |x \oplus y\rangle,
\end{align*}
\]  

(11)

where \( x \oplus y := x + y \mod 2 \).

**Rotate gate (R-gate):** The 2-qubit R-gate is defined as

\[
U(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix},
\]  

(12)

where \( \theta \) is a rotation angle.
Unitary gate (U-gate): The U-gate is defined as
\[ U = \begin{bmatrix} 1 & 0 \\ 0 & U \end{bmatrix}. \] (13)

Generally, all other gates can be created by using H-gate, P-gate, XOR-gate, R-gate, and U-gate.

4) QUANTUM DATA

Data can be stored by using qubits and the states of data presentation is expressed as \( \ell_2 \) normalised vectors in a space of complex vector. A quantum computing platform is a component to perform the calculations using information presentation under quantum mechanics [54]. A state of \( n \) qubits can be written as
\[ |\psi_i\rangle = \sum_{x \in \{0,1\}^n} s_x |x\rangle, \] (14)
where \( s_x \in \mathbb{C} \) with \( \sum_{x \in \{0,1\}^n} |s_x|^2 = 1 \) and the state \( |x\rangle \) refers to a computational basic. In some cases, we can also use the quantum states for storing data as group of elements \( g \in G \). An arbitrary superposition of group \( G \) is shown as
\[ |\Theta\rangle = \sum_{g \in G} b_g |g\rangle, \] (15)
where \( b_g \in \mathbb{C} \) with \( \sum_{g \in G} |b_g|^2 = 1 \).

For any finite set of data \( Z \), the normalised uniform superposition of the elements of the state \( |Z\rangle \) can be presented as
\[ |Z\rangle := \frac{1}{\sqrt{|Z|}} \sum_{z \in Z} |z\rangle. \] (16)

For example, the states \( |\Psi\rangle \) and \( |\Theta\rangle \) are stored in two different registers of a quantum computer. We can use the tensor product for the representation of overall state of those two states as \( |\Psi\rangle \otimes |\Theta\rangle \) or \( |\Psi, \Theta\rangle \). This can be called density matrices for the statistical mixtures of quantum states.

5) QUANTUM ANNEALING

Also called quantum stochastic optimization, is a classical algorithm with randomness using good heuristics for solving NP-hard optimization problem. In [55], quantum annealing is a variant of the simulated annealing algorithm for finding approximate solutions of the combination problems.

E. QUANTUM-INSPIRED OPTIMIZATION PROBLEMS AND ALGORITHMS

In general, the quantum-inspired optimization employs vectors that represents quantum bits and assumes quantum-based mechanics such as quantum superposition [56]. As an example of this approach, an elitist quantum evolutionary algorithm can be employed to optimize user pairing in non-orthogonal multiple access [57]. Here, the optimization solution is presented as an array of “qubit” vectors. Each \( i \)th “qubit” \( |\psi_i\rangle \) assumes quantum-inspired variables \( \alpha_i \) and \( \beta_i \), where \( |\psi_i\rangle = \alpha_i |0\rangle + \beta_i |1\rangle \) and \( |\alpha_i|^2 + |\beta_i|^2 = 1 \). As presented in Fig. 4, main operations of the algorithm can be summarised as follows. First, a quantum-inspired operation is employed to alter the value of \( \alpha_i \) and \( \beta_i \), \( \forall i \). Second, the “measurement” operation is performed to obtain the solution indexes. Subsequently, the fittest solution of the \( t \)th iteration may be used again if its leads to a higher performance. Finally, the parameter for the \( (t+1) \)th iteration is updated. The performance of elitist quantum evolutionary algorithm is exhibited in Fig. 5.

F. QUANTUM-INSPIRED MACHINE LEARNING

In contrast with classical-based machine learning, quantum-based machine learning employs qubit-based computation. As presented in Fig. 6 quantum-based learning employs
quantum operations for its inference. In particular, controlled quantum gates such as controlled-Y (“C_y”) and controlled-Z (“C_z”) gates are used to “connect” layers and neurons in the feed-forward quantum neural network, respectively [58]. Additionally, weight parameters for the learning model may be introduced using quantum-based parameterised gates such as rotation-Y (“R_y”) gates [58]. Theses quantum gates are employed to enable connections between neurons and layers.

