Quantum-Inspired Resource Optimization for 6G Networks: A Survey

Muhammad Omair Butt, Nazar Waheed, Trung Q. Duong, and Waleed Ejaz

***Abstract*—The Internet of things (IoT) drives an exponential surge in computing and communication devices. Consequently, it triggers capacity, coverage, interference, latency, and security issues in the existing communication networks. The forthcoming sixth-generation (6G) networks will address these issues by providing comprehensive solutions. In particular, quantum communication technology can potentially address the challenges of 6G networks. However, its implementation requires substantial infrastructure upgrades. Therefore, the quantum-inspired (QI) techniques offer an intermediate resort due to their ability to utilize the classical communication infrastructure for design and implementation. Hence, we review QI techniques in this survey that address radio resource optimization challenges across various communication aspects, including channel assignment, reconfigurable intelligent surfaces, spectrum sensing, unmanned aerial vehicle-assisted networks, and related areas. The analysis explores diverse aspects, including objectives, constraints, problem characterization, proposed solutions, and lessons learnt. Research indicates that QI techniques offer advantages such as faster convergence and reduced complexity, providing promising solutions to complex optimization problems in communication networks. Furthermore, we identify the future directions, research gaps, and ongoing challenges from the QI radio resource optimization dataset.**

***Index Terms*—Machine learning, meta-heuristics, optimization, quantum communication, quantum computation, quantum-inspired, sixth-generation**

I. Introduction

Sixth-generation (6G) networks set ambitious performance goals, promising significantly enhanced data rates, lower latency, and greater capacity than fifth-generation (5G) standards. Fig. 1 illustrates key performance indicators, enabling technologies, and diverse use cases for 6G networks. The key performance indicators are categorized into various aspects such as capacity, coverage, data rate, and others [1]. 6G networks aim for peak data rates in the terabits per second range, a substantial leap from 5G's peak data rate of 20 gigabits per second. While 5G offers user-experienced data rates in the range of megabits per second, 6G targets 1 gigabit per second. Additionally, 6G aspires to achieve sub-millisecond latency, enabling real-time applications, compared to 5G's 1-millisecond latency. Moreover, 6G seeks to support the connection density of ten times higher with up to 10 million connections per square kilometer and double the mobility speed, reaching 1000 km/h. It also aims for centimeter-level positioning accuracy, a hundredfold improvement in energy efficiency, 99.9999% availability, and ultra-reliable connectivity. This can be achieved by integrating heterogeneous networks encompassing terrestrial and non-terrestrial elements such as cellular, fiber optic, satellite, and unmanned aerial vehicles (UAVs). However, achieving optimized interoperability among these diverse networks poses significant challenges [2].

The authors of [3] investigated resource allocation strategies for space-air-ground integrated networks, which are critical for achieving the service-everywhere requirement in the 6G networks. As radio resource optimization complexities increase with the advent of 6G networks, innovative approaches such as dynamic optimization, mathematical optimization, game theory, and artificial intelligence-based methods become essential. Similarly, the authors of [4] highlighted the limitations of current communication systems regarding capacity and reliability, proposing a cell-less networking approach for radio resource management in 6G networks. This approach enables user connectivity with multiple access points, improving system capacity and mitigating interference while achieving energy efficiency and optimized latency. Consequently, the authors of [5] introduced an optimization framework focused on minimizing delay and energy consumption for emergency vehicle users in UAV-assisted air-ground integrated networks, enhancing emergency response through federated learning and prioritized experience replay.

The optimization of constrained wireless resources is necessary to support the evolving requirements of users and applications. Despite the significant progress of wireless networks, achieving the desired key performance indicators of 6G networks requires addressing several issues that include devising an efficient resource optimization technique while considering different parameters such as limited bandwidth, high data rate, low latency, extended range, and ensuring unprecedented security. The high density of nodes in Industry 4.0 and the Internet of things (IoT) complicates large-scale resource optimization. The 6G networks can incorporate quantum communication and computing technologies to ensure seamless and massive device connectivity [6].

Quantum technology is in the early stages of develop-

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We acknowledge the support of the Natural Sciences and Engineering Research Council of Canada (NSERC). The work of T. Q. Duong was supported in part by the Canada Excellence Research Chair (CERC) Program CERC-2022-00109.

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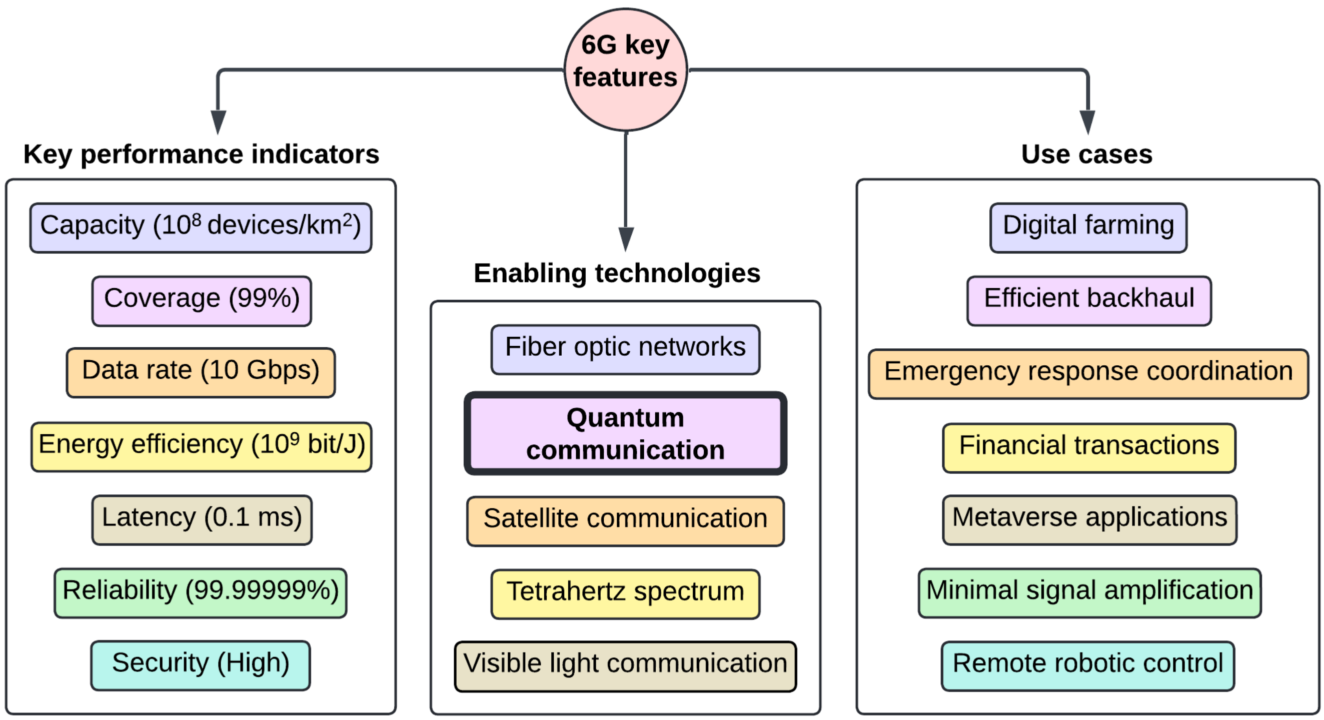

Fig. 1. The key performance indicators of 6G, its enabling technologies and use cases [1].

ment and can potentially optimize radio resources in tasks such as channel assignment, IoT, UAV trajectory planning, and related areas. Transitioning from classical to quantum communication paradigms is challenging because it involves integrating quantum elements into existing communication infrastructure [7]. The lack of infrastructure and expertise makes large-scale adoption of quantum communication difficult. Therefore, quantum-inspired (QI) techniques are advantageous due to their compatibility with existing systems and incremental improvements, enabling a gradual transition to true quantum communication. QI optimization techniques offer a promising approach to handle the complexity and scalability requirements of 6G networks, which will integrate numerous IoT devices, UAVs, and ultra-reliable low latency (URLLC) applications. In such a complex scenario, classical optimization methods may struggle to optimize radio resources in dynamic environments, such as spectrum allocation and energy usage. For instance, clustering numerous ground users based on constraints like latency, channel gain, and quality of experience can be managed more effectively. Recent research views QI techniques as a middle ground, providing quantum-like enhancements while being implementable on classical communication networks [8]. Table I lists the acronyms used in this survey paper.

Fig. 2 demonstrates that quantum information science is a key driver of QI optimization, enhancing classical meta-heuristics and machine learning (ML) methods. By incorporating quantum-like enhancements, it improves the optimization of classical communication networks. QI techniques are preferred for their ability to enhance efficiency and performance without requiring infrastructure upgrades. These techniques

TABLE I
LIST OF ACRONYMS USED IN THIS PAPER.

Acronyms	
5G	Fifth-generation
6G	Sixth-generation
AI	Artificial intelligence
AR	Augmented reality
BS	Base station
GPS	Global positioning system
IoT	Internet of things
IoV	Internet of vehicles
IRS	Intelligent reflective surfaces
MIMO	Multiple input multiple output
ML	Machine learning
NN	Neural network
NOMA	Non-orthogonal multiple access
NP-hard	Non-deterministic polynomial time hard
PSO	Particle swarm optimization
QI	Quantum-inspired
QKD	Quantum key distribution
QML	Quantum machine learning
QNN	Quantum neural network
QPSO	Quantum particle swarm optimization
QRL	Quantum reinforcement learning
QUBO	Quadratic unconstrained binary optimization
RIS	Reconfigurable intelligent surface
RL	Reinforcement learning
UAV	Unmanned aerial vehicles
URLLC	Ultra-reliable low latency communication
VR	Virtual reality

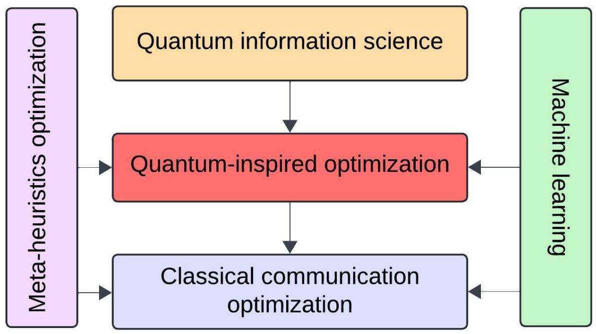

Fig. 2. Quantum-inspired optimization connecting domains.

Fig. 3. Selection of related papers in the collection process.

are typically classified as meta-heuristics and ML approaches. Despite using classical infrastructure, they significantly enhance scalability and the ability to handle complexity, which is crucial for 6G networks integrating IoT devices, UAVs, and applications requiring URLLC. QI techniques can efficiently manage numerous ground users in dynamic scenarios such as spectrum allocation and energy usage, focusing on constraints like latency, channel gain, and quality of experience. Recent research positions QI techniques as a middle ground, incorporating quantum-like enhancements while remaining adaptable to classical communication networks [8]. These advancements in QI algorithms enable enhancement in training duration and capacity within ML-based supervised learning frameworks, like support vector machines. QI techniques improve communication, computation, and privacy by integrating quantum concepts, including parallelism and superposition. They can be applied to diverse domains, including cryptography, financial modeling, ML, and optimization, by reducing computational complexity, exploring large solution spaces, implementing post-quantum cryptography, and mitigating noise and errors typical in quantum-like systems.

A. Literature Search Process

This paper identifies various QI techniques available in the literature to address the resource optimization problems in the 6G networks. The prime focus is to analyze objectives, constraints, problem types, and solutions to address concerns arising due to incorporating non-classical and QI computational solutions. A dataset comprising papers from 2019 to 2024 is gathered by employing different queries in the IEEE, Science Direct, Arxiv , American physical society (APS), and optical society of America (OSA) repositories as tabulated in Table II. The search queries include “quantum communication”, “quantum-inspired”, “quantum key distribution”, “wireless networks”, 6G, “machine learning”, meta-heuristics, optimization, “neural network”, “reinforcement learning”, “genetic algorithm”, “quantum key distribution”, “resource optimization”, and closely related keywords. The survey builds on a dataset comprising different types of papers such as surveys, journals, and magazine papers. Fig. 3 depicts paper collection criteria. The technical discussion of mathematical modeling and implementation details available in the literature is beyond the scope of this paper and can be considered as future work. The papers of interest are selected based on their relevance and the optimization problem formulation.

B. Contributions

The key contributions of our survey paper are summarized as follows:

- **Principles and Components of Quantum Communication:** We provide an overview of the fundamentals and components of quantum communication, while providing a comparison with the principles of classical communication systems.

TABLE II
ARTICLES SEARCH QUERIES AND THE DATASET DETAILS.

Query	Database	Total	Filtered
Quantum-Inspired AND (Heuristics OR “Machine Learning” OR “Game Theory” OR “Federated Learning” OR “Neural Network” OR “Reinforcement Learning” OR “Support Vector Machine” OR Optimization OR “Wireless Communication” OR 6G)	IEEE	191	31
	Science Direct	237	9
	Arixv.org	197	6
Quantum-Inspired AND (Wireless OR 6G) AND Optimization	IEEE	14	12
Quantum-Inspired AND Optimization AND “Wireless Communication”	APS	52	9
Quantum-Inspired AND Optimization	OSA	4	4

- **Comprehensive Literature Review (2019-2024):** We review and analyze recent papers from 2019 to 2024 to study how QI approaches are used in optimizing wireless network resources. This review ensures that our analysis stays up-to-date by incorporating the most recent research and findings.
- **Categorization of QI Optimization Techniques:** We organize QI optimization techniques into meta-heuristics, ML and specialized solutions. We detail the methods, key factors, challenges, and how these techniques can be applied to the important services expected in the upcoming 6G networks.
- **Novel Categorization Framework:** To the best of our knowledge, this is the first attempt to arrange the QI optimization approaches systematically across different areas of communication. This involves comparing our work with previous research, demonstrating our paper's new perspectives, and establishing its relation to other studies in the field.
- **Lessons Learnt:** We provide insights into the research gaps identified in the literature on QI radio resource optimization scenarios, highlighting areas that require further investigation.
- **Use Case of Vertical Farming:** We provide insights into an intriguing case study of vertical farming, demonstrating how QI optimization techniques can enhance efficiency and productivity.
- **Future Research Directions and Challenges:** We discussed various potential future avenues of research for QI optimization techniques and outlined the challenges that need to be addressed.

C. Organization of paper

Fig. 4 illustrates the roadmap of our paper, highlighting the section numbers and providing the sub-categorizations. Section II provides a detailed review of existing survey studies on quantum communication and computing. Section III presents basic concepts of quantum communication and enlists the quantum communication components to develop an understanding of the reference area. Section IV explains the QI optimization approaches such as meta-heuristics and ML. Section V categorizes and comprehensively analyzes the reviewed resource optimization problems and their solution techniques. Section VI discusses the use case of QI optimization in vertical and digital farming. Section VII discusses future directions and challenges. Finally, section VIII concludes the survey.

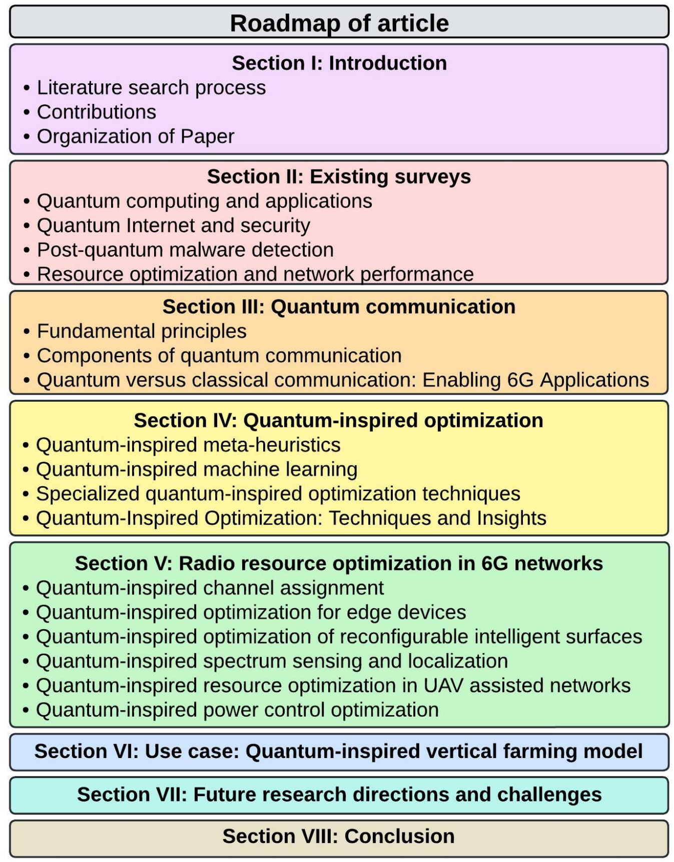

Fig. 4. Organization of this paper.

II. Existing Surveys

In this section, we analyze key insights from available surveys on quantum communication and computing for wireless networks. We categorize the existing surveys into different domains such as quantum computing and applications, quantum Internet [9] and security, post-quantum malware detection, resource optimization and network performance. We identify the correlations between key findings from previous surveys and utilize this information to build our survey paper.

A. Quantum Computing and Applications

The authors of [10] presented a survey on quantum computing-based techniques to solve physical and network layer issues in wireless communication systems. This paper identified the application areas and analyzes the complexity of several quantum computing techniques. The target categories for optimization include big data analysis, indoor localization, joint channel estimation, multi-objective routing, multi-user detection, and transmission. The quantum-based solutions can significantly reduce complexity budgets compared to their classical counterparts. A comprehensive survey on QI meta-heuristics was presented in [11]. This review encompassed various algorithms, such as evolutionary, multi-objective, social evolution, and swarm intelligence, providing valuable insights into identifying practical QI meta-heuristics candidates for quantum computers. Various benchmark problems, including 0-1/multidimensional knapsack, combinatorial optimization, continuous optimization, logic circuit design, and traveling salesman, were considered to evaluate QI algorithms. The evaluation of the QI Acromyrmex evolutionary algorithm on 15 benchmark test functions showed superior performance compared to the genetic and advanced genetic quantum algorithms. Similarly, the real-QI evolutionary algorithm outperformed fast evolutionary programming, particle swarm optimization (PSO), and stochastic genetic algorithm. Lastly, the quantum artificial bee colony algorithm performed the best compared to the quantum swarm evolutionary algorithm and genetic algorithm in optimizing the three benchmark test functions.