In addition, for model optimization, gradient may be calculated using different approaches such as parameter-shift rule [59], [60]. Gradient-free approaches such as rotosolve [61] may also be leveraged. Considering \( f(\theta) \) as the quantum-based machine learning model with parameter \( \theta \) and \( s \) as the “shift” parameter, the gradient can be calculated using parameter-shift rule as [59], [60]

\[
\nabla_{\theta} f(\theta) = \varphi(f(\theta + s) - f(\theta - s)),
\]

FIGURE 6. The general framework of a feed-forward quantum neural network [58]. Here, different qubit register is assigned as different “neuron.” In addition, quantum gates are employed to enable connections between neurons and layers.
where $\varphi = \frac{1}{2\sqrt{\mu_0 T}}$ may be assumed. Subsequently, the model parameter may be updated using gradient descent approaches. For example, assuming $\mathcal{L}$ as the loss, the parameter for iteration $t+1$ may be updated as

$$\theta[t+1] := \theta[t] - \mu \nabla \theta \mathcal{L}, \quad (18)$$

where $\mu$ is the learning step.

Moreover, challenges may occur if we have classical data to be used as input for our quantum-based model. To solve this issue, the classical input may be encoded into the quantum circuit using parameterised gates [62].

**G. QUANTUM-INSPIRED REAL-TIME OPTIMIZATION PROBLEM-SOLVING**

1) QUANTUM-INSPIRED REAL-TIME GENETIC (EVOLUTIONARY) OPTIMIZATION

Genetic algorithms (GAs), a large part of evolutionary algorithms (EAs), are to utilise heuristic search schemes based on natural selection and genetics with historical data to achieve a better performance region in solution space [47], [63]. The search space consists the population of individuals and each individual represents a possible solution to the natural selection procedure. Each individual is often a series of character/integer/bits. As consequence, the implementation of GAs is induced as combinatorial problems which are the most NP-hard problems in optimization fields. For large-scale problems, the process of natural selection in GAs is not easy to implement caused by a huge number of individuals. The complexity of this procedure can be exponentially increased with the size of the population.

A promising combination of quantum computing and GAs, called quantum genetic optimization algorithm (QGOA), offers the advantages in both quantum computation and classical computing platform for solving NP-hard problems, i.e., combinatorial optimization problems. They are frequently used in classical GAs (EAs) for creating new individuals by the changes of individuals. The probability of superposition of stages change can be influenced by high probability of mutation and crossover operators. In these cases, the performance of QEOA can be decreased. On the other hand, when mutation and crossover are controlled or they are only small changes, QEOA is an efficient approach for real-time scenarios since the population size (the number of qubit chromosomes) is kept in all time and the convergence of QEOA is also better than classical EAs.

2) HYBRID QUANTUM-CLASSICAL (HQC) SCHEME FOR APPROXIMATE OPTIMIZATION ALGORITHM

Quantum approximate optimization algorithms (QAOAs) have been potential method based on hybrid-classical computing platform for solving NP-hard problems, i.e., combinatorial optimization problems. Some popular combinatorial problems are traffic scheduling problems, network scheduling, routing problem and cluster selection [64], [65], [66]. For representation of considered combinatorial problems, a quadratic unconstrained binary optimization (QUBO) is an appropriate model. Then, quantum annealing (AQ) is to evaluate and enable heuristic quantum mechanics for capturing the cost function and parameter setting in the optimization problems as the classical algorithm done.

A general form of QUBO that the AQ is used to minimize from $Q$-bit individuals is randomly generated. The next step is evaluating the fitness values of individual binary string in $P(t)$ to select the best candidate for updates. Finally, $Q(t+1)$ is updated based on the results of fitness evaluations in previous step by applying some appropriate quantum gates $U(t)$. For example, rotate gates (R-gate) as defined in (12)

$$U(t) = \begin{bmatrix} \cos(t) & -\sin(t) \\ \sin(t) & \cos(t) \end{bmatrix}. \quad (20)$$

It should be noted that QEOA can ignore some genetic operators such as mutation and crossover. These operators are frequently used in classical GAs (EAs) for creating new individuals by the changes of individuals. The probability of superposition of stages change can be influenced by high probability of mutation and crossover operators. In these cases, the performance of QEOA can be decreased. On the other hand, when mutation and crossover are controlled or they are only small changes, QEOA is an efficient approach for real-time scenarios since the population size (the number of qubit chromosomes) is kept in all time and the convergence of QEOA is also better than classical EAs.
where $x \in \{0, 1\}^N$ is a vector of binary variables and $Q \in \mathbb{R}^{N \times N}$ is a matrix of variable relationship. An explicit form of QUBO can be given as

$$H(x, Q) = \sum_{i=1}^{N} q_{i,i}x_i + \sum_{i \neq j} q_{i,j}x_ix_j$$

(22)

where $x_i \in \{0, 1\}$.

Indeed, the binary variables in (21) or (22) are mapped to qubits in the quantum computer as $H(x, Q)|x\rangle = f(x)|x\rangle$. Unfortunately, since physical quantum hardware is still limited in body connectivity, a binary variable is represented by using multiple qubits in the links of subtrees. This step is to ensure each pair of binary variables in a quadratic term that is connected with a pair of qubits in their subtree. An example of small QUBO problem is as below

$$H(x) = x_1^2 + 2x_2^2 - 4x_1x_2 + x_1x_3 - 3x_2x_3$$

(23)

where $x = [x_1 \ x_2 \ x_3]^T$ and $Q = \begin{bmatrix} 1 & -4 & 1 \\ 0 & 2 & -3 \\ 0 & 0 & 0 \end{bmatrix}$.

The hybrid quantum-classical approach operates based on tree search algorithm. A quantum annealer is to implement a relaxation of the problem into the unconstrained optimization problem. A global search centre will be built for decision-making of solvers of subproblems from the solution set in quantum annealer. Then, classical computer is used as the solver for solving subproblems of the tree search. The implementation time of combinatorial problem solving can be notably decreased since the classical computer only works with sub-spaces of the global tree by applying quantum annealing decomposition.

The Hamiltonian problem (21) can be approximated by introducing a penalty function as follows:

$$H(x, Q) = H_{obj} + \lambda H_{con}$$

(24)

where $\lambda \in \mathbb{R}^+$ is the positive constant coefficient. The constraints of binary variables is moved into the objective function by the penalty function. Next, the mixing Hamiltonian $H_M$ is defined as

$$H_M = \sum_{i=1}^{N} \phi_i^x$$

(25)

where $\phi_i^x$ is a Pauli-X operator for the $i$th qubit. The Pauli-X operator is as a NOT operator (bit-flip). The pair of parameters $(\gamma, \eta)$ based Hamiltonian problem and mixing Hamiltonian is designed for providing the solution set.

$$(f(x)|_{\gamma, \eta} = \langle \gamma, \eta | H(x) | \gamma, \eta \rangle$$

(26)

The optimal solution of $(\gamma, \eta)$ is achieved by using a simple optimization procedure.