In [12], an overview of QI-ML was presented for the security and resource optimization of 6G networks. The computational and time complexity of classical ML algorithms often makes them unsuitable for handling large-scale data analytics, which is essential in 6G networks. The QI-ML algorithms are favorable as they leverage the superposition of quantum states and parallelism for exponential speed up in the learning process. An overview of quantum algorithms for real-time optimization was presented in [8]. The authors considered quantum optimization primarily for solving combinatorial problems using heuristic approaches. A comprehensive survey on QI-ML was presented in [13]. The authors categorized quantum-based ML approaches into quantum ML (QML), QI-ML, and hybrid classical-quantum ML. The QI-ML techniques refer to developing classical ML algorithms while incorporating the principles of quantum mechanics and do not require quantum computers. The authors have highlighted resources to implement QI-ML approaches and open issues.

The authors of [14] reviewed the rapid advancements in quantum technologies and emphasized their significance in academia and industry. The paper categorized quantum computing components into quantum computers, quantum cryptography, QML, and quantum networks. The foundational quantum mechanics principles, such as superposition and entanglement, were explained. The difference between universal quantum computers and quantum annealers was highlighted. Furthermore, the implications of decoherence and quantum error correction were discussed. The paper served as a comprehensive resource for identifying future research directions and potential applications of quantum computing and communication in various domains.

The authors of [15] explored advanced concepts in quantum communications, including superadditivity, superactivation, and causal activation. These phenomena challenge the classical notions of channel capacity. The paper provided insights into using these phenomena to enhance communication protocols and contribute to the development of future quantum networks. It was highlighted that quantum channels can transmit information through entangled states, whereas classical channels cannot. This paper can be considered for understanding the implications of quantum mechanics in communication technologies.

B. *Quantum Internet and Security*

The authors of [6] comprehensively reviewed the infrastructure requirements and technological advancements required for the quantum Internet. The authors anticipated that the quantum Internet would incorporate security measures based on quantum key distribution (QKD) algorithms for networking classical and quantum entities. However, the fragility of quantum information due to decoherence is a significant challenge in realizing the quantum Internet. Similarly, the interfacing of discrete and continuous variables is essential, where the discrete variables refer to data represented by discrete features, such as the polarization of single photons detected by single-photon detectors, and the continuous variable refers to information encoded onto an optical field constituting infinite Hilbert space (to analyze vectors using inner products).

The authors of [16] analyzed the integration of quantum computing with drone technology, identifying quantum algorithms and architectures that enabled efficient and secure communication within the Internet of quantum drones. The roles of quantum drones and satellites were examined in futuristic scenarios and real-time applications. The integration of artificial intelligence (AI) and ML with quantum drones was also analyzed. The survey highlighted technological advancements in quantum computing and drone technology while reviewing the security implications and investigating the effects of quantum attacks on different cryptosystems.

The authors of [17] reviewed quantum secure direct communication and considered it a promising method to communicate securely. This approach allowed secret messages to be sent directly over quantum channels without requiring pre-shared cryptographic keys. The increase in threats to the classical cryptographic systems from quantum computing necessitates novel communication methods. The paper discussed conceptual foundations, experimental implementations, and different secure communication protocols, showing their advantages over QKD. A hybrid approach was proposed, combining quantum secure direct communication with classical systems to improve the security of next-generation communications, highlighting the potential of the quantum Internet.

In [18], the authors reviewed the cybersecurity enhancements required in satellite-based communication. The authors dissect the literature on satellite communication security into physical layer security and cryptographic techniques. They preferred the symmetric cryptographic solutions over public-key infrastructure setups due to the swiftness of encryption and decryption procedures. The key replacement and update are time-expensive tasks, and the key establishment is usually performed on satellite-to-ground and satellite-to-satellite links in satellite communication. They highlighted that incorporating quantum computation in satellite links can offer a promising level of security. However, the passive-side channel attacks can compromise the physical layer security of the QKD signal, and researchers have yet to explore this aspect in the literature. Furthermore, the authors of [19] considered physical layer security an emerging and alternative method to classical cryptography. The authors highlighted that quantum cryptography utilizes Heisenberg's uncertainty principle and avoids using public keys. They classified the physical layer security schemes into artificial noise, channel adaptation, and code. A security and privacy-based overview of 6G networks was given while focusing on the underlying technologies of physical, connection, and service layers.

C. *Post-Quantum Malware Detection*

The authors of [20] overviewed AI-driven malware detection techniques and categorized them into continuous learning and enhanced explainability through visualization. They considered quantum technology an enabler of unprecedented security and a strong candidate for future communication networks. The survey emphasized the necessity of balanced datasets to learn and accurately detect malware. Similarly, the privacy-enhancing technologies were comprehensively reviewed in [21] based on post-quantum cryptographic primitives, particularly when quantum computers become a reality. They provide insights into various threats in IoT and intelligent infrastructures. They preferred digital signatures and lattice-based schemes in comparison to other post-quantum cryptographic schemes for multiple constrained IoT and intelligent infrastructure platforms.

D. Resource Optimization and Network Performance

In [22], the authors provided an overview of the quantum search algorithms for maximizing wireless system performance. Additionally, they presented a feasibility analysis of QML techniques across various use cases. The optimization techniques were oracle-based, variational quantum eigensolver, and quantum approximate optimization algorithm. These techniques find application in energy efficiency, error correction, physical layer, security, and signal intelligence scenarios. In [7], the authors comprehensively reviewed the quantum network structure and its development stages. They highlighted the key differences compared to the classical networks in terms of the routing metrics. A robust and scalable entanglement-assisted network design incorporating heterogeneity and cost-effectiveness was deemed necessary. Furthermore, the standardization of such networks is essential to successfully transitioning towards heterogeneous networking schemes. The authors in [2] reviewed the challenges of resource optimization in integrated 6G networks. They only considered the optimization of classical networking elements. Their proposed hierarchical paradigm developed on four integration levels, including space-air-ground-sea network segments.

Lessons Learnt: Table III provides a summary of the contributions of the existing papers surveyed in relation to QI optimization. A critical analysis is performed to identify the current scope of research work that includes quantum basics, quantum components, optimization techniques, and our remarks. This analysis forms the foundation of our paper, which focuses on comprehensively reviewing and categorizing the QI optimization schemes. The QI communication and computation is an initial step towards a fully realizable integrated quantum-classical network topology. This domain provides several benefits over classical communication, such as lowering the computational complexity, improving energy efficiency, and incorporating the quantum effects for better security.

III. QUANTUM COMMUNICATION

This section introduces basic principles governing quantum communication and provides an overview of the key components to enable quantum communication networks. Fig. 5 illustrates a quantum communication system composed of various elements based on the logic of experimental setups presented in [23], [24]. The tunable laser generates unpolarized photons, which then pass through a polarization state generator to become oriented into specific polarization states relevant to quantum information. This information can be transmitted through an optical fiber or free-space channel, where noise can adversely affect the transmitted qubits, potentially leading to decoherence. Following this, quarter-wave and half-wave plates are used to modify the polarization states of the photons, converting circular and diagonal polarizations into linear states. Finally, a beam splitter separates the linear polarization states into their respective paths, where photon detectors can measure the incoming photons.

A. Fundamental Principles

Quantum communication is built on the principles of quantum mechanics, enabling secure and efficient information transfer. Quantum communication systems offer significantly higher capabilities compared to classical communication systems due to the unique properties of quantum states. This section discusses foundational concepts such as qubits, superposition, quantum entanglement, the no-cloning theorem, and quantum teleportation. These principles support quantum communication's advantages and potential applications in modern technology.

1) Quantum Bits: Qubits are the basic informational unit in quantum computing. They can coexist simultaneously in multiple states, allowing for a higher degree of efficiency in computations compared to classical bits. Environmental factors such as noise and temperature fluctuations can impair delicate qubits, leading to different errors or decoherence of entangled states [25]. An n-qubit quantum system can simultaneously represent 2^n different states. In contrast, classical bits in classical communication systems only exist in one of two possible states of 0 or 1, and they do not experience quantum impairments such as decoherence.

The Dirac notation concisely represents quantum states, probability distributions, normalization, and operators. Dirac notation can analyze quantum states through the vectors of bra ($\langle x|$) and ket ($|y\rangle$), where x and y are basis states. The inner product of bra and ket vectors helps compute probabilities and determine overlaps between quantum states, revealing their essential properties. This can be represented as [26]:

$$\langle x|y\rangle = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \times \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \tag{1}$$

$$\langle x|y\rangle = (x_1y_1) + (x_2y_2) + ... + (x_ny_n), \tag{2}$$

where $x_1, ..., x_n$ and $y_1, ..., y_n$ can represent the coefficients or amplitudes of quantum states and n represents the dimension of vectors. Similarly, the qubits can be expressed in terms of their basis states, and density matrix (ρ) can be used to represent both mixed and pure quantum states as [27]:

$$|\psi\rangle = \alpha|x\rangle + \beta|y\rangle, \tag{3}$$

TABLE III
SUMMARY OF EXISTING SURVEYS ON QI RADIO RESOURCE OPTIMIZATION.
REF.: REFERENCE; QB: QUANTUM BASICS; QC: QUANTUM COMPONENTS; QIO: QUANTUM-INSPIRED OPTIMIZATION; MH: META-HEURISTIC; ML: MACHINE LEARNING; RRO: RADIO RESOURCE OPTIMIZATION.

Year	Ref.	QB	QC	QIO		RRM	Remarks
				MH	ML		
Quantum Computing and Applications							
2019	[10]	✓	✗	✓	✗	✓	Reviewed different types of quantum algorithms for wireless communication, including cryptographic, meta-heuristics and search.
2020	[11]	✗	✗	✓	✗	✗	Comprehensively reviewed the QI meta-heuristics algorithms.
2022	[12]	✓	✗	✗	✓	✗	Reviewed quantum computing and its potential through ML and discussed the suitable applications for enhancing resource optimization and network security in 6G networks.
2022	[8]	✓	✗	✓	✓	✗	Analyzed the potential of QI real-time optimization in the context of 6G and provided a brief discussion on heuristic and ML-based optimization.
2022	[15]	✓	✗	✗	✗	✗	Reviewed advanced phenomena in quantum communication towards channel capacity enhancement and does not focus on QI optimization.
2023	[13]	✗	✗	✗	✓	✗	Comprehensively reviewed the QI-ML while explaining its different research areas, recent progress, real-world uses, and future directions, thereby the paper served as a valuable resource for both researchers and practitioners.
2023	[14]	✓	✓	✗	✗	✗	Comprehensively reviewed the components of quantum Internet, and does not focus on QI optimization approaches.
Quantum Internet and Security							
2021	[6]	✓	✓	✗	✗	✗	Comprehensively reviewed the applications, enabling technologies, functions, and open challenges of the quantum Internet and there is no discussion on optimization.
2021	[16]	✗	✗	✗	✗	✗	The paper focused on quantum drones-based communication while considering post-quantum cryptography and security.
2022	[18]	✗	✗	✗	✗	✗	Comprehensively reviewed the link-layer security threats, solutions, and challenges in deploying and operating satellite communication systems while considering QKD and other cryptographic techniques.
2024	[17]	✓	✗	✗	✗	✗	The paper reviewed quantum secure direct communication and its integration with classical systems for the quantum Internet.
Post-Quantum Malware Detection							
2022	[20]	✗	✗	✗	✗	✗	Comprehensively reviewed data-driven malware detection literature, with emphasis towards continuous learning techniques and novel visualization methods to efficiently detect malware and enhance malware identification and its interpretability in large-scale, data-intensive environments.
Resource Optimization and Network Performance							
2023	[22]	✓	✗	✗	✓	✓	The paper examined how QML and quantum search algorithms can enhance wireless system performance, explored potential solutions, and addressed their applicability and feasibility challenges in this context while briefly discussing security and error correction.
2023	[7]	✓	✓	✗	✗	✓	Provided a comprehensive review of entanglement-assisted quantum networks while discussing the network structure, development stages, and challenges in constructing wide area networks and does not focus on QI optimization.
2023	[2]	✗	✗	✗	✗	✗	Provided a categorization of resource optimization techniques, discussed challenges and future directions for space, aerial, ground, and sea integrated networks and there is no discussion on QI optimization.
2024	Our Survey	✓	✓	✓	✓	✓	Provided a detailed analysis of the fundamentals of quantum communication, categorization of various QI solutions available in the literature, prospective use cases, and future directions.

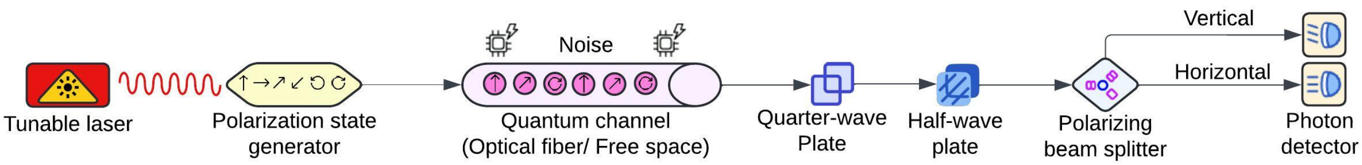

Fig. 5. Example of transmission and detection in quantum communication.

$$\rho = |\Psi\rangle\langle\Psi| = \begin{pmatrix} |\alpha|^2 & \alpha\beta^* \\ \alpha^*\beta & |\beta|^2 \end{pmatrix}, \tag{4}$$

where ψ, x and y denote the quantum state, horizontal and vertical polarization, respectively. The coefficients α and β are the amplitudes for respective basis states. Hence, (3) demonstrates the qubit's capacity to embody both polarizations simultaneously. The commonly used polarizations in quantum communication include linear, diagonal, and circular polarizations. These are analytically expressed in (5) to (10) [27]:

$$\rightarrow = |x\rangle, \tag{5}$$

$$\uparrow = |y\rangle, \tag{6}$$

$$\nearrow = \frac{1}{\sqrt{2}}\left(|x\rangle + |y\rangle\right), \tag{7}$$

$$\searrow = \frac{1}{\sqrt{2}}\left(|x\rangle - |y\rangle\right), \tag{8}$$

$$\curvearrowright = \frac{1}{\sqrt{2}}\left(|x\rangle - i|y\rangle\right), \tag{9}$$

$$\curvearrowleft = \frac{1}{\sqrt{2}}\left(|x\rangle + i|y\rangle\right), \tag{10}$$

where $\rightarrow$, $\uparrow$, $\nearrow$, $\searrow$, $\curvearrowright$ and $\curvearrowleft$ represent horizontal, vertical, $45°$ diagonal, $-45°$ diagonal, clockwise, and anticlockwise polarizations, respectively. Furthermore, the measurement of polarization states affects the qubits, and the probability of obtaining a particular polarization state can be computed through the inner product of the corresponding bra and ket vectors. Specifically, (11) can be used to measure the probability of horizontal polarization ($P(\rightarrow)$). Similarly, the probabilities for other polarization states can be derived from their respective bra and ket representations. Unlike qubits, the state of classical bits can be read without disturbing the system.

$$P(\rightarrow) = |\langle\rightarrow|\psi\rangle|^2. \tag{11}$$

To enhance the control and manipulation of quantum states, the quantum Hamiltonian learning algorithm (a function representing the kinetic and potential energy of the system) [28] and quantum state tomography (reconstructing a quantum state by measuring a system in different bases) [29] can be employed. These techniques facilitate the efficient management of quantum systems and the accurate reconstruction of quantum states.

2) Superposition: According to this principle, a qubit can exist in multiple states simultaneously. It enables parallelism by simultaneously allowing computations on multiple inputs and empowers quantum and QI algorithms to explore various potential solutions more efficiently [27]. In contrast, a classical bit can only be in a 0 or 1 state, leading to sequential computations by processing one input at a time. Although both quantum and classical communication systems share foundational principles of information processing, the superposition of qubits represents a transformative shift in how information is processed and transmitted. It offers significant advantages in computational efficiency and security. Fig. 6 depicts a qubit in a superposition state, with the ($|0\rangle$), ($|1\rangle$) and z denote the horizontal, vertical, and superposition dimensions, respectively.

A qubit's state remains uncertain until measured, illustrating that quantum states are inherently unpredictable. This uncertainty before measurement distinguishes it from classical methods, where the state is always clear and definite. For instance, Grover's algorithm provides a quadratic speedup for searching an unsorted database, allowing it to search through N items in approximately $\sqrt{N}$ steps, compared to N steps in a classical search [30]. Similarly, Shor's algorithm, designed for factoring large integers, achieves exponential speedup compared to classical algorithms [25]. These quantum algorithms exploit the principles of superposition and interference to evaluate multiple possibilities simultaneously, a capability beyond the reach of classical systems.

3) Quantum Entanglement: It allows qubits to become correlated with each other, regardless of the distance separating them. The state of one qubit directly influences the state of its entangled partner. This property enables secure data transfer through techniques like QKD to create unbreakable keys and enhances computational power by allowing multiple simultaneous calculations [9]. Careful management is required to maintain the entangled states of qubits, and it is indeed possible to entangle multiple qubits, creating complex states that increase computational capabilities. Although it is theoretically feasible to entangle multiple qubits, its practical implementation is challenging due to decoherence and noise.

A density matrix captures the intrinsic correlation between entangled qubits. Bell states are specific two-qubit states that exhibit maximal entanglement, making them vital for quantum information protocols such as cryptography and teleportation [26]. These states can be generated using quantum gates or spontaneous parametric down-conversion in optical experiments. The analytical representation of a Bell state, expressed via the outer product, illustrates the entangled nature of qubits.