III. POTENTIAL APPLICATIONS OF QUANTUM-INSPIRED REAL-TIME OPTIMIZATION FOR 6G NETWORK AND BEYOND

Quantum computing makes possible the shift from academic research to real-world problem-solving via the industrial communication. Most real-world problems in the future encounter large amounts of data irrespective of their research field on application domain. Some potential metrics need to be discussed: (i) what is the minimum amount of time needed to complete a large set of tasks for satisfying desired outcomes?, (ii) how can we make an real-time decision which maximises the expected profit at a given level of exposure to constraints?, (iii) what is the optimal fraction of resources in a large-scale network scenario which can be allocated for as many users as possible? Although many studies are implemented for optimization problems on classical computers, almost practical problems fall into the class of NP-hard problems. It is obvious that as their size increases they immediately become complex and impossible to solve exactly and fast, even with supercomputers. By exploiting the natural phenomena of quantum in many regimes, quantum computing will be a potential platform to overcome classical barriers and solve NP-hard problems of large sizes.

On the other hand, in a constrained binary optimization problem, one needs to transform the objective function of the problem and its constraints into a Hamiltonian operator acting on the quantum computer’s qubits. However, this
process is not effortless. In fact, it is very hard to include in the Hamiltonian operator between qubits, since qubits are generally coupled only via two-body interactions. Thus, the issue is how we should handle the objective function with more than two binary variables. As discussed in this work, an efficient approach is to embed binary constraints on a quantum computer for transforming the problem into QUBO (Quadratic Unconstrained Binary optimization). This step will provide softening constraints, decomposing body interactions into 2-body ones, and embedding the result into a graph of a target quantum computer’s connectivity.

Designing and building quantum computers have greeted at many parts of the world in recent years. Nevertheless, major breakthroughs of quantum computers are only an indication of the possibility of solving problems exponentially faster than classical computers. There is as yet no practical use of quantum computers from the current results. Therefore, an urgent work is to discover useful, relevant problems in the real applications that quantum computers could solve.

A. HEURISTIC QUANTUM OPTIMIZATION FOR 6G WIRELESS COMMUNICATIONS

Modern wireless communication systems are designed with efficient and high-performance computational power for satisfying the biggest challenges in very high throughput and ultra-low latency [67]. To deal with RFES requirements of 6G networks as shown in Fig. 8, a new computing architecture for wireless communication, like quantum computing, is tremendously necessary. Quantum-inspired RTO can reach optimal solutions faster than the classical computing platform for large scale and complex optimization problems of wireless systems, which cause limitations in network performance. A few first studies have shown promising results of quantum-based wireless communication, e.g., a MIMO detector and an error control decoding based on quantum annealing, processing heavy optimization of CRAN computational resource to partition hundreds of remote radio heads (RHHs) and solving optimization problems of wireless networks by using a noisy-intermediate-scale quantum (NISQ) [67].

B. QUANTUM COMPUTING-BASED OPTIMIZATION FOR 6G CONNECTED AUTONOMOUS COMMUNICATIONS

Many works have recognized that quantum computers will break the complexity of the most NP-hard optimization problem, e.g., combinatorial optimization. This novel computing platform can obtain the best options from a huge option pool of complex optimization problems for achieving the greatest solution. One of the most relevant applications of combinatorial optimization problems is to estimate the efficient routing of connected and autonomous vehicles network based on an extensive communication, information-gathering, and situation awareness. Quantum computing will be an effective solution for working with the growing amounts of data (location, time and situational information) in connected autonomous communications. Moreover, IoT technology, machine learning models and big-data analysis are believed to have the potential to meet RTO needs under quantum computing.

C. 6G COMMUNICATION NETWORKS WITH QUANTUM MACHINE LEARNING

Massive connectivity, rapid feed-backs, multiple dimensions, large intelligent surfaces, and real-time learning network states are the visions of 6G issues. An amalgamation of machine learning and quantum computing (QML) has been considered as kernel 6G enablers in wireless communication networks [68]. Current prospects of quantum computing through discoveries on quantum mechanics such as inherent parallelism, more qubits integrated and quantum algorithms, clearly indicate a significant outperformance in terms of computational capability compared to conventional computing systems. Furthermore, supervised, unsupervised, and reinforcement learning in machine learning will enable big-data analytic to assist self-organising wireless networks based on the nature of data synthesis and the learning objective procedure. Consequently, a joint quantum computing and machine learning is an appropriate solution for utilising their joint benefits in the deployment of wireless systems. The parallelism concepts of qubit, entanglement, and superposition can handle huge data under large-dimensional vectors in large spaces and generate statistical data patterns for machine learning methods.

IV. OPEN ISSUES AND FUTURE WORKS

In this tutorial, an overview of quantum computing for RTO has been presented. Enormously benefits of quantum-inspired RTO are provided for the development of modern wireless networks (6G and beyond). The promising combination of quantum computing and low-complexity optimization algorithms is a potential research direction for real-time contexts. However, in many cases, the blind application of quantum techniques to optimization may not yield a practical or efficient algorithm. Therefore, the design of quantum-based solving framework for practical wireless systems is
still an open issue attracting much attention from the research community.

Non-deterministic problems (combinatorial problems) often require large memory accesses that impact the execution time of problem-solving. Quantum-inspired optimization algorithms are to provide the superposition state of qubits for performing random and parallel accesses to hardware in the reality. However, only some classes of problems can be solved with a significant speed-up of efficiency by quantum computing. Consequently, an important research direction is to determine the kinds of problems that quantum computing can handle with high and fast precision.

Finally, depending on the models of optimization problems in wireless communications, we need a clear strategy to choose and utilise the flexibility of hybrid quantum-classical platform that satisfies the requirements of real-time decision making and applications. Therefore, a comprehensive study providing strategies in applying quantum-based solutions can be conducted to practical realise full potential of quantum computing in the next generation of wireless systems.

V. CONCLUSION

Mobile wireless communication has completely shaped the world in a revolutionised way. As the next generation of wireless technology by 2030, 6G will be a game-changer to support human in many aspects of life through the Internet of Everything. However, 6G is also characterised by many extreme KPIs in terms of ultra-high data rates, ultra-reliable transmission, and near-zero latency, which are many orders higher than previous generation 5G. Real-time optimal radio resource allocation empowered by quantum computing is a key enabler to support these extreme requirements. This article for the first time has introduced a new concept of quantum-inspired RTO that can fully satisfy the demand of time-sensitive and computation-sensitive data in 6G. In the coming years, with the rapid pace of quantum computing technology, quantum-inspired RTO and/or machine learning will revolutionise the wireless industry. This article therefore will shed lights on this important optimization technology empowered by quantum computing which will lay the foundation to develop fast and intelligent mobile communication networks in the future.