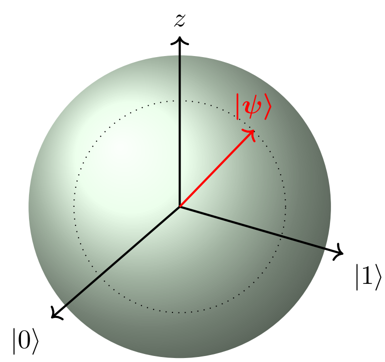

Fig. 6. Qubit representation through Bloch sphere, showing its existence in a superposition state ($|\psi\rangle$).

In (12), an entangled Bell state ($|\psi^+\rangle$) is generated from two qubits $|\psi_1\rangle$ and $|\psi_2\rangle$, that are initially in $|0\rangle$ state [27]. Furthermore, the quantum circuits are computational models manipulating qubits using quantum gates, effectively demonstrating quantum entanglement. Fig. 7 shows that applying a Hadamard gate to qubit $|\psi_1\rangle$ and a controlled-NOT gate with $|\psi_1\rangle$ as control and $|\psi_2\rangle$ as target leads to the maximally entangled Bell state as [25]:

$$|\Psi^+\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle). \tag{12}$$

Furthermore, developing robust quantum communication networks requires addressing challenges like reliable entanglement creation and quantum memory management [9]. In contrast, classical bits are independent and do not exhibit the interconnected behavior seen in quantum systems. Classical communication faces issues like signal degradation over long distances and the need for effective security measures to protect data during transmission. Classical networks employ error correction codes and parallel processing to improve reliability and efficiency. Both classical and quantum systems utilize optimization techniques to tackle the challenges of respective domains. Classical algorithms, such as simulated annealing and genetic algorithms, can enhance communication processes, while quantum techniques, such as quantum annealing and quantum neural networks (QNN), improve entanglement protocols. Furthermore, hybrid approaches combining both systems can leverage classical computation for tasks that do not require quantum properties while employing effective entanglement protocols.

The authors of [31] formulated a mixed integer non-linear programming problem to maximize the successful generation of entangled qubit pairs. They solved it using an interior-point algorithm while considering constrained quantum memory capacity. Similarly, the authors of [32] minimized the latency of entangled pair generation with linear time complexity by selecting optimal swapping trees while accounting for a $3/2$ factor for throttled trees and capacity violations. Furthermore, the authors of [33] maximized the entanglement distribution rate by designing a remote entanglement distribution protocol incorporating graph theory and classical flow networks for a chain of homogeneous repeaters. The authors of [34]

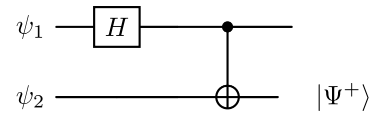

Fig. 7. Quantum entanglement of qubits.

experimentally demonstrated high visibility entanglement of photon-pair shared among three users within 17 km reach for a tree-shaped optical network. Furthermore, while entanglement assistance significantly boosts communication rates, its unreliability in entanglement-breaking channels renders the combination of the assisted and unassisted coding suboptimal [35].

4) No-Cloning Theorem: This theorem states that creating an exact copy of an arbitrary quantum state is impossible. This limitation arises from the principle of linearity, which requires that if a quantum copier gets a superposition of states as input, then the output must also reflect that superposition [25]. Therefore, any attempts to clone quantum states disrupt this requirement, as illustrated in Fig. 8. Consequently, the eavesdroppers attempting to intercept or duplicate quantum information can be swiftly detected through the QKD protocol. However, cloning specific states, such as orthogonal states, is possible, but the quantum copier must be designed explicitly for such states. The classical communication systems do not possess this property, and an eavesdropper can easily copy the classical information without detection, compromising information confidentiality.

5) Quantum Teleportation: It involves transferring quantum information between two distant locations without physically moving the quantum state [26]. Fig. 9 shows that the process of teleportation begins with entangled qubits at both the source and the destination nodes. The source gets a third qubit whose information needs to be transmitted. It performs a Bell measurement on the entangled partner and the incoming qubit. This measurement collapses the quantum states and produces a classical outcome. The measurement result is then sent to the destination node via a classical communication channel, adhering to the speed of light limit. At the destination, the entangled qubit undergoes a quantum operation based on the received classical information and transforms into a replica of the third qubit's state. Therefore, quantum teleportation depends on transmitting measurement results through classical communication methods. Quantum teleportation can alleviate the challenges of a data-driven metaverse through quantum anonymous communication and variational quantum computing [36]. In contrast, classical communication systems allow easy copying and transmission of information without quantum considerations.

B. Components of Quantum Communication

Classical communication systems can incorporate QI optimization techniques without imposing infrastructural updates on network providers. However, the cohesive

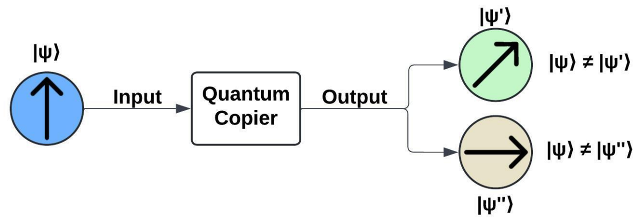

Fig. 8. Failure in cloning arbitrary quantum states.

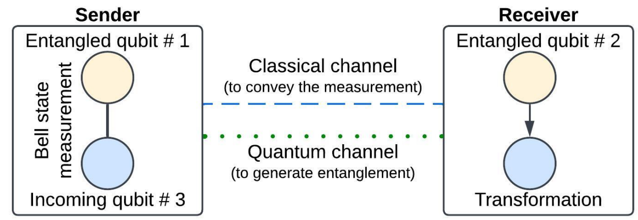

Fig. 9. The process of teleporting quantum information.

operation of classical and quantum systems requires only software-based updates, such as encoding and decoding procedures. In contrast, implementing purely quantum communication requires specific enabling components, explained in this subsection.

1) Qubit Source and Detector: Quantum communication depends on accurate generation and detection of qubit states. Common qubit sources include coherent states, entangled photons, single photons, and squeezed states, each designed for the respective quantum communication protocols. These sources utilize devices such as lasers, non-linear crystals, parametric oscillators, and quantum dots to generate the required quantum states [27]. The quantum dot chains can be employed for wireless communication due to reduced threshold current densities and strong vertical emission for terahertz quantum cascade lasers at room temperature [37]. On the contrary, classical communication systems utilize continuous signals, such as electrical pulses or radio waves, to generate classical bits, which do not require the same level of precision.

Similarly, the quantum detection methods vary depending on the qubit generation technique. Devices such as charged coupled device cameras, quasiparticle traps, radio frequency superconducting quantum interference devices, single-photon detectors, and transition edge sensors are commonly used to detect quantum states with high sensitivity [26]. Classical bit detectors are relatively simpler and typically use photodiodes or other conventional detectors that do not require the same level of precision in resolving states.

2) Quantum Gates: Quantum gates perform operations on qubits that exist in superposition. They serve as the fundamental building blocks of quantum circuits, enabling various computational tasks on qubits. Common types of quantum gates include the controlled-NOT, Hadamard, Pauli, Rotation, Swap, and Toffoli gates, each designed for specific functions within quantum computations [26]. In contrast, classical gates process information in a binary manner by operating on binary values of bits. Unlike classical gates, quantum gates exploit the principles of quantum mechanics, such as entanglement and superposition, to perform complex operations and enhance computational power. It allows quantum algorithms to tackle tasks often inefficient for classical systems, such as factoring large numbers or simulating quantum systems, which would require impractical amounts of time and resources with classical computing methods.

The gate set tomography can also be employed to evaluate the performance of a group of quantum gates through experimental measurement data. In this regard, authors of [38] proposed a compressive gate set tomography technique by employing low-rank approximations and random gate sequences to enhance the measurement efficiency and reduce experimental complexity. QI optimization approaches view quantum gates as essential conceptual tools rather than merely physical operations. In this framework, quantum gates are crucial in implementing quantum algorithms and protocols that enhance overall performance and efficiency. By harnessing the unique properties of quantum gates, QI strategies can enable higher computational capability, even within classical computing environments.

3) Quantum Repeaters: Quantum and classical repeaters primarily aim to extend communication distances. However, they use different principles and have distinct features. Classical repeaters amplify and regenerate signals to mitigate transmission losses and noise impairments. In contrast, quantum repeaters entangle quantum states across different segments of the communication link and perform entanglement swapping to establish a direct link between distant nodes without amplifying or copying the quantum signal [27]. Fig. 10 illustrates a chain of quantum repeaters connecting two distant quantum nodes, with the quantum channel being either fiber optic or free space. Quantum repeaters mitigate signal impairments in extended quantum channels by utilizing quantum memory to store and synchronize quantum states effectively. Entanglement swapping performed by the repeaters enables reliable and scalable communication between distant nodes. These features make quantum repeaters indispensable for overcoming the limitations of direct quantum transmission.

Quantum repeaters can be classified into trusted and non-trusted types. Trusted quantum repeaters assume secure internal operations and merely facilitate the connection. Non-trusted quantum repeaters do not rely on assumptions of trustworthiness and instead utilize cryptographic methods to safeguard against potential eavesdropping. Ultimately, quantum repeaters maintain the integrity of delicate quantum information over long distances, enabling quantum Internet and secure quantum communication systems. Different types of quantum repeaters include distributed phase reference, entanglement swapping, error correction-based, hybrid, measurement-based, and memory-based. Furthermore, there is a need to explore the performance of noisy intermediate-scale quantum networks in terms of scalability and integration with classical communication networks to achieve the global quantum Internet [39].

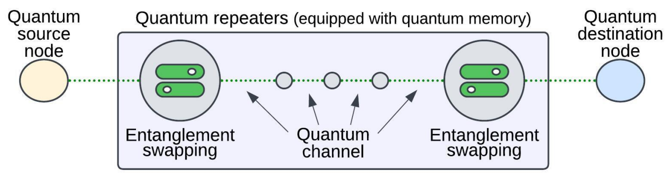

Fig. 10. Quantum repeaters connecting the quantum nodes.

4) Quantum Memory: It stores qubits that exist in superposition, enabling enhanced processing capabilities. However, retrieving data from quantum memory necessitates measuring qubits, which collapses their superposition into a definite state and alters their original condition. Quantum memory operates through various physical systems, such as atoms, ions, or photons, to encode quantum states in qubits. Techniques that regulate light and matter interactions enable quantum memories to store quantum states, such as superpositions and entangled states, for varying durations, depending on the technology and environmental conditions [27].

In contrast, classical memory stores deterministic information in binary form through technologies such as dynamic random-access memory. It relies on magnetic or electronic means for reliable storage. Classical memory has a simpler structure and does not require the advanced capabilities of quantum memory, which must tackle challenges like decoherence and signal loss to preserve quantum states. Overall, while both classical and quantum memories serve the purpose of storing information, they operate through fundamentally different mechanisms.

5) Quantum Information Processing: It pertains to the analysis and operations of quantum information using quantum systems. It encompasses many tasks, including cryptography, data analysis, ML, and optimization. Qubit states are manipulated through quantum gates, which exploit quantum properties such as entanglement, parallelism, and superposition to achieve significant speedups for various computational tasks and algorithms [25]. In contrast, classical communication relies on bits for information processing and often faces limitations in handling complex problems. Many classical algorithms struggle to find efficient solutions for large-scale optimization, factoring large integers, and simulating quantum systems, where the computational complexity can grow exponentially with input size. For instance, the authors of [40] proposed a quantum multi-clustering technique utilizing a variational quantum eigensolver to tackle real-world clustering problems on noisy intermediate-scale quantum devices, significantly reducing computational requirements through the use of non-orthogonal qubit states.

6) Quantum Security Protocols: The unique properties of qubits, such as entanglement and the no-cloning theorem, offer security that greatly surpasses classical systems, which can be compromised by cryptanalysis. Quantum security protocols, including QKD, quantum digital signatures, quantum coin flipping, and quantum secure multi-party computation, leverage these quantum properties to achieve unparalleled security [26]. QKD specifically uses qubits to exchange cryptographic keys securely. However, practical QKD systems face challenges like optimizing key rates, extending communication distances, improving scalability, detecting eavesdropping, and managing quantum memory. Addressing these challenges requires advancements in techniques such as quantum error correction, quantum repeaters, and enhanced protocols.

The authors of [41] proposed a network scheduling policy to maximize secure key rates among quantum devices. The secret-key rates were also improved by employing a dynamic attenuation scheme for free-space channels through real-time monitoring and adjusting transmittance [42]. Similarly, in [43], a time-bin entanglement-based QKD scheme was proposed that utilized the E91 protocol on free-space optical channels, aiming to maximize the secret keys rate while considering the system average symbol error rate and outage probability. In [44], upper bounds on device independent keys secure against a non-signaling adversary were obtained through squashed secrecy monotones, which quantify the maximum secure key generation rate from a quantum state. A squashed nonlocality-based security condition was formulated to identify the domains where secure key distillation was impossible and provide the tightest known upper bounds.

Furthermore, a holistic QKD-based communication technique was introduced in [45] to ensure security for aerial, ground, and space nodes. Additionally, the authors of [46] integrated QKD with classical data traffic to extend transmission distances by minimizing spontaneous Raman scattering noise, enhancing security in wavelength division multiplexing networks. The authors of [47] proposed an algorithmic framework to strengthen the resilience of QKD-integrated optical networks against link failures via a secret-key recovery technique. A three-layered QKD semantic information communication architecture for resource optimization and routing decisions was developed in [48]. Similarly, an NP-complete optimization problem was formulated in [49] to minimize the number of QKD repeaters in fiber optic networks and enable secure communication over wide areas. Lastly, the feasibility of QKD protocols, including discrete variable and distributed phase reference, was analyzed in [50], considering noise and wind impairments on various communication links. A continuous variable QKD scheme for terahertz bands using multicarrier modulation was proposed in [51]. Additionally, the quantum Byzantine fault tolerance protocol can mitigate issues related to security, noise, and faults in applications like the human-centric metaverse [52].

7) Quantum Error Correction: It is essential to maintain the integrity of quantum communication, especially in the presence of various noise impairments. It addresses challenges such as amplitude damping, bit flips, decoherence, depolarization, and phase damping but induces significant overheads. Various techniques for quantum error correction include redundant encoding, stabilization codes, syndrome measurement-based unitary correction, and topological protection [26]. These methods detect and correct errors by employing measurements that provide information about errors without fully collapsing the superposition and entanglement of qubits. A simpler procedure called purification can be used to detect errors [27].

In classical communication, Gaussian noise is the dominant noise-contributing element, and error correction methods such as Hamming and Reed-Solomon codes detect and correct errors by adding redundant bits to the transmitted data. Although both approaches seek to preserve data integrity, quantum error correction functions within a fundamentally different framework that reflects the unique characteristics of quantum mechanics. Adaptive frameworks can effectively estimate time-varying quantum noise in diverse communication scenarios [53], which can be leveraged to devise suitable quantum error correction techniques.

Calderbank-Steane-Shor codes combine two classical linear codes to protect quantum information from bit-flip and phase-flip errors, with the proposed quantum low-density-generator-matrix codes outperforming quantum low-density-parity check codes in correcting errors in phase-flip dominant depolarizing channels [54]. Furthermore, non-Calderbank-Steane-Shor quantum low-density-generator-matrix codes can address the limitations of classical non-Calderbank-Steane-Shor constructions for enhanced error correction. The authors of [55] performed specific row operations on quantum parity check matrices to devise new codes with better performance and increased design flexibility as compared to the existing Calderbank-Steane-Shor quantum low-density generator matrix and low-density parity check codes.

C. Quantum versus Classical Communication: Enabling 6G Applications

This subsection provides a comparative analysis of classical and quantum communication, summarizing key discussions from Section III. The parameters in Table IV highlight the advantages of quantum communication, particularly in its use of qubits, which enable probabilistic representation, superposition, and greater parallelism, while classical communication is limited to deterministic bit transmission. Quantum technologies will play a significant role in 6G networks by offering enhanced security through QKD and facilitating innovations such as quantum-enhanced sensor networks and secure multi-party computations. Alongside classical communication, it remains essential in scenarios where established infrastructure exists, and simplicity of implementation is required. An intelligent trade-off between both paradigms is crucial for maximizing their potential in future networks. Quantum communication can enhance various applications expected in the 6G networks, listed follows:

- **High-speed connectivity:** Through superposition and entanglement to transmit data swiftly.
- **Enhanced security:** Through QKD relays to protect sensitive information.
- **Massive IoT support:** Efficient data handling from numerous IoT devices through exponential storage capabilities.
- **Real-Time applications:** High parallelism can aid in meeting the real-time requirements of augmented reality (AR) and virtual reality (VR) experiences.

In summary, Section III has provided a foundational understanding of the differences between classical and quantum communication. It offers a brief overview of the fundamental quantum principles, including the concept of qubits, the phenomenon of superposition, qubits entanglement, and the significance of the no-cloning theorem. Additionally, it has discussed the functionalities of critical components such as quantum gates, repeaters, memory units, and error correction mechanisms, highlighting their roles in the quantum communication scenario. Lastly, a comparative analysis is presented between quantum and classical communication while presenting the plausible 6G applications enabling quantum technologies.

IV. Quantum-Inspired Optimization

Rapid growth of edge computing devices, IoT sensors, and mobile users requires significant improvements in wireless communication networks. These improvements include increasing the capacity and data rate and reducing interference, latency, and similar factors. Accommodating the advanced features anticipated in future 6G networks may prove challenging for classical networks. Alongside, implementing a global quantum communication network is challenging due to current infrastructure and technological limitations, including the need for quantum repeaters to maintain entanglement across vast distances, the high sensitivity of quantum states to environmental disturbances, and the absence of a well-established global quantum framework. Furthermore, integrating quantum

TABLE IV
Comparison between classical and quantum communication.