REFERENCES

[1] E. P. DeBenedictis, “A future with quantum machine learning,” Computer, vol. 51, no. 2, pp. 68–71, Feb. 2018.
[2] V. Kulkarni, M. Kulkarni, and A. Pant, “Quantum computing methods for supervised learning,” Quantum Mach. Intell., vol. 3, no. 2, pp. 1–14, 2021.
[3] “Ericsson mobility report, November 2020.” [Online]. Available: https://www.ericsson.com/49d3a0/assets/local/reports-papers/mobility-report/documents/2022/ericsson-mobility-report-june-2022.pdf (Accessed: Dec. 4, 2022).
[4] “Study on scenarios and requirements for next generation access technologies, version 15.0.0,” 3GPP, Sophia Antipolis, France, Rep. TR 38.913, 2018.
[5] “Release 16 description, version 1.0.0,” 3GPP, Sophia Antipolis, France, Rep. TR 21.916, 2020.
[6] H. Tataria, M. Shaﬁ, A. F. Molisch, M. Dohler, H. Sjoland, and F. Tufvesson, “6G wireless systems: Vision, requirements, challenges, insights, and opportunities,” Proc. IEEE, vol. 109, no. 7, pp. 1166–1199, Jul. 2021.
[7] L. Nguyen, T. Duong, and H. Tuan, Real Time Convex Optimisation for 5G Networks and Beyond (Telecommunications Series). Stevenage, U.K.: Inst. Eng. Technol., 2022. [Online]. Available: https://books.google.com.vn/books?id=k4JkzgEACAAJ
[8] G. Arun and V. Mishra, “A review on quantum computing and communication,” in Proc. 2nd Int. Conf. Emerg. Technol. Trends Electron. Commun. Netw., 2014, pp. 1–5.
[9] S. Inre, “Quantum communications: Explained for communication engineers,” IEEE Commun. Mag., vol. 51, no. 8, pp. 28–35, Aug. 2013.
[10] S. Imre and F. Balazs, Quantum Computing and Communications: An Engineering Approach. Hoboken, NJ, USA: Wiley, 2005.
[11] T. M. Khan and A. Robles-Kelly, “Machine learning: Quantum vs classical,” IEEE Access, vol. 8, pp. 219275–219294, 2020.
[12] M. Nagy and S. G. Akl, “Quantum computation and quantum information,” Int. J. Parallel Emergent Distrib. Syst., vol. 21, no. 1, pp. 1–59, 2006.
[13] T. Paul, “Quantum computation and quantum information,” Math. Struct. Comput. Sci., vol. 17, no. 6, p. 1115, 2007.
[14] P. Benioﬀ, “The computer as a physical system: A microscopic quantum mechanical hamiltonian model of computers as represented by turning machines,” J. Stat. Phys., vol. 22, no. 5, pp. 563–591, 1980.
[15] R. P. Feynman, “Simulating physics with computers,” Int. J. Theor. Phys., vol. 21, nos. 6–7, pp. 467–488, Jun. 1982.
[16] I. L. Chuang, N. Gershenfeld, and M. Kubinec, “Experimental implementation of fast quantum searching,” Phys. Rev. Lett., vol. 80, no. 15, p. 3408, 1998.
[17] J. Bardin, “Beyond-classical computing using Superconducting quantum processors,” in Proc. IEEE Intl. Solid-State Circuits Conf. (ISSCC), vol. 65, 2022, pp. 422–424.
[18] L. Gyongyosi and S. Imre, “A survey on quantum computing technology,” Comput. Sci. Rev., vol. 31, pp. 51–71, Feb. 2019.
[19] T. S. Humble, H. Thapliyal, E. Munoz-Coreas, F. A. Mohiyaddin, and R. S. Bennink, “Quantum computing circuits and devices,” IEEE Design Test, vol. 36, no. 3, pp. 69–94, Jun. 2019.
[20] P. R. Giri and V. E. Korepin, “A review on quantum search algorithms,” Quantum Inf. Process., vol. 16, no. 12, pp. 1–36, 2017.
[21] G. Acampora, Quantum Machine Intelligence. Cham, Switzerland: Springer, 2019, pp. 1–3.
[22] D. P. Bertsekas, Nonlinear Programming, Belmont, MA, USA: Athena Sci., 1999.
[23] A. Juditsky and A. Nemirovski, “First order methods for nonsmooth convex large-scale optimization. I: General purpose methods,” in Optimization for Machine Learning, Cambridge, MA, USA: MIT Press, 2011, pp. 121–148.
[24] R. Fletcher, Practical Methods of Optimization. Hoboken, NJ, USA: Wiley, 2013.
[25] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, “Distributed optimization and statistical learning via the alternating direction method of multipliers,” Found. Trends Mach. Learn., vol. 3, no. 1, pp. 1–122, 2011.
[26] D. E. Rumelhart and J. L. McClelland, Parallel Distributed Processing, vol. 1. Cambridge, MA, USA: MIT Press, 1987.
[27] A. Grama, Introduction to Parallel Computing, Pearson Educ., 2003.
[28] A. Migdalas, P. M. Pardalos, and S. Stetsy, Parallel Computing in Optimization, vol. 7. New York, NY, USA: Springer, 2013.
[29] G. Bhutani, “Application of machine-learning based prediction techniques in wireless networks,” Int. J. Commun. Netw. Syst. Sci., vol. 7, no. 5, p. 131, 2014.
[30] M. A. Alsheikh, S. Lin, D. Niyato, and H.-P. Tan, “Machine learning in wireless sensor networks: Algorithms, strategies, and applications,” IEEE Commun. Surveys Tuts., vol. 16, no. 4, pp. 1990–2018, 4th Quart., 2014.
[31] C. Jiang, H. Zhang, Y. Ren, Z. Han, K.-C. Chen, and L. Hanzo, “Machine learning paradigms for next-generation wireless networks,” IEEE Wireless Commun., vol. 24, no. 2, pp. 98–105, Apr. 2017.
[32] P. V. Klaine, M. A. Imran, O. Onireti, and R. D. Souza, “A survey of machine learning techniques applied to self-organizing cellular networks,” IEEE Commun. Surveys Tuts., vol. 19, no. 4, pp. 2392–2431, 4th Quart., 2017.
[33] M. Chen, U. Chalita, W. Saad, C. Yin, and M. Debbah, “Machine learning for wireless networks with artificial intelligence: A tutorial on neural networks,” 2017, arXiv:1710.02913.