Parameters	Classical Communication	Quantum Communication
Unit	Bits (0 or 1)	0, 1, or superposition of both
Representation	Deterministic	Probabilistic
Parallelism	Limited due to sequential bit operations	High due to superposition
Speed	Slow (signal processing and transmission delays)	Faster (superposition and entanglement)
Measurement	Non-intrusive	Intrusive (qubit collapses to certain state)
Security	Vulnerable to eavesdropping	Enhanced due to no-cloning and QKD
Repeaters	Amplify signals over distances	Extend entanglement over long distances
Gates	Deterministic operations on bits	Complex operations and parallelism on qubits
Memory	Linear information storage in conventional cells	Exponential storage capability due to superposition

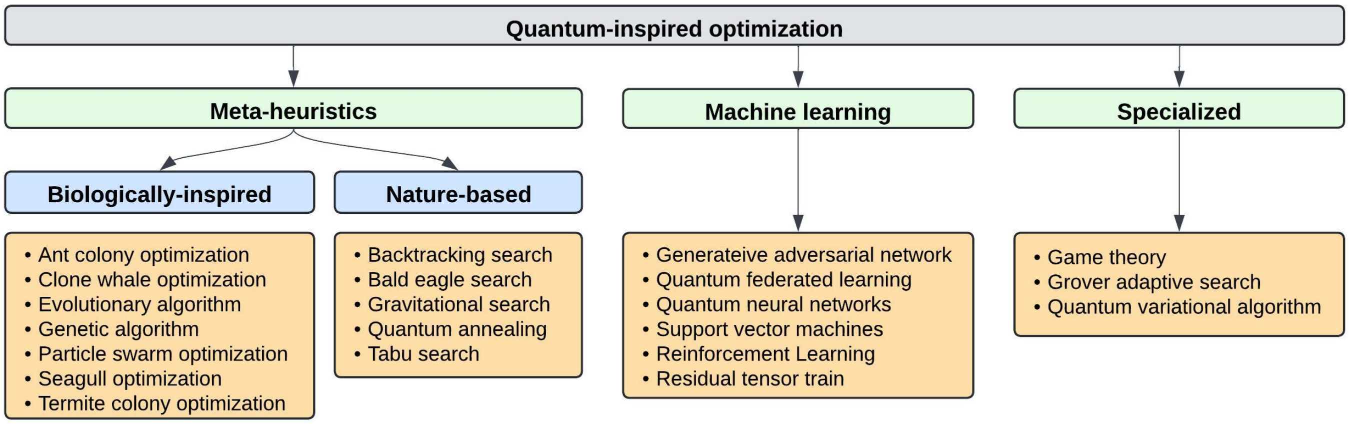

Fig. 11. Classification of QI optimization approaches.

systems with classical networks requires significant advances in both hardware and protocols. Therefore, a potential solution lies in applying quantum principles to classical networks, referred to as QI techniques, to achieve quantum-like benefits. Fig. 11 depicts the categorization of QI optimization techniques into meta-heuristics, ML, and specialized algorithms. This section reviews QI algorithms and their conceptual frameworks, includes flowcharts of the optimization process, summarizes key strengths and weaknesses, examines applications in radio resource management, and analyzes the frequency of their use in optimizing radio resources.

A. *Quantum-Inspired Meta-Heuristics*

Meta-heuristics can be broadly categorized as nature-based or biologically-inspired algorithms seeking near-optimal solutions through repeated solution space exploration. QI meta-heuristics enhance exploration without compromising exploitation by leveraging quantum principles such as entanglement, tunneling, and superposition. Unlike classical meta-heuristics, which explore solutions sequentially, QI meta-heuristics utilize quantum parallelism to simultaneously evaluate multiple solutions. In a classical register, only one of the 2^n possible values can be stored, whereas an n-qubit register can represent all 2^n states at once, allowing for more efficient searches. This results in superior convergence speed and solution quality for large-scale optimization tasks.

Figs. 12 and 13 illustrate generic flowcharts of classical and QI meta-heuristics optimization algorithms, respectively. Classical meta-heuristics optimization methods rely on deterministic population initialization and solution generation, whereas QI optimization begins by initializing qubit states in superposition, leveraging quantum parallelism to evaluate multiple solutions simultaneously. Furthermore, QI techniques employ probabilistic selection and use quantum gates to update qubit states, enabling enhanced exploration and faster convergence compared to classical methods. Overall, both approaches iteratively generate candidate solutions, evaluate fitness, and check stopping criteria, and QI optimization introduces quantum-specific features. In particular, in QI meta-heuristics, the three-dimensional properties of qubits are simplified into a two-dimensional representation using rotation angles and probability amplitudes to guide the optimization process. These algorithms can also optimize decision variables in collaborative inference frameworks for intelligent mobile services with linear time complexity [56], [57]. Here, we briefly explain the algorithms identified in the reviewed literature and their QI conceptualization.

*1) **Biologically-Inspired Meta-Heuristics Optimization**:*

These optimization algorithms leverage principles from natural phenomena to address complex challenges. This subsection presents a curated list of biologically-inspired meta-heuristics, highlighting key insights and implementations from the filtered literature that specifically focuses on solutions for radio resource optimization.

i. *Quantum-Inspired Ant Colony Optimization:* It relies on artificial ants depositing pheromones on the paths they traverse, thereby influencing the likelihood of subsequent ants choosing those paths. Each ant probabilistically selects a route by considering the pheromone levels and heuristic information, such as the distance from the food source to their colony. The classical ant colony optimization algorithm has a $O(M^2)$ complexity, where M refers to the number of IoT nodes. In contrast, its QI implementation demonstrates a lower computational complexity as indicated in [58]. QI ant colony optimization integrates principles of quantum computing by using qubits to represent pheromone information, which is updated through quantum gates. This approach enables parallelism due to the superposition of states, allowing for the exploration of multiple solutions simultaneously.

ii. *Quantum Clone Whale Optimization:* The classical whale optimization algorithm enhances local search capability for NP-hard optimization problems while maintaining lower computational complexity. However, it tends to fall into local optima. To address this, the quantum clonal whale optimization algorithm was proposed in [60] for optimized clustering of wireless sensor nodes. This algorithm follows a stepwise approach, including population initialization, fitness

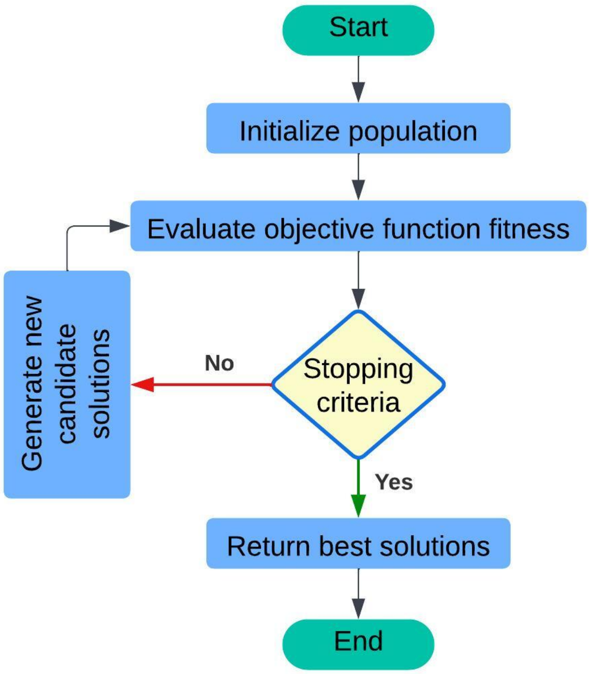

Fig. 12. General flowchart of classical meta-heuristics optimization [59].

calculation, encirclement and predation, bubble-net attacking, a random search for prey, clonal expansion, quantum gate operations, and termination. The quantum clonal whale optimization algorithm is robust and slightly more complex than the classical counterpart due to the clonal expansion, which guides individuals in the population toward the optimal solution. Its computational complexity is $3 \times i_{max} \times P_s \times M$, where i_{max}, P_s, and M refer to the maximum number of iterations, population size, and sensor nodes, respectively. Furthermore, it demonstrates superior energy balancing for wireless sensor nodes compared to benchmark algorithms, where noticeable energy fluctuations occur.

iii. *Quantum-Inspired Evolutionary Algorithm:* It is a generational, population-based iterative algorithm designed to address complex optimization problems. In each iteration, quantum gates such as Hadamard, NOT, and rotation gates are employed to update individuals in the population, guiding them toward better solutions. Key characteristics of this algorithm include the probabilistic representation of individuals (as qubits), evaluation functions, and population dynamics. The underlying mechanisms leverage quantum principles, such as the probabilistic nature of qubits and quantum gate operations, to effectively explore and exploit the search space of a specific optimization problem. This algorithm is especially useful for solving combinatorial and non-linear integer programming optimization problems, where finding the optimal solution within polynomial time is difficult.

For instance, in [61], joint caching and user association optimization for adaptive bit-rate video streaming was tackled through the QI evolutionary algorithm, resulting in the lowest total content delivery delay and reduced UAV transmission power compared to classical randomized caching and user

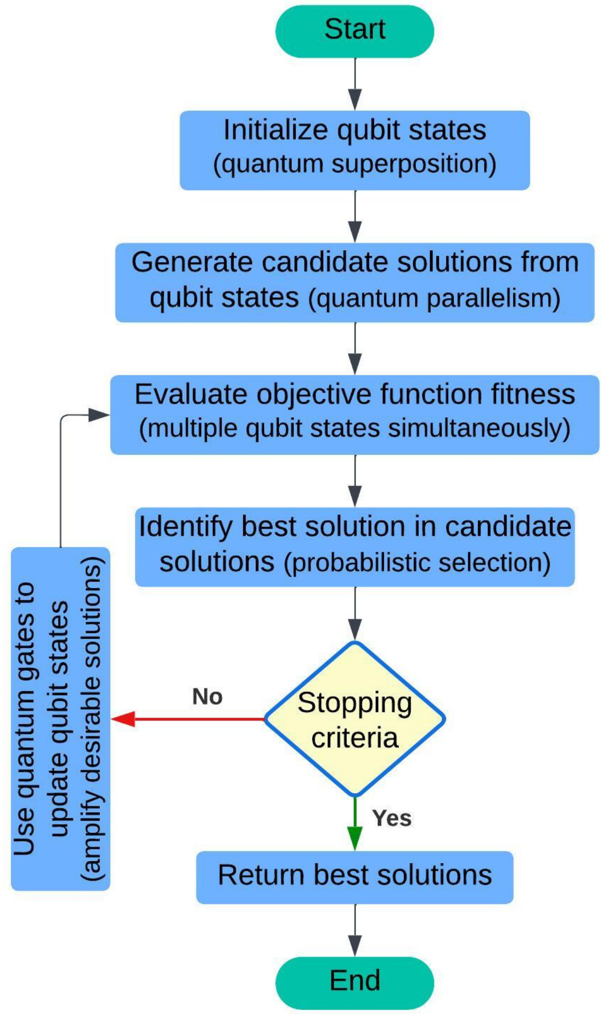

Fig. 13. General flowchart of QI meta-heuristics optimization [57].

association methods. Furthermore, the NP-hard optimization problem of reducing the peak-to-average power ratio in multicarrier modulation systems was solved through the QI evolutionary algorithm with a computational complexity of $P_s \times G \cdot O(N_c \log N_c)$, where P_s, G, and N_c represent the population size, generation count, and the number of sub-carriers, respectively [62]. The benchmarks used for comparisons, such as the artificial bee colony and cross-entropy-based selective mapping algorithms, showed significantly higher complexity regarding the number of fast Fourier transforms required to meet the desired criteria of the peak-to-average power ratio.

iv. *Quantum-Inspired Genetic Algorithm:* It effectively combines the probabilistic and heuristic strengths of classical genetic algorithms with quantum principles and improves the exploration and exploitation in complex search spaces. The qubit chromosomes are initially considered in a linear superposition of equally likely states having $1/\sqrt{2}$ value. They provide binary candidate solutions that aid in selecting the best solution. The iterative process of updating candidate solutions continues until a termination condition is met. Quantum gates are used to update qubit chromosomes for the next-generation.

In [63], the overall complexity of the QI genetic algorithm for resource-constrained project scheduling is found to be $O(G.K.n_d^2)$ through a stepwise approach where G, K, and n_d represent the number of generations, resource types, and decision variables, respectively. The QI genetic algorithm converges faster than the classical genetic algorithm. Similarly, a quantum-genetic-based optimal link-state routing protocol was proposed for mobile Ad hoc networks to optimize the multi-point relay set selection and perform adaptive routing decisions [64]. This strategy showed the least network topology control overhead compared to benchmarks such as classical optimal link-state routing protocol, optimal link-state routing protocol-neighborhood state self-adaptive update, and cartography-enhanced optimal link-state routing protocol.

v. ***Quantum Particle Swarm Optimization (QPSO):*** It is inspired by the foraging behavior of birds and enhances the classical PSO algorithm. Originally, PSO was designed to solve complex optimization tasks by simulating the movement of particles within a multidimensional search space. In QPSO, each particle's position and velocity are initialized, and their movements are guided by both their individual best positions and a global best position, evaluated through a fitness function. The algorithm iterates until a predefined maximum number of iterations is reached. QPSO has a time complexity of $O(i_{max}N_p)$, where i_{max} and N_p represent the maximum number of iterations and particles, respectively.

Fig. 14 illustrates the iterative optimization process of QPSO, which integrates quantum principles like superposition and tunneling to enhance solution space exploration. Unlike conventional PSO, QPSO employs probabilistic states and QI updates to overcome local convergence issues, ensuring effective exploration and optimal convergence. QPSO algorithm was used in [65] to maximize energy efficiency in device-to-device edge computing, where it significantly outperformed the conventional PSO algorithm due to its ability to converge toward a global suboptimal solution. QPSO can be a powerful tool for solving mixed integer non-linear programming and other complex optimization problems related to resource allocation [66]–[74].

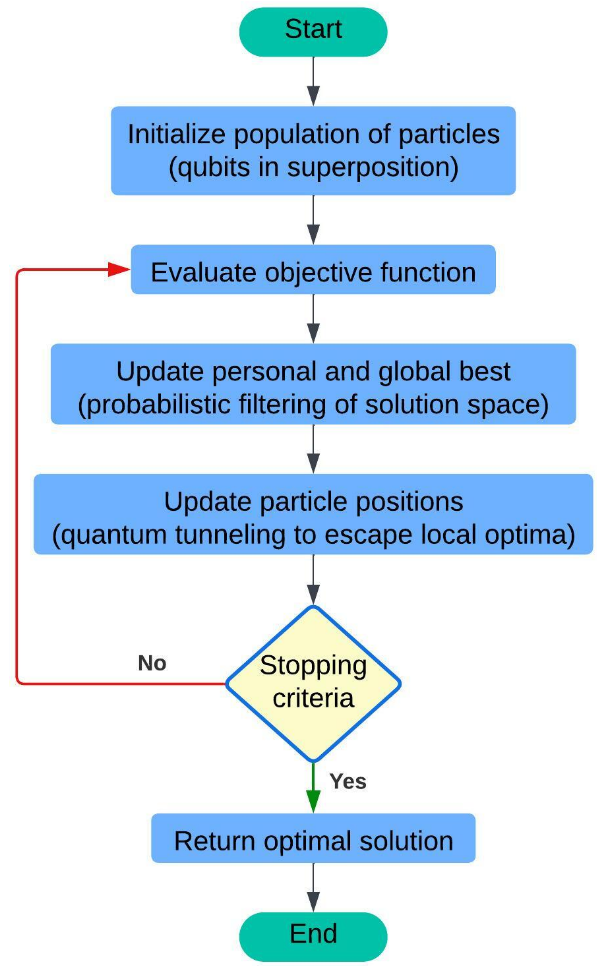

Fig. 14. General flowchart of QPSO algorithm [75].

vi. ***Quantum-Inspired Seagull Optimization:*** The classical seagull optimization algorithm mimics the behavior of seagulls as they move in groups towards a destination while skillfully avoiding collisions with one another. After navigating these challenges, the seagulls optimize their movement based on local information. Additionally, they display a local search behavior characterized by a spiral movement when attacking other birds. In contrast, the QI seagull optimization algorithm incorporates the neighboring seagulls to enhance interaction, thereby influencing each seagull's flight direction.

Therefore, the algorithm proposed in [76] employed a variable angular-distance rotation gate to update the probability magnitudes of the seagulls, allowing for more adaptive behavior. This algorithm utilizes dynamic archives to store Pareto solutions, improving solution space exploration. The algorithm efficiently scales the number of seagulls, exhibiting a time complexity of $O(M_s^2)$, where M_s represents the number of seagulls. Experimental results validate the superiority of the QI seagull optimization algorithm over different benchmark algorithms, such as multi-objective PSO and non-dominated sorting genetic algorithm II, particularly in terms of convergence and distribution across diverse multi-objective optimization tasks. Overall, enhanced solution diversity and convergence speed make the QI seagull optimization algorithm a plausible choice for solving complex optimization problems.

vii. ***Quantum-Inspired Termite Colony Optimization:*** It employs a colony of quantum termites to navigate among the solutions in a D-dimensional space, where D is the maximal dimension of the optimization task. The positions of individual termites represent potential solutions, and the highest-performing positions are considered the local and global optima. The algorithm iteratively updates the pheromone contents using quantum rotation angles and pheromone levels at each termite's position. All pheromone levels are initially set to zero, and each termite uses its information and that of its neighbors to adjust its trajectory based on the defined search radius. The algorithm concludes upon reaching the maximum number of iterations.

In [77], the quantum termite colony optimization algorithm was applied to maximize the energy efficiency and transmission capacity of MIMO systems, which belong to the category of NP-hard optimization problems. Its computational complexity was $O(i(5P_s + 3P_s n))$, where i, P_s, and n represent the number of iterations, population size, and dimension of each quantum termite (vector), respectively. The quantum termite colony optimization algorithm demonstrated superior convergence speed and population diversity due to its reliance on quantum evolution strategies and global information sharing. It effectively and reliably solved energy efficiency optimization problems with multiple constraints compared to various benchmark algorithms, such as termite colony optimization, PSO, backtracking search optimization, and half-power-random resource allocation.

Table V highlights the advantages and disadvantages of biologically inspired QI meta-heuristics optimization approaches. It offers key insights into their strengths and limitations in diverse scenarios.

*2) **Nature-Inspired Meta-Heuristics Optimization**:* These optimization algorithms harness techniques from natural processes to solve optimization problems. This subsection provides insights into the QI nature-inspired algorithms for solving radio resource optimization issues.

i. *Quantum-Inspired Backtracking Search:* It is an innovative optimization technique that combines the backtracking search optimization algorithm and principles of quantum computing. The algorithm employs L quantum individuals, each defined by n dimensions that reflect the optimization task's complexity. The QI backtracking search evaluates the fitness of each quantum individual based on a specific optimization objective and maintains a record of historically measured states to enhance the search process. The historical memory set updates systematically by recording the current state when a randomly generated variable $\alpha 1$ is less than another variable $\alpha 2$ and otherwise keeps the previous state unchanged. This mechanism and the random shuffling of stored solutions promote diversity in the solutions generated during each iteration. New quantum individuals are then produced via evolutionary strategies that leverage historical data and the states of other quantum individuals, ensuring a comprehensive search for optimal solutions.

In [78], the QI backtracking search was employed on massive MIMO systems for joint antenna selection and power allocation, exhibiting a complexity of $O(i(5L+4Ln))$, where i, L, and n refer to the number of iterations, population size, and dimension of each individual, respectively. The QI backtracking search optimization algorithm demonstrated superior convergence accuracy compared to various benchmarks, including PSO, discrete PSO, artificial physics optimization,

TABLE V
KEY INSIGHTS INTO THE BIOLOGICALLY-INSPIRED META-HEURISTICS QI OPTIMIZATION TECHNIQUES.

QI Technique	Ref.	Remarks
QI Ant Colony Optimization	[58]	• Improved network-lifetime for energy constrained sensors. • Lower node energy consumption. • Significantly longer execution time per round than traditional counterparts.
Quantum Clone Whale Optimization	[60]	• Robust clustering and extended network lifetime in energy system sensor networks. • Highest count of working rounds of network. • Ensures high accuracy and stability in node energy control. • Lowest average data transmission delay.
QI Evolutionary Algorithm	[61], [62]	• Faster convergence of algorithm for video caching. • Lower content delivery delay. • Offers superior peak-to-average power ratio and bit error rate performance. • Lower implementation complexity.
QI Genetic Algorithm	[64]	• Lowest network control overhead in mobile Ad hoc networks. • Superior reliability in terms of successful packet delivery rate. • Lowest end-to-end packets transmission delay between nodes.
Quantum Particle Swarm Optimization	[65]–[74]	• Solves complex optimization tasks more accurately and quickly than classical methods. • Improves scalability through parallelism. • Optimizes user satisfaction and resource efficiency. • Improves IoV performance with high throughput, low packet loss, and minimal delays. • Enhances energy efficiency in device-to-device-assisted edge computing. • Involves higher decision-making overhead.
QI Seagull Optimization	[76]	• Superior UAV path planning performance.
QI Termite Colony Optimization	[77]	• Enables diversity of population. • Global information sharing leads to swift convergence. • Achieves optimal transmission capacity in massive MIMO networks. • Stable and reliable in energy efficiency optimization.

and the classical backtracking search optimization algorithm. This QI backtracking search optimization algorithm has enhanced performance due to its ability to effectively incorporate information from current and historical quantum individuals, which mitigates the issues of local convergence. Therefore, the QI backtracking search optimization algorithm is robust in solving complex wireless communication systems related optimization problems.

ii. *Quantum-Inspired Bald Eagle Search:* It integrates principles of quantum computing with the natural behaviors of bald eagles, specifically their selection, searching, and swooping tactics. In this algorithm, a population of quantum bald eagles explores a D-dimensional search space, where each eagle's position is represented by quantum bits. The algorithm iteratively updates these positions based on fitness evaluations, facilitating efficient convergence toward global optima. The core mechanism of QI bald eagle search involves simulating the hunting behaviors of bald eagles, where they share information and adjust their positions using quantum rotation angles. Dynamic adaptation enhances search strategies, improving both efficiency and effectiveness.

This approach was used in [79] to maximize secrecy energy efficiency in IRS-aided wireless communication, exhibiting a computational complexity of $O(iP_s(3D+2))$, where i, P_s, and D represent the number of iterations, population size, and dimension of the optimization problem, respectively. Upon comparison with benchmarks such as bald eagle search, PSO, and Dinkelbach algorithms, the complexities of all techniques were similar due to equivalent population sizes and dimensions. However, the QI bald eagle search showed robustness in prolonged iterations, whereas benchmark algorithms showed premature convergence.

iii. *Quantum-Inspired Gravitational Search Algorithm:* It integrates principles from gravitational search algorithm and quantum computing to address quadri-valent problems effectively. The individual qubits are represented as a pair of parameters (α, β), which can exist in states 0, 1, 2, 3, or a superposition of these states. Terms α^2 and β^2 define the state probabilities with their sum equal to one. The population of agents is initialized for a D-dimensional search space. An observation function is employed by individual agents to collapse the quantum states to a specific value, leading to a set of candidate solutions. The fitness of solutions is evaluated, and upon finding a better fitness, the set of best solutions is updated. The mass of each agent is calculated based on its fitness relative to the worst solution, influencing its movement through a gravitationally-inspired mechanism. The angular velocity of each qubit is adjusted using a rotational quantum gate, which facilitates dynamic exploration of the solution space. Quadri-valent QI gravitational search algorithm was used in [80] to solve the NP-hard problem of operational mode assignment to wireless sensor nodes, and it increased the lifetime of the network compared to the classical benchmarks such as binary genetic algorithm and binary PSO.

iv. *Quantum-Inspired Annealing:* It is a computational technique that leverages principles of quantum mechanics to solve combinatorial optimization problems. The optimization problems are encoded into a suitable format for quantum annealers by transforming them into quadratic unconstrained binary optimization forms. The algorithm aims to find the lowest energy state of a Hamiltonian, which corresponds to an optimal solution. The NP-complete wavelength assignment problem in optical communications has been solved in [81] by employing a QI annealing algorithm called a simulator coherent Ising machine (a device using magnetic spin interactions to solve optimization problems). The algorithm reduces the number of quadratic unconstrained binary optimization problems and enhances robustness against suboptimal solutions. This transformation employs an extended binary vector incorporating both wavelength assignments and auxiliary variables, allowing for a more efficient minimization process.

QI annealing shows better scalability and has a lower average solution time, especially for larger problem sizes, as compared to classical benchmarks such as largest degree first, commercial Gurobi optimization software, and open-source mixed integer programming solver-GNU linear programming kit. In [82], an adaptive bit-rate control methodology was formulated as a quadratic unconstrained binary optimization problem, where increased bit-rate and reduced rebuffering maximize the quality of experience. The digital annealer performed better in solving the optimization problem in most cases compared to different benchmarks such as rate-based, buffer-based, and model-predictive control. The digital annealers have also been employed in [83] and [84] to identify optimized migration plans for legacy optical networks, where they exhibited superior performance compared to classical mixed integer programming. Similarly, several other applications of quantum annealing confirm the superiority in solving combinatorial optimization problems [30], [85], and [86]. This suggests that QI annealing may effectively shift the tractability boundaries for solving large-scale combinatorial problems.

v. *Quantum-Inspired Tabu Search:* It identifies suboptimal solutions by iteratively exploring the neighborhood of a current solution while employing a tabu list to avoid cycling back to previously explored solutions. This approach generally begins with an initial candidate solution, incorporating a greedy search to evaluate neighboring solutions, and employs a memory structure that guides the search away from previously visited states. In contrast, the QI tabu search algorithm enhances this framework by leveraging quantum mechanics to represent and manipulate potential solutions effectively. By measuring the probability distributions of qubits, QI tabu search identifies promising solutions while maintaining a diverse search space. This uniqueness enables QI tabu search to adaptively refine its search trajectory and improve solution space exploration.

QI tabu search was employed to identify a better duplex mode in [88], where it demonstrated superior efficacy compared to different benchmarks such as exhaustive search, greedy search, and fixed duplex mode. Specifically, it initializes a quantum population where each qubit can collapse into states representing different duplex modes for access points. It achieved higher secrecy spectral efficiency gains, which validate its effectiveness in meeting the secrecy requirements

TABLE VI
KEY INSIGHTS INTO THE NATURE-INSPIRED META-HEURISTICS QI OPTIMIZATION TECHNIQUES.

QI Technique	Ref.	Remarks
QI Backtracking Search	[78]	• Enhanced diversity of solution and search ability. • Superior secrecy capacity and secrecy energy efficiency.
QI Bald Eagle Search	[79]	• Significantly higher convergence performance. • Superior secrecy energy efficiency.
QI Gravitational Search	[80]	• Superior lifetime of wireless sensor networks. • The fitness value improves with increase in population size. • Parallel implementation increases throughput without impacting power of processor. • Effective in handling extensive networks.
Quantum Annealing	[81], [82], [85]	• Improves scalability and runtime for graph coloring and combinatorial optimization. • Comparable performance to industry-grade solvers for combinatorial tasks. • Stable increase in performance at higher levels of parallelism. • Superior performance for adaptive video streaming in static and dynamic scenarios.
QI Social-Emotional Optimization	[87]	• Enables fast and accurate convergence through diversity and strong search capabilities. • Superior power control strategy for massive MIMO networks. • The power control strategy is highly sensitive to hardware impairments. • Classical counterpart is prone to local convergence.
QI Tabu Search	[88]	• Higher number of possible solutions leads to faster convergence. • Secrecy spectral efficiency comparable to exhaustive search in massive MIMO systems.

in cell-free massive MIMO systems. The iterative mechanism of QI tabu search, which includes updating the tabu list and applying quantum gates for state transitions, enables it to navigate the solution space with complexity often lower than that of exhaustive search methods.

Table VI highlights the advantages and disadvantages of naturally inspired QI meta-heuristics optimization approaches. It offers key insights into their strengths and limitations in diverse scenarios.

B. Quantum-Inspired Machine Learning

Classical ML techniques enable computers to learn from data and make autonomous decisions or predictions using classical bits (0 and 1). Figs. 15 and 16 present the generic flowcharts of classical ML and QI-ML algorithms, respectively. Classical ML relies on traditional data processing and model training, while QI-ML utilizes superposition for enriched data processing, enables mapping of higher-dimensional features, and improves database exploration and parameter tuning through QI optimization techniques. These techniques are categorized into supervised learning, which leverages labeled data for predictions; unsupervised learning, which uncovers patterns in unlabeled data; and reinforcement learning, where an agent maximizes rewards through trial and error interactions with its environment and various other methods. The QI-ML leverages principles of quantum mechanics like superposition and entanglement to enhance computational efficiency and tackle complex optimization problems across various learning paradigms. Although designed for classical computers, QI-ML can aid in solving large-scale optimization problems. In particular, the QI-ML can provide superior resource optimization solutions by efficiently handling large datasets, faster convergence, and reduced complexity.

Furthermore, QML requires quantum devices and fundamentally differs from QI-ML. In this context, the authors of [90] provided a feasibility analysis of integrating quantum resources with classical ML. They discussed issues using deep learning techniques in 6G networks under stringent latency requirements. There are various QI-ML techniques in literature [91]–[93], which can guide the transformation of different classical ML algorithms into their QI counterparts, including deep learning [94], federated learning, generative adversarial networks [95], neural networks (NN), reinforcement learning, and support vector machines. The QI conceptualization of ML techniques can enhance managing complex data and generalization. This section examines QI-ML approaches from the filtered sub-set that address radio resource optimization, highlighting core principles and distinct strategies.

i. ***Quantum-Inspired Generative Artificial Intelligence:*** Generative AI synthesizes new data by learning patterns from existing data through audio, images, and text. Generative adversarial networks are a specific type of generative AI that produces realistic outputs using two competing components: the generator and the discriminator. The synergy between generative AI and quantum computing networks can facilitate the creation of novel algorithms to solve complex optimization problems. In this context, the authors of [97] comprehensively reviewed quantum generative adversarial networks and emphasized their potential by leveraging the unique properties of quantum computing for advanced generative modeling.

Similarly, an intelligent resource allocation framework in uncertain fidelity was devised in [98] to manage quantum resources such as qubits, quantum channels, and entangled pairs. In [99], generative learning enhancements were explored with quantum models like quantum circuit-born and tensor

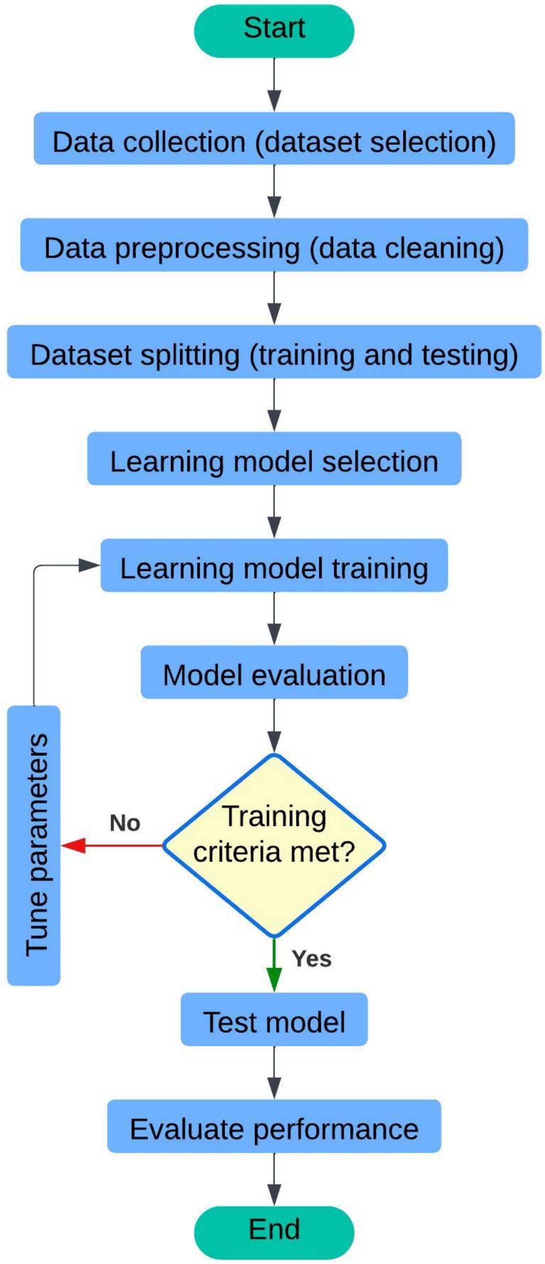

Fig. 15. General flow of a classical ML algorithm [89].

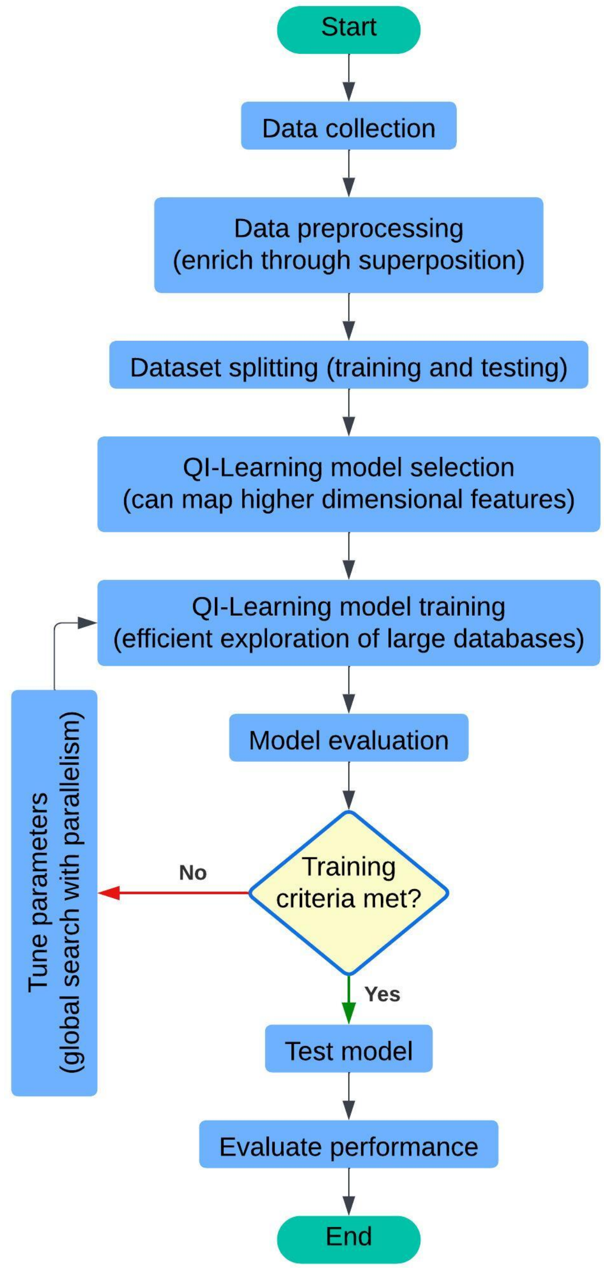

Fig. 16. General flow of a QI-ML algorithm [96].

network-born machines, which leverage quantum mechanics to capture data correlations more efficiently than classical models, potentially enhancing generative task performance. The authors of [100] highlighted that scaling up quantum systems will increase errors, and generative AI can help devise robust error correction schemes. In [101], generative AI was used in social media analysis and interactive learning to generate images from language inputs and evaluate content relevance via fuzzy similarity scores. QI generative models could enhance this by enabling advanced pattern recognition and data synthesis through quantum computational advantages.

ii. ***Quantum Federated Learning:*** It is a decentralized approach that enables multiple clients to train a shared model while maintaining data privacy collaboratively. Each client processes its data and sends updates to a central server, aggregating them to improve the global model. Clients evaluate a variational quantum algorithm, accommodating varying data distributions and enhancing the model's robustness and accuracy in classification, combinatorial optimization, and quantum chemistry. In [102], a digital twin-assisted quantum federated learning algorithm was proposed for real-time training of personalized NNs across hospitals to maintain data privacy and enhance accuracy. Similarly, a flexible quantum federated learning method was developed specifically for satellite-ground communications in [103], achieving greater communication efficiency and computational gains compared to classical federated learning.