[34] T. D. Ladd, F. Jelezko, R. Laflamme, Y. Nakamura, C. Monroe, and J. L. O’Brien, “Quantum computers,” Nature, vol. 464, no. 7285, pp. 45–52, 2010.

[35] M. A. Nielsen and I. L. Chuang, Quantum Computation and Quantum Information. Cambridge, UK: Cambridge Univ. Press, 2010.

[36] A. Das and B. K. Chakrabarti, Quantum Annealing and Related Optimization Methods, vol. 679. Heidelberg, Germany: Springer, 2005.

[37] T. Hogg and D. Portnov, “Quantum optimization,” Inf. Sci., vol. 128, nos. 3–4, pp. 181–197, 2000.

[38] S. Suzuki and M. Okada, “Simulated quantum annealing by the real-time evolution,” in Quantum Annealing and Other Optimization Methods. Heidelberg, Germany: Springer, 2005, pp. 207–238.

[39] E. Farhi, J. Goldstone, and S. Gutmann, “A quantum approximate optimization algorithm,” 2014, arXiv:1411.0428.

[40] M. Marzec, “Portfolio optimization: Applications in quantum computing,” in Handbook of High-Frequency Trading and Modeling in Finance, vol. 9. Hoboken, NJ, USA: Wiley, 2016, p. 73.

[41] A. Gilyén, S. Arunachalam, and N. Wiebe, “Optimizing quantum search algorithms via faster quantum gradient computation,” 2017, arXiv:1711.00465.

[42] M. Schuld, I. Sinayskiy, and F. Petruccione, “An introduction to quantum machine learning,” Contemporary Phys., vol. 56, no. 2, pp. 172–185, 2015.

[43] J. M. Wing, “Computational thinking,” Commun. ACM, vol. 49, no. 3, pp. 30–33, 2006.

[44] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, “Quantum machine learning,” Nature, vol. 549, no. 7671, p. 195, 2017.

[45] P. Rebentrost, M. Mohseni, and S. Lloyd, “Quantum support vector machine for big data classification,” Phys. Rev. Lett., vol. 113, no. 13, 2014, Art. no. 130503.

[46] S. C. Kak, “Quantum neural computing,” in Advances in Imaging and Electron Physics, vol. 94. San Diego, CA, USA: Elsevier, 1995, pp. 259–313.

[47] A. Malossini, E. Blanzieri, and T. Calarco, “Quantum genetic optimization,” IEEE Trans. Evol. Comput., vol. 12, no. 2, pp. 231–241, Apr. 2008.

[48] M. Neely, Stochastic Network Optimization with Application to Communication and Queueing Systems. San Rafael, CA, USA: Morgan & Claypool, 2010. Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6813406.

[49] F. Baccelli and B. Blaszczyszyn, “Stochastic geometry and wireless networks: Volume II applications,” Found. Trends Netw., vol. 4, nos. 1–2, pp. 1–312, 2010.