Furthermore, [104] highlighted the difficulty in copying quantum data and emphasized the necessity of a collaborative framework to aggregate data of different quantum machines. They proposed a robust quantum federated learning framework that performed well with a significant proportion of noisy data. Similarly, the quantum federated learning framework proposed in [105] effectively manages non-independent and identically distributed data, addressing challenges like unbalanced training frequencies through efficient communication protocols. Local models generate predictions, and the server creates a shared model that optimizes each local model. Model gradients are encrypted before transmission to ensure data privacy. Clients then update their local parameters and repeat the training process until convergence. Regarding benchmarks, quantum federated learning demonstrates significant advantages over classical centralized methods, especially in handling large, privacy-sensitive datasets. Additionally, kernel encoding methods for quantum data enhance data representation efficiency by requiring fewer qubits than classical techniques.

iii. *Quantum Neural Networks (QNN):* It utilizes qubits and quantum gates, which enable superposition and entanglement. Hence, multiple states can be explored simultaneously, improving optimization efficiency and introducing parallelism. In contrast, the classical NN deals with deterministic states, and its parallelism is constrained by the capabilities of classical hardware [106]. In [107], a hybrid quantum deep NN was proposed to enhance indoor localization accuracy through fingerprinting. The model incorporated gradient descent for optimization and could handle complex data while training on a small dataset with an accelerated training procedure. The scheme considered standalone measurements and a fusion of received signal strength and time of flight datasets. The hybrid quantum deep NN was evaluated in a real-time environment, and it achieved the lowest localization error compared to different benchmarks, such as Euclidean-based K-nearest neighbors, classical deep NN, and classical deep NN with dropout. QNNs are frequently employed in various scenarios, including communication [108], clustering [109], [110], security [111], [112], and user experience [113].

iv. *Quantum-Inspired Support Vector Machine:* It is a supervised learning algorithm for classification and regression that finds the optimal hyperplane to separate data points within a high-dimensional space. In this context, the authors of [114] proposed a QI counterpart of support vector machine that incorporates an improved fast sampling technique to sample the kernel matrix efficiently. The labeled data is transformed into an arborescent data structure, allowing for logarithmic time sampling of vectors. This enables classification with an arbitrary success probability in logarithmic time relative to the data dimension and the number of data points. The analysis showed the potential of an exponential speedup in classification as compared to the classical support vector machine.

v. *Quantum-Inspired Reinforcement Learning:* Classically, RL is modeled as a Markov decision process, which involves an agent learning to make decisions through interaction with its environment. The agent aims to maximize cumulative rewards by exploring and exploiting actions based on observed states through trial and error. However, classical methods face challenges in exploring large state-action spaces due to the curse of dimensionality. On the contrary, the QI-RL enhances learning efficiency through quantum parallelism. In [116], a QI-RL approach was proposed for optimized wireless VR streaming within industrial IoT systems. It involved initializing quantum actions, executing observed actions, updating Q-values based on rewards, and applying Grover's iteration to amplify successful actions. The proposed framework significantly enhanced average stalling rate and energy consumption compared to benchmarks such as static scheme, joint optimization without content correlation, and greedy offloading with random allocation. Furthermore, the QI-RL algorithm showed faster convergence than the Q-learning algorithm by exploiting quantum search instead of using an unstructured exploration and exploitation. Due to their improved efficiency and enhanced learning capabilities, QI-RL has been applied frequently in diversified scenarios, including IoV [117]–[120], [122], smart trains [121], UAV path planning [123], [126], wireless sensor networks [115] and wireless VR [124].

vi. *Quantum-Inspired Residual Tensor Train:* It is conventionally used for tensor decomposition. It enables efficient representation and compression of high-dimensional data through multilinear residual information. This approach enhances computational efficiency in ML tasks. However, the modeling of multilinear correlations is considered challenging due to computational and memory requirements. The tensor train was initially developed for many-body quantum systems to create multilinear models by embedding input features into a high-dimensional Hilbert space.

The authors of [125] proposed a robust QI residual tensor train model incorporating skip connections to learn multiple multilinear feature correlations. The proposed model was applied to practical examples with limited data, such as average localization error and Boston housing datasets. The average localization error dataset was used as an application in wireless sensor networks. It comprised four features: anchor ratio, iteration count, node density, and sensor transmission range. The QI residual train showed superior performance in terms of R2 score and root mean square error compared to different benchmark schemes, including linear regression, polynomial regression, ridge regression, polynomial ridge regression, lasso regression, polynomial lasso regression, support vector regression, and multilayer perception. The QI approach showed a higher time and memory complexity due to increased parameters for additional connections. It showed immunity to exploding and vanishing gradient problems observed in the classical tensor train models.

Table VII summarizes the advantages and disadvantages of ML-based QI optimization approaches. It provides valuable insights into their strengths and limitations across diverse scenarios, facilitating the assessment of their suitability for different optimization tasks.

TABLE VII
KEY INSIGHTS INTO THE MACHINE LEARNING-BASED QI OPTIMIZATION TECHNIQUES.

QI Technique	Ref.	Remarks
QI Generative AI	[100], [101]	• Quantum computing enhances generative AI model training. • It accelerates data preprocessing. • Quantum computational intelligence improves human-machine interaction.
Quantum Federated Learning	[102]	• Enables accurate training without local data while preserving privacy. • Robust against single and mixed quantum noise.
Quantum Neural Networks	[106]–[108], [113]	• It has a lower complexity as compared to conventional method. • Enables parallel training, simultaneously updating the weights. • Significantly enhances the accuracy of indoor localization.
QI Support Vector Machines	[114]	• The approach does not require quantum resources. • Sampling technique enables exponential speedups. • Enables arbitrary success probability in logarithmic time for data dimensions. • Performance should be explored on high-rank datasets without approximations.
QI Reinforcement Learning	[115]–[124]	• Quantum search enables faster learning and convergence than classical method. • Adapts rapidly to highly dynamic and complex environments such as IoV. • Coordinated unitary transformation allows concurrent state updates. • Superior rewards with reduced delay, energy consumption and CPU cycles. • Optimizes relay and transmit power for high throughput and energy efficiency.
QI Residual Tensor Train	[125]	• Ensures reliable performance on problems with limited data. • Solves vanishing and exploding gradient issues seen in classical counterparts. • Capable to build robust classification boundary in high-dimensional space.

C. *Quantum-Inspired Specialized Approaches:*

These methodologies also leverage quantum mechanics principles to provide specialized solutions for specific tasks across various domains. This subsection presents an overview of underlying approaches identified in the filtered literature of QI optimization and highlights their distinctive strategies to address complex optimization problems.

i. ***Quantum-Inspired Game Theory:*** Classically, game theory provides an analytical framework to analyze competitive situations where the outcomes depend on the actions of multiple players. Key elements include players, strategies, payoffs, and Nash equilibria, where no player can benefit from unilaterally changing their strategy given the strategies of others. The authors of [127] analyzed the quantum Colonel Blotto game, where players allocate resources across multiple battlefields to maximize control. They modeled jamming in quantum communication networks due to the susceptibility to interference and jamming, which can disrupt communication. The players utilized quantum strategies, such as superposition and phase manipulation, to enhance tactical options compared to classical strategies. The quantum model enhanced classical methods by enabling jammers to add amplitude and phase noise. Additionally, the complexity of determining Nash equilibria increased significantly with the quantum approach as the number of potential strategies increased exponentially.

ii. ***Grover Adaptive Search:*** It utilizes classical probabilistic and heuristic methods inspired by the principles of Grover's algorithm; however, it does not achieve the quadratic speedup that Grover's quantum algorithm provides. The original Grover's search algorithm employs qubits and quantum gates to amplify amplitude, resulting in a quadratic speedup for finding a target in an unstructured database. Grover's adaptive search algorithm can achieve significant speedup for quadratic and higher-order unconstrained binary optimization problems, reaching a query complexity of $O(\sqrt{2^{n_b}})$ compared to the classical exhaustive search, which requires $O(2^{n_b})$ operations, where n_b refers to the number of binary variables [128]. The Grover quantum search was applied iteratively in [129] to identify transmitted codewords swiftly.

iii. ***Quantum Variational Algorithms:*** These algorithms combine classical and quantum computing resources to solve complex optimization problems. They include variational quantum eigensolvers, which minimize the Hamiltonian's expected value; quantum approximate optimization algorithms, which address combinatorial optimization iteratively; variational quantum classifiers, which classify patterns using parameterized circuits; and hybrid variational algorithms, which tackle multi-objective problems. Each algorithm leverages quantum circuits and classical optimizers to address computationally demanding tasks. Fig. 17 presents the flowchart of generic quantum variational algorithms, highlighting an iterative process of parameter optimization and loss evaluation to refine a quantum model until convergence.

In [132], the quantum approximate optimization algorithm was employed to solve the NP-hard combinatorial optimization problem of maximum likelihood detection. The algorithm encoded the problem into a Hamiltonian framework and used parametrized quantum circuits and variational parameters. The quantum adiabatic evolution aided in preparing the initial state and achieving the ground state of Hamiltonian. The complexity of the quantum approximate optimization algorithm depends

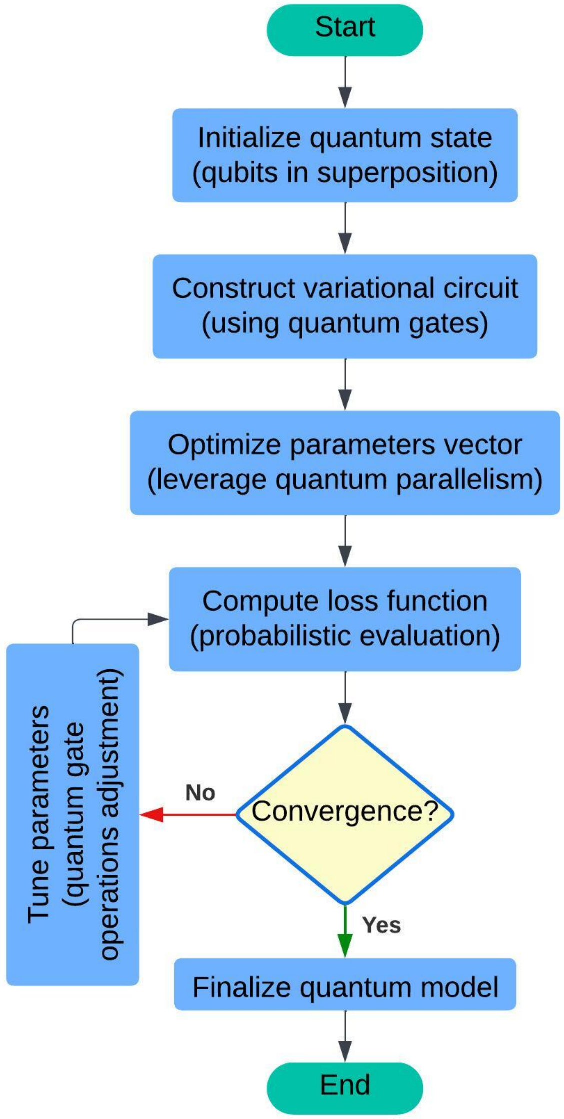

Fig. 17. General flow of a quantum variational algorithm [130].

upon the number of quantum gates, and it showed comparable performance to classical maximum likelihood and minimum mean squared error detectors in terms of bit error rate. Similarly, variational quantum eigensolver with constraints can optimize the Lagrangian function by employing a hybrid quantum-classical approach to solve constrained binary optimization and large-scale linear programming tasks [133].

Table VIII summarizes the advantages and disadvantages of specialized QI optimization approaches. It provides valuable insights into their strengths and limitations.

D. *Quantum-Inspired Optimization: Techniques and Insights*

The QI approaches have been applied to a multitude of domains and provide advantages such as lower complexity and faster convergence [134], [135], necessary to meet the demands of 6G networks. This section discussed the key QI techniques in the filtered dataset of papers that address the radio resource optimization issues, explains different QI optimization approaches to tackle complex optimization problems. For example, the digital annealer can solve complex combinatorial problems with large datasets [136]. The hybrid quantum-classical computing frameworks can alleviate challenges in resource optimization [137], and Gurobi's mixed integer programming models effectively solve complex scheduling problems [138]. The power network optimization and reconfiguration are also considered through quantum-classical hybrid approaches [139] and [140]. Hybrid classical-quantum optimization: Similarly, [141] also solves a QUBO problem by employing a hybrid classical-quantum approach that outperformed the classical simulated annealing method. The semiconducting magnetic energy storage systems can be used for global search in optimization problems by employing the modified QPSO technique [142].

Table IX provides an overview of QI techniques, detailing a specific focus on radio resource optimization and the frequency with which each technique is applied to various problem types. Notably, QI techniques based on generative AI, support vector machines, residual tensor train, and game theory have not been utilized for radio resource optimization tasks. In contrast, the QPSO and QI-RL algorithms have seen frequent application, with both used 10 times each. Figs. 18 and 19 show a breakdown of the annual usage of QPSO and QI-RL, respectively. QPSO has been applied in diverse scenarios including the optimization of channel assignment, edge devices, spectrum sensing, localization, and UAV-assisted networks. QI-RL has been utilized for optimizing edge devices, UAV-assisted networks, and power control.

TABLE VIII
KEY INSIGHTS INTO THE SPECIALIZED QI OPTIMIZATION TECHNIQUES.

QI Technique	Ref.	Remarks
QI Game Theory	[127]	• Quantum strategies efficiently counter jamming with effective mechanisms. • Complexity grows exponentially with servers due to the "Curse of Dimensionality."
Grover Adaptive Search	[126], [128], [131]	• Better balancing of exploration and exploitation as compared to classical counterparts. • Quadratic speedups in solving higher-order unconstrained binary optimization tasks. • Significantly lower number of qubits and query complexity. • Higher number of quantum gates required.
Quantum Approximate Optimization	[132]	• Scalable to solve combinatorial problems. • High memory and computational power requirements.

TABLE IX
THE DETAILS OF DIFFERENT QI APPROACHES USED IN LITERATURE TO SOLVE THE RADIO RESOURCE MANAGEMENT PROBLEMS. THE USE CASES ARE CATEGORIZED ACCORDING TO SECTION V. A: CHANNEL ASSIGNMENT, B: EDGE DEVICES, C: RECONFIGURABLE INTELLIGENT SURFACES, D: SPECTRUM SENSING AND LOCALIZATION, E: UAV-ASSISTED NETWORKS, AND F: POWER CONTROL.

Quantum-Inspired Optimization Techniques	**References**	**Radio Resource Optimization Focus**						**Frequency**
		A	B	C	D	E	F	
Quantum-Inspired Meta-Heuristics								
QI Ant Colony Optimization	[58]		✓					1
Quantum Clone Whale Optimization	[60]		✓					1
QI Evolutionary Algorithm	[61], [62]		✓				✓	2
QI Genetic Algorithm	[64]		✓					1
Quantum Particle Swarm Optimization	[65]–[74]	✓	✓		✓	✓		10
QI Seagull Optimization	[76]					✓		1
QI Termite Colony Optimization	[77]						✓	1
QI Backtracking Search	[78]						✓	1
QI Bald Eagle Search	[79]			✓				1
QI Gravitational Search	[80]		✓					1
Quantum Annealing	[81], [82], [85]	✓	✓	✓				3
QI Social-Emotional Optimization	[87]	✓						1
QI Tabu Search	[88]				✓			1
Quantum-Inspired Machine Learning								
QI Generative AI	[100], [101]							0
Quantum Federated Learning	[102]		✓					1
Quantum Neural Networks	[106]–[108], [113]	✓	✓		✓		✓	4
QI Support Vector Machines	[114]							0
QI Reinforcement Learning	[115]–[124]		✓			✓	✓	10
QI Residual Tensor Train	[125]							0
Quantum-Inspired Specialized Approaches								
QI Game Theory	[127]							0
Grover Adaptive Search	[126], [128], [131]	✓	✓		✓			3
Quantum Approximate Optimization	[132]	✓						1

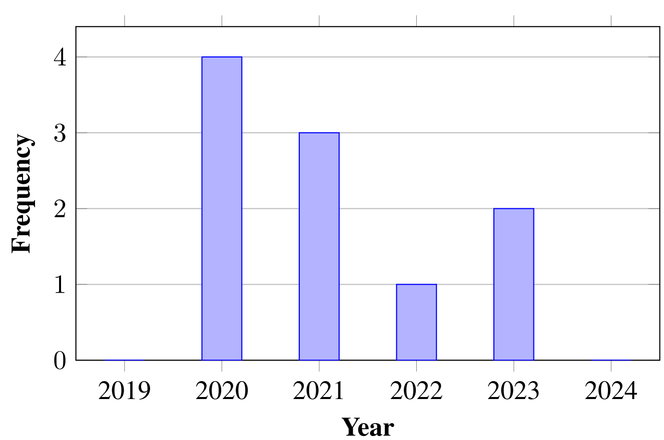

Fig. 18. Frequency of QPSO algorithm over the years.

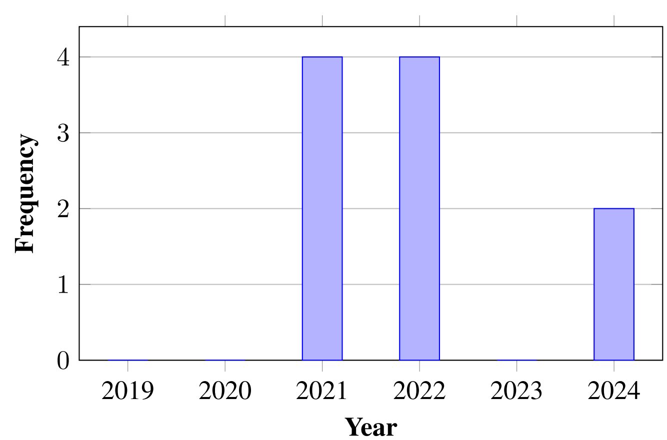

Fig. 19. Frequency of QI-RL over the years.

V. QUANTUM-INSPIRED RADIO RESOURCE OPTIMIZATION IN 6G NETWORKS

This section comprehensively explores the QI techniques applied to radio resource optimization within the context of 6G networks, systematically categorizing the existing body of research. Fig. 20 illustrates the categorization of different aspects of communication networks where the QI approaches of the filtered dataset have been applied. These include channel assignment, edge devices, power allocation, RIS, spectrum sensing and localization, and UAV-assisted networks. The papers of each category are reviewed to extract the objectives, constraints, solution techniques, and key contributions inherent

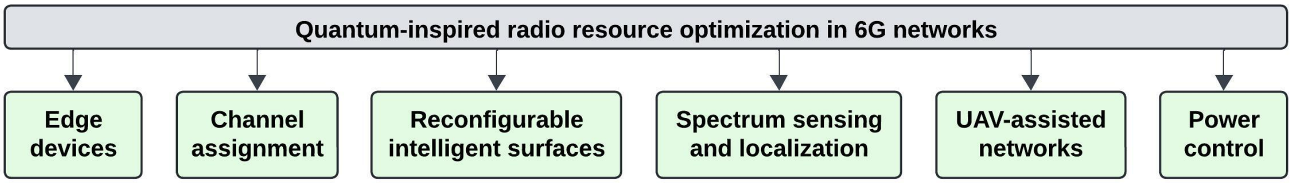

Fig. 20. Application areas of QI optimization in communication networks.

in the respective studies. Additionally, this section rigorously identifies existing research gaps and synthesizes the lessons learnt, thereby offering a thorough understanding and delineating future research trajectories in this evolving domain. Fig. 21 illustrates a comprehensive communication system with vertical segments, where each aspect requires distinct resource optimization solutions depending on the identified categories of radio resource optimization.

A. *Quantum-Inspired Channel Assignment*

Channel assignment refers to allocating frequency bands or time slots to devices in the communication network. It facilitates efficient and interference-free communication while optimizing the limited spectrum. Fig. 22 depicts a wireless networking scenario where diverse edge devices, such as mobile users, IoT sensors, UAVs, and smart computing elements, connect to base stations. It emphasizes the need for an efficient channel assignment scheme to meet heterogeneous requirements of these devices, ensuring low latency, high reliability, and massive connectivity in 6G networks.

The QI methods can enhance classical channel assignment solutions by drawing inspiration from quantum computing concepts, such as superposition, entanglement, and quantum parallelism. The concurrent exploration of broader solution spaces can yield optimal channel assignments. QI algorithms such as quantum annealing, genetic algorithms, quantum walks, and ML adaptations can offer novel solutions to complex dynamic communication networks. Leveraging QI methods on classical computers can augment the effectiveness of channel assignment algorithms and offers a viable path forward, although practical quantum computation is in its early stages. Channel assignment techniques require tailoring to address the unique challenges that quantum communication networks pose, including dealing with the quantum nature of information and the corresponding security requirements. This subsection examines papers that address channel assignment optimization using QI techniques.

Considering the inherent limitation of radio spectrum resources, the increasing number of user terminals and the surging demand for mobile traffic necessitates optimization of

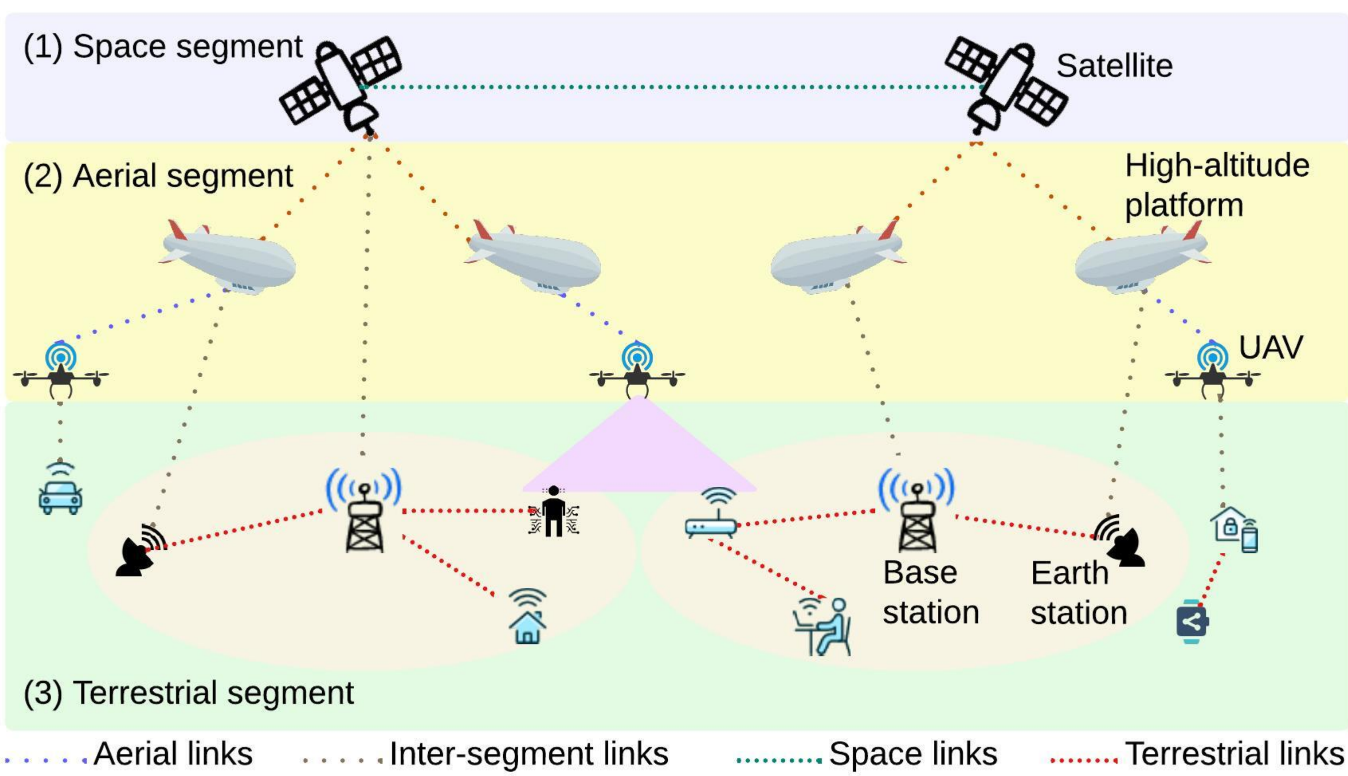

Fig. 21. Different segments of the communication network requiring resource management.

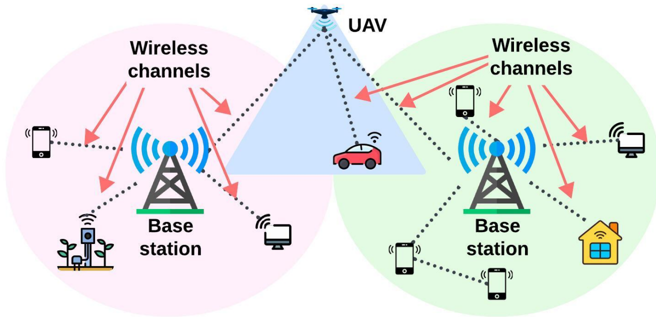

Fig. 22. Wireless network scenario requiring optimal channel assignment.

wireless channels. The wireless channel assignment is an NP-hard problem conventionally solved through the one-hot encoding of channel indices. The authors of [128] formulated this problem as a higher-order unconstrained binary optimization problem by considering the binary ascending and descending encoding of channel indices and solved it through the Grover adaptive search algorithm with a quadratic speedup in identifying the solution. The objective was to minimize interference between access points. The constraints for wireless channel assignment encompass two key aspects. Firstly, each access point is restricted to utilizing only a single channel, ensuring no channel sharing among access points. Secondly, it is crucial to avoid the usage of nonexistent channels, thereby limiting the assignment to available and valid channels. The analysis showed that the proposed approach employing descending encoding requires a significantly lower number of qubits and query complexity.

Similarly, efficient resource optimization in a heterogeneous networking scenario is necessary due to the varying quality of service requirements imposed by different operators. In this regard, the authors of [66] proposed a quality of service-aware virtualization resource optimization mechanism for converged network architecture and employed the QPSO algorithm to solve the global optimization problem. The objective was to minimize tuning overhead and the load balancing ratio. The constraints included ensuring that the traffic load on each wavelength does not exceed its maximum capacity, assigning at least one wavelength to each virtualization heterogeneous cloud radio access network, maintaining the unchanged state of optical network units within each heterogeneous cloud radio access network, and ensuring that each activated wavelength was assigned at least one optical network unit. A penalty function was used to transform the constrained optimization problem into an unconstrained one. The benchmarks considered in this paper include order acceptance and scheduling, and workflow scheduling algorithm.

In [132], the maximum likelihood detection of binary symbols over a MIMO channel was encoded into the Hamiltonian operator. The maximum likelihood detection task was transformed into a multi-level quantum approximate optimization algorithm circuit, and its analytical expression was derived. It was a combinatorial NP-hard optimization problem of selecting the most likely transmitted signal from the dataset. The performance of the proposed quantum approximate optimization algorithm-based maximum likelihood detector depended on the graph's structure associated with the Hamiltonian function. The benchmarks used for comparison included classical and minimum mean square error detectors.

In [81], the authors transformed the wavelength assignment task into a graph coloring problem and solved it through the QUBO algorithm by identifying the spins that minimize energy. The coherent Ising machine solver was used to solve the combinatorial NP-complete optimization problem, and Lagrange multipliers reduce hyperparameters. The two objectives of the proposed technique included reducing the number of QUBO problems to be solved and introducing robustness against finding suboptimal solutions. The constraints entailed assigning each vertex to only one wavelength and ensuring that two adjacent vertices are not assigned the same wavelength. The benchmarks considered for comparison included Gurobi optimization software, GNU linear programming kit-mixed integer programming solver, largest degree first, and original QUBO. Experimentation was performed on a synthetically generated dataset comprising 900 randomly generated graphs, with nodes ranging between 10 and 100.

The authors in [87] devised an optimized power control technique for the massive MIMO uplink using a QI social-emotional optimization algorithm. It developed on assuming a single-cell massive MIMO system with BS having hardware impairments. The objective was to perform antenna selection effectively and solve the multi-constrained non-convex power allocation problem that maximizes energy and spectral efficiency. There were constraints on the power and data rate of each user. The proposed technique leveraged quantum evolution and social-emotional optimization to achieve strong searching ability and fast convergence. The complexity of the proposed approach was $O(i(5P_s + 3P_s n))$ where i, P_s, and n refer to iterations, population size, and maximum dimensional number, respectively. The benchmarks used for comparison included social-emotional optimization, fractional programming, and maximum power allocation.

UAV-assisted cellular networks were considered for adaptive bit-rate video streaming by performing the joint optimization of caching and user association in [61]. The proposed QI evolutionary algorithm was used iteratively to solve the formulated NP-hard problem while aiming to minimize the total content delivery delay. Several constraints included the total size of video chunks cached at each UAV being lower than the UAV's caching capacity, each user associating with only one UAV, and the optimization variables being binary. The benchmark algorithms used for comparison included solely QI evolutionary algorithm-based techniques for channel assignment and user association, as well as random channel assignment and user association techniques.

Cell-free MIMO systems can aid in coverage extension without cell boundaries. Therefore, authors of [108] proposed a quantum NN-based algorithm for optimized assignment of transmitter-user in cell-free MIMO systems. The objective was to enhance the minimum achievable sum rate among users with a fair distribution of resources. There was a constraint on the precoding vector, which enables optimized transmission of signals and manages interference. A Rayleigh channel with

TABLE X
CHANNEL ASSIGNMENT USING QI OPTIMIZATION TECHNIQUES.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[61]	Minimize total content delivery delay	Caching capacity and binary optimization variables	NP-hard, non-linear integer programming	QI evolutionary algorithm	The content delivery delay minimization problem is formulated as a non-linear integer programming optimization problem, and QI evolutionary algorithm is proposed to obtain optimal caching and user association.
[66]	Minimize tuning overhead and load balancing ratio	Traffic load does not exceed wavelength's capacity, and virtualization heterogeneous cloud radio access network is assigned at least one wavelength	Mathematics model	QPSO and quality of service mapping algorithm	The paper formulated the wavelength assignment problem as a mathematical optimization model and solved it using a QPSO algorithm. It also proposed a quality-of-service mapping algorithm to allocate 5G traffic to priority queues in a time and wavelength division multiplexed passive optical network. It introduced a resource scheduling algorithm for the downstream traffic.
[81]	Reduce count of QUBO problems and avoid suboptimal solutions	Each vertex is assigned to only one wavelength and two adjacent vertices are not assigned the same wavelength	NP-hard	QUBO, QI annealing	In this paper the NP-hard, routing and wavelength assignment problem was solved by simulating coherent Iising machine-based QI optimization solver.
[108]	Maximize the minimum achievable sum rate	Precoding vector	Transmitter-user assignment	Quantum NN	The paper proposed a quantum NN for fair allocation of communication resources.
[128]	Optimal channel assignment	Communication resource	NP-hard	Grover adaptive search algorithm	The NP-hard problem is formulated as a hybrid unconstrained optimization problem by considering channel indices as binary numbers, and the specific quantum circuit is created, while deriving exact number of qubits and quantum gates required by Grover adaptive search.
[132]	Selecting most likely transmitted signal from the dataset	Number of transmit symbols from discrete set	NP-hard, Maximum likelihood detection	Multi-level quantum approximate optimization algorithm	The paper aimed at maximum likelihood detection of binary symbols transmitted over MIMO channel.
[87]	Maximize energy and spectral efficiency	Power and data rate of each user	Non-convex	QI social-emotional optimization	The paper aimed to jointly optimize antenna selection, power allocation, and QoS constraints for energy-efficient massive MIMO uplink networks through QI social-emotional optimization algorithm.

variations in mean value was considered for the performance of simulations between the average sum rate and transmission signal to noise ratio. The complexity of the proposed scheme was $i.r$, where i and r represent the number of iterations and single gradient calculation, respectively.

Table X illustrates the details of the reviewed papers, including problem objective identification, considered constraints, type of problem, solution approach, and remarks related to the contribution of research work.

Lessons Learnt: The comprehensive literature review of the dataset has aided in identifying several significant gaps, paving the way for future research in channel assignment techniques. Various techniques for advancing research on radio resource optimization concerning channel assignment can be summarized as follows:

- ***Minimizing Quantum Gates:*** Efforts to minimize the number of quantum gates are identified as a future direction, mainly due to the increased quantum gates requirement outlined in [128].
- ***Energy Efficiency in Connectivity:*** Providing high en-

ergy efficiency in scenarios with massive connectivity poses a significant challenge, as highlighted in [66].

- ***Heterogeneous Computing:*** The proposed technique can undergo revision and evaluation to enhance applicability in heterogeneous computing scenarios, including multi-core central and graphics processing units [81].
- ***From Single-Cell to Multi-Cell:*** There is potential for extension of the proposed single-cell technique to more complex environments such as massive MIMO with imperfect channel state information in multi-cell settings, integrating cognitive radio and co-time co-frequency fully duplex systems [87]. Furthermore, the joint analysis of UAV deployment, resource optimization, content caching, and user association for adaptive bit-rate video streaming can be performed [61].

B. Quantum-Inspired Optimization for Edge Devices

Fig. 23 depicts various edge devices, including base stations, coverage extension drone, IoT sensors, IoV and mobile users. It emphasizes the need for efficient radio resource optimization and task offloading to overcome computational power limitations in edge platforms and ensure seamless performance in interconnected environments. Therefore, efficiently managing constrained resources such as bandwidth, computational power, energy, and navigation is essential. However, optimizing resources in these networks presents numerous challenges, including complexity stemming from bandwidth optimization, complex data, device heterogeneity, edge and fog computing, limited energy resources, mobility in IoV, varied quality of service requirements, and security and privacy concerns. The QI optimization techniques offer a promising approach by exploiting entanglement, parallelism, and superposition to explore multiple potential solutions concurrently, thus enhancing systematic performance in terms of efficiency and reliability. These techniques are adaptable to dynamic environments, making them favorable for optimizing resources in IoT and IoV systems with time-varying conditions. This subsection provides a review of the papers focusing on the QI IoT and IoV resource optimization.

Swarm intelligence and evolutionary algorithms are commonly employed for NP-hard task scheduling problems. The complex network topologies and diverse applications make task scheduling in cooperative environments challenging. The authors in [68] formulated the task device-edge-cloud cooperative scheduling problem through mixed integer non-linear programming and proposed a QPSO based approach to identify the global best solution. The objective was to maximize the number of tasks while employing constraints on deadline and resource capacity. The proposed technique was compared with benchmark heuristic methods such as earliest finish time first, least average completion time, least slack time first, PSO, genetic algorithm, and variants of the QPSO algorithm. Performance metrics used in the paper included the number of finished tasks, computing length completion, input data size processed, computing resource utilization, cost efficiency, and time consumed in decision-making.