[50] M. Haenggi, J. G. Andrews, F. Baccelli, O. Dousse, and M. Franceschetti, “Stochastic geometry and random graphs for the analysis and design of wireless networks,” IEEE J. Sel. Areas Commun., vol. 27, no. 7, pp. 1029–1046, Sep. 2009.

[51] H. ElSawy, E. Hossain, and M. Haenggi, “Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey,” IEEE Commun. Surv. Tuts., vol. 15, no. 3, pp. 996–1019, 3rd Quart., 2013.

[52] M. J. Neely, E. Modiano, and C.-P. Li, “Fairness and optimal stochastic control in heterogeneous networks,” IEEE/ACM Trans. Netw., vol. 16, no. 2, pp. 396–409, Apr. 2008.

[53] S. Yang, M. Wang, and L. Jiao, “A quantum particle swarm optimization,” in Proc. Evol. Comput., vol. 1, 2004, pp. 320–324.

[54] A. M. Childs and W. Van Dam, “Quantum algorithms for algebraic problems,” Rev. Modern Phys., vol. 82, no. 1, p. 1, 2010.

[55] B. Apolloni, N. Cesa-Bianchi, and D. De Falco, “A numerical implementation of quantum annealing,” in Proc. Ascona-Locarno Conf. Stochastic Processes Phys. Geometry, 1990, pp. 97–111.

[56] G. Zhang, “Quantum-inspired evolutionary algorithms: A survey and empirical study,” J. Heurist., vol. 17, no. 3, pp. 303–351, 2011.

[57] B. Narottama, D. K. Hendraningrat, and S. Y. Shin, “Quantum-inspired evolutionary algorithms for NOMA user pairing,” IET Exp., vol. 8, no. 1, pp. 11–17, 2012.

[58] A. Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, “The power of quantum neural networks,” Nat. Comput. Sci., vol. 1, pp. 403–409, Jun. 2021.

[59] K. Mitarai, M. Negoro, M. Kitagawa, and K. Fujii, “Quantum circuit learning,” Phys. Rev. A, vol. 98, no. 3, 2018, Art. no. 32309.

[60] M. Schuld, V. Bergholm, C. Gogolin, J. Izaac, and N. Killoran, “Evaluating analytic gradients on quantum hardware,” Phys. Rev. A, vol. 99, no. 3, 2018, Art. no. 32331.

[61] M. Ostaszewski, E. Grant, and M. Benedetti, “Structure optimization for parameterized quantum circuits,” Quantum, vol. 5, p. 391, Jan. 2021.

[62] M. Schuld, R. Sweke, and J. J. Meyer, “Effect of data encoding on the expressive power of variational quantum-machine-learning models,” Phys. Rev. A, vol. 103, Mar. 2021, Art. no. 32430. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevA.103.032430.

[63] K.-H. Han and J.-H. Kim, “Genetic quantum algorithm and its application to combinatorial optimization problem,” in Proc. Congr. Evol. Comput., vol. 2, 2000, pp. 1354–1360.

[64] T. T. Tran et al., “A hybrid quantum-classical approach to solving scheduling problems,” in Proc. 9th Annu. Symp. Combinatorial Search, 2016, pp. 98–106.

[65] J. Choi, S. Oh, and J. Kim, “Energy-efficient cluster head selection via quantum approximate optimization,” Electronics, vol. 9, no. 10, p. 1669, 2020.

[66] J. Choi, S. Oh, and J. Kim, “Quantum approximation for wireless scheduling,” Appl. Sci., vol. 10, no. 20, p. 7116, 2020.

[67] M. Kim, S. Kasi, P. A. Lott, D. Venturelli, J. Kaeveli, and K. Jamieson, “Heuristic quantum optimization for 6G wireless communications,” IEEE Netw., vol. 35, no. 4, pp. 8–15, Jul./Aug. 2021.

[68] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary, and M. Asaduzzaman, “Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future,” IEEE Access, vol. 7, pp. 46317–46350, 2019.

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