The constrained resources of mobile edge computing devices can be a bottleneck in delivering high-quality services to users, and the mobility and network state fluctuations can impose adverse effects on service quality. Hence, [67] presented a service migration scheme from initial nodes to other edge nodes while minimizing delay and energy consumption. The problem was formulated as a binary programming problem, and a particle swarm-based service migration scheme was proposed to provide better services. The proposed scheme developed a queuing delay prediction algorithm, a delay-aware computation resource allocation algorithm, and a modified QPSO. The queuing delay prediction algorithm identified average and individual task queuing delays, the delay-aware computation resource allocation algorithm performed dynamic allocation of computational resources, and the modified QPSO performed an efficient search that avoids local extreme point constraints. The motion of users was simulated through random walks. The system performance was evaluated before and after service migration for enhanced mobile broadband and URLLC tasks for the proposed and benchmark techniques, such as QPSO and the greedy algorithm [67].

A mixed integer non-linear programming problem for resource optimization was formulated in [65] to maximize energy efficiency. The constrained optimization problem was transformed into an unconstrained problem through the penalty function. The suboptimal solution was obtained using the QPSO algorithm. Several constraints include the offloaded task completion time of different users not exceeding the total computation delay, the energy consumption of different users being less than the energy harvested, transmitting power having an upper bound, and a distance decision for energy harvesting. The benchmarks used for comparison include local-edge-auxiliary-transfer, local-edge-auxiliary, local-edge, local-auxiliary, and local-only. However, this technique considered single relay unit for the transfer of computational tasks.

The relay and transmission power control for wireless sensors in IoT is crucial due to the continuous reduction in sensor size. The authors in [115] proposed QRL-based joint optimization of relay and transmission power selection using Grover's iterative method. The objective was to maximize the throughput of each link in the system, subjecting to minimized energy consumption. The system model incorporated constraints on transmission power in each time slot, energy flow, data rate, data buffer overflow, and boundary conditions on allocated power. The relay and transmission power selection has been modeled as a Markov decision process, and QRL was applied for optimization. The channels were assumed to be quasi-static block Rayleigh fading where the channel gain remains constant within one timeslot but varies over different timeslots. The benchmark schemes used for comparison include a deep RL-based relay selection scheme, a quantum-enabled RL framework for joint optimal relay and transmit power selection, and random selection. The performance metrics included throughput, energy consumption, and utility.

Air-borne nanotechnology-based sensors operating over terahertz bands in vehicular networks necessitate optimizing energy efficiency and wireless power transfer due to battery constraints. Quantum-behaved and improved discrete particle swarm-based algorithms were proposed in [69] to maximize energy efficiency. The non-convex mixed integer non-linear

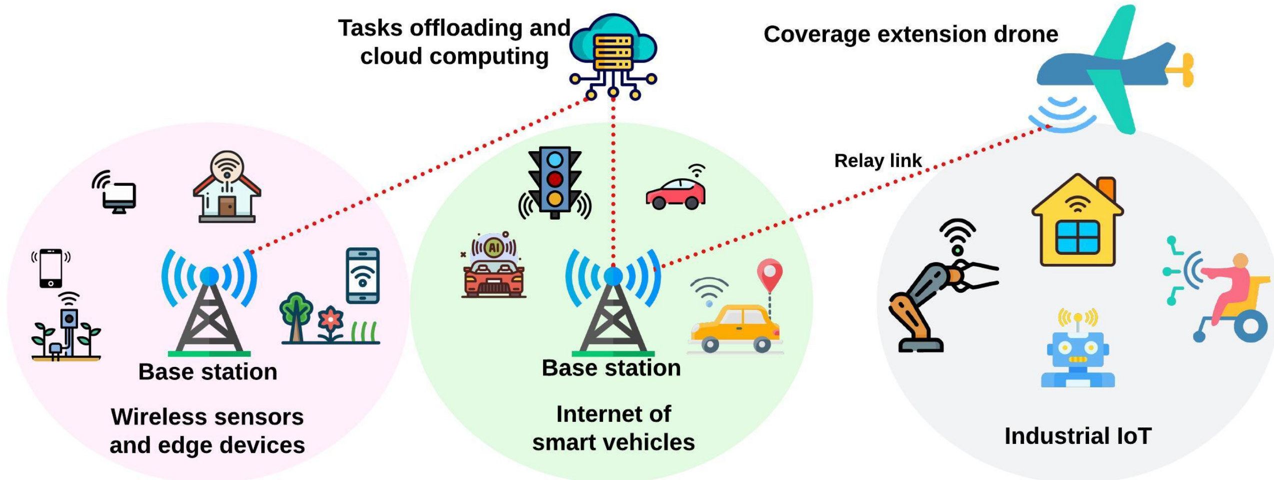

Fig. 23. Wireless network requiring optimal task offloading for edge devices.

programming optimization problem was converted into a series of energy efficiency resource optimization tasks over different time slots using the equivalent transformation method. The constraints included the orthogonality of terahertz channels and power. The benchmarks used for comparison include quantum-behaved particle swarm-based energy efficiency optimization and PSO. The performance metrics included energy efficiency, convergence time, and effective constraint handling.

Addressing battery size constraints and growing computational demands on IoT sensors complicates extending the network lifetime. Therefore, [58] proposed an undirected graph-based energy optimization model for IoT environments, where sensor nodes and their wireless links were represented as vertices and edges, respectively. This NP-hard QI green communication framework aimed to minimize the energy cost of relaying paths from a source node, subject to qubit state probability constraints. The qubit population generated binary solutions with a repair technique for constraint violations. Performance benchmarks included quantum-based and classical ant colony optimization methods, focusing on quantum representation, measurement, and rotation angle. The performance metrics included network lifetime, node energy consumption, and average node residual energy.

Furthermore, IoT devices are crucial in achieving maximum automation and enhancing efficiency. However, the reliability of the IoT environment can be compromised by data errors, missing segments, and falsified perceptions. Therefore, the authors in [143] proposed a novel quantum computing-inspired IoT optimization technique to maximize the data accuracy by acquiring the data in quantum form. Two parameters, such as sensors in the vicinity and optimal sensor space, were used to identify IoT-sensor space. The aim was to determine optimal sensor space that maximizes overall stato-dynamic sensing ability. This technique eliminated distant nodes prone to falsified data generation. The constraint on sensors in the vicinity reduced the sensor space for every object. The conventional optimization task was non-polynomial with an asymptomatic complexity of $O(2^L)$, where L is the number of qubits. The quantum formalization reduced this optimization problem into a bounded-error quantum polynomial time class with running time complexity of $O(L)$, searching time of $O(X)$, and time complexity of $\Omega((L^3 log(1/\epsilon))/log(L))$, where X and ϵ are complex matrix of size $2L \times 2L$ and computing error, respectively. Particularly, the search time complexity was reduced from $O(2^X)$ to $O(X)$ by incorporating quantum computing. The proposed technique was evaluated through three key performance indicators: data accuracy, cost, and temporal efficiency. A total of 11 crucial parameters, encompassing range, span, accuracy, and others, were considered in a stochastic environment to ensure optimal real-time delivery of IoT services. The proposed technique was compared with genetic bio-inspired optimization, differential evolution, and PSO. The performance evaluation metrics included temporal efficiency, statistical analysis, and reliability.

The productivity of an industrial IoT environment can be improved through wireless VR, enabling workers to engage in industrial activities flexibly and remotely. In this context, [116] formulated a joint optimization problem considering task offloading, computing, and spectrum resource optimization by incorporating content correlation between VR equipment, channel variations, and VR quality of experience. Dual approximation was employed to transform the problem into a Markov decision process, and an online QI-RL algorithm was designed to identify optimal policy and apply quantum parallelism for dimensionality reduction. The objective was to reduce the energy consumption of VR devices and ensure a smooth experience. There were constraints on the spectrum, computing resources, edge computing-assisted access point computational capacity, buffer size, and quality of experience. The system model considered a fiber link between edge computing-assisted access points and VR service providers. The performance of the proposed scheme was evaluated in comparison to various baseline schemes such as static, joint optimization without content correlation, and greedy offloading with random allocation. The performance evaluation metrics included energy consumption and average stalling rate.

The emerging applications undoubtedly increase users' quality of experience in the IoV but also impose a significant computational load on resource-constrained vehicles. In [117], an edge intelligence-assisted model was designed that integrated WiFi-based mobile edge computing and 5G-based cloud computing. The communication and computation resource optimization scheme was formulated as a Markov decision process. The aim was to minimize average task processing latency. The proposed QI-RL method considered the resource optimization of an NP-hard non-convex problem as a quantum uncertainty problem. The aim was to minimize the long-term average time delay through joint optimization. Several constraints were considered, such as the mobile edge computing server's computational resources, BS's bandwidth, total task execution delay, transmission strategy, offloading strategy, energy consumption, and economic cost of resources. The convergence rate was minimized through quantum parallelism. The benchmark schemes used for comparison include local computing, random selection, Q-learning, QRL without mobile edge computing, and QRL without the cloud. The metrics used to evaluate performance include learning convergence and processing delay.

Furthermore, the heterogeneity characteristics must be considered to harness the benefits of network coding in terms of error control and throughput improvement. In [70], the problem of multi-user accessing tasks and a multi-layered service scheduling framework between users and control entities was formulated. A statistical fairness measurement model was constructed to ensure the end user's independence. The proposed scheduling scheme in a multi-user IoV environment was called dynamic resource optimization scheduling, where the scheduling service aimed to maximize the total utility of all the network coding sets. Furthermore, a coding cache queue control algorithm called QPSO and the proportional integral model collectively achieved the global optimal solution for active queue control. The constraints included service budget for the end user from the system and service execution time for the end user. The benchmark schemes used for comparison included minimum latency aggregation scheduling, balanced shortest path tree, round robin pairing and scheduling, distributed data aggregation scheduling algorithm, and fast data aggregation protocol. The key performance indices evaluated include fairness index, network throughput, packet loss rate, time slice allocation, service scheduling rate, average system response time, and average end-to-end delay.

Similarly, the large amount of data processing required in the IoV imposes a serious need for task offloading. Hence, the authors in [71] considered an NP-hard resource optimization problem of mobile edge computing-enabled IoV. The joint offloading QPSO was proposed to perform optimal task offloading and minimize the execution time. The crossover probability was defined to improve the searchability and convergence speed of the proposed scheme. The constraints included maximum tolerance time, continuously connected time, and system utility. Collaborative offloading was considered for remote cloud, edge servers, and vehicles. The proposed technique was compared with different benchmarks, such as classical PSO, local computing, vehicle-to-vehicle offloading, and vehicle-to-infrastructure offloading. The performance evaluation metrics included average energy consumption, average time delay, and normalized system utility.

The authors of [118] ensured energy-efficient intelligence retrieval through a non-fungible tokens-based green network intelligence scheme utilizing the orthogonal frequency division of multiple access links between vehicles and BS. The intelligent networking problem was formulated as a Markov decision process, where intelligence can be retrieved from BS, dedicated short-range communication, and BS relay. The constraints included bandwidth, payment decisions, acquisition mode decisions, obtaining intelligence from pre-stored nodes, acquiring each block only once, delay, and energy. The NP-hard joint optimization problem was solved through the QI-RL algorithm while aiming to maximize the long-term average revenue. The benchmarks used for comparison included hypertext transfer protocol-based retrieval schemes with/without cache and interplanetary file system-based schemes with random techniques. The metrics for performance evaluation included average reward and delays for the number of blocks and vehicles.

Considering the time-sensitivity of decision-making in connected and autonomous vehicles, the authors in [119] formulated a distributed vehicles selection problem according to energy, communication, computing, and quantification of intelligence as a many-to-many matching game. Gale-Shapely algorithm with a linear complexity was employed for the solution. Furthermore, spectrum resource optimization was formulated as a Markov decision process, and QI-RL was employed to identify the optimal policy. The QI-RL technique provided a good trade-off between exploration and exploitation. The Grover iterations aided in accelerating convergence and improving unordered search. A collective learning technique was proposed considering the many-to-many matching game and the QI-RL algorithm. The cooperative participants in the many-to-many matching game and the QI-RL technique included master participating vehicles, slave participating vehicles, and trusted participating roadside units. The benchmarks used for comparison included many-to-many matching with a random allocation technique and a random technique. The performance evaluation metrics included average delay and energy consumption.

The authors of [120] formulated an NP-hard joint optimization problem for non-fungible token-based distributed intelligence learning through a discrete Markov decision process. The QI-RL algorithm was employed to achieve fast convergence while considering constraints such as bandwidth, delay, and energy; only pre-stored nodes could provide intelligence, and each block was allocated only once. The benchmarks used for comparison included hypertext transfer protocol-based retrieval without cache, hypertext transfer protocol-based retrieval with cache, and random interplanetary file system-based retrieval.

The IoV can be considered a fog computing paradigm operating in an uncertain environment, demanding timely and intelligent decision-making. In this regard, the authors of [131] proposed a quantum exploration-based multi-armed bandit technique for task offloading, aiming to minimize the expected unit cost. Suboptimal amplitude amplification was anticipated due to unresolved issues, such as the lack of a direct mapping between phase and probability amplitudes and the non-smooth nature of arbitrary cost estimates, especially in environments with incomplete feedback and variability. To address this, the proposed quantum learning-based exploration technique, called quantum amplitude amplification, modified the probability amplitudes of potential actions through Grover iterations before collapsing. These iterations entailed oracle queries and diffusion operations. Quantum measurement and superposition also leverage trade-offs between exploitation and exploration to enhance learning.

Furthermore, [121] proposed a QI risk-sensitive RL algorithm and train-edge-cloud collaborative computing technique for smart trains. This work considered the real-time computation of several intelligent tasks, such as driver fatigue and infrastructure fault detection. Hence, the objective was to minimize the task average processing latency of all computing tasks while incorporating the constraints on edge intelligence servers, such as risk, computing capacity, and maximum number of offloaded tasks. Two Q-value functions were employed to assess the cost and risk. Independent updates were performed, and the weighted sum of Q-value functions was utilized to decide the action. Hence, the aim was to jointly minimize the risk and maximize the edge intelligence server computing resource. The general Q-learning and RL-based ϵ-greedy algorithm were used as benchmarks for comparison.

The IoV is expected to cater to capacity concerns of multidimensional spaces comprising actuators, edge devices, and IoT. In [122], a multi-objective technique was proposed to enhance the sensor state's quantization ratio through its coverage range, efficiency, and node-centric metrics. The objective was task offloading while ensuring low latency and resource utilization efficiency through accurate node deployment. It was an NP-hard problem involving constraints of offloading decision rate, resource potentiality, channel, qubit state-error probability, and fusion variance. A QI online node consolidation algorithm was developed for a time-sensitive measurement reinforcement system with global positioning system (GPS) enabled active nodes and computation serving and relaying hypernodes. Latency concerns were tackled by performing node localization alongside an angle-based node position analysis using the T-gate. The simulation setup considered three qubits and a controlled combination of T-gates and H-gates to aid in mapping classical states. The benchmark schemes used for comparison included deep quantum routing agent, node deployment using quantum theory, quantum approximate optimization algorithm, and QI green communication framework for energy balancing in sensor-enabled cyber-physical systems. The performance metrics included consolidation error rate, iteration completion time, node selection error rate, offloading reduction, and service reliability.

A smart healthcare framework relies on the Internet of medical things and requires real-time training, efficient learning, and strong privacy protections. The authors of [102] proposed a digital twin-assisted quantum federated learning algorithm designed to enhance the training of variational QNN in various healthcare applications. The robustness of the proposed scheme was demonstrated through its superior performance in the presence of different types of quantum noise, including amplitude damping, depolarization, bit flips and phase flips.

The adaptive bit-rate algorithms are considered necessary to maintain a suitable quality of experience for different users while avoiding network congestion. The adaptive bit-rate techniques are classified into rate-based, buffer-based, and hybrid. Wei et al. have considered evolving quantum technology and proposed a QI dynamic adaptive streaming over hypertext transfer protocol technique in [82] to optimize the bit-rate of video streaming. The problem was formulated as a QUBO task considering the video quality, bit-rate change, and rebuffering events. The one-bit-rate constraint was considered in the formulation. A digital annealer was used to minimize the objective function. The proposed technique was evaluated for three scenarios: static, walking, and moving on a bus. BigBuckBunny video content was encoded into six different bit-rates and used for evaluation. The benchmarks used for comparison included rate-based, buffer-based, model-predictive control, and RL.

The mobile Ad hoc networks have a highly dynamic topology requiring an optimized routing scheme. In this regard, the authors of [64] proposed a quantum-genetic-based optimal link-state routing protocol augmented with a Q-learning strategy to maximize the selection of multi-point relay sets in such highly mobile networks. They optimized the routing decisions while considering node energy and link reliability. The proposed technique achieved superior performance regarding network control overhead, successful packet delivery, and end-to-end delay compared to benchmarks such as neighborhood state self-adaptive update and classical and cartography-enhanced optimal link-state routing protocols.

The authors of [60] proposed a high-performance clustering protocol-based on a quantum clone whale optimization algorithm. The clustering of integrated energy system-based wireless sensor nodes is an NP-hard problem due to several involved factors in obtaining the solution. The proposed algorithm utilized random search behavior within the global scope to explore the solution space, and each qubit needed to be updated according to the optimal individual after clonal expansion. Quantum probability amplitude and clonal expansion guide individuals in the population toward an optimal solution. There were constraints on intra-cluster distance and BS distance factor. The single-hop routing was adopted within a cluster, and single-hop or multiple-hop routing was considered for the BS. The proposed technique demonstrated superior accuracy and stability, with slightly increased complexity compared to several benchmark clustering schemes. The performance metrics included the largest number of surviving nodes because of considering the remaining energy of nodes and distance within the cluster.

Similarly, efficient clustering in wireless sensor networks has various benefits. These include reduced communication overhead, maximization, and increased network lifetime. However, the cluster heads are potentially exposed to heavy loads, which can cause premature death of cluster head nodes in a cluster and consequently reduce the lifetime of the wireless sensor network. Hence, cluster head load reduction is necessary for energy efficiency enhancement in wireless sensor networks. The system model proposed in [72] considered N nodes being grouped into disjoint clusters through K-means clustering. An approach was devised to optimize the cluster head node's load by formulating two objective functions to characterize the optimal part of the load of the cluster head, which shall be assigned to each node in the cluster and minimize the energy consumption of the nodes. There was a constraint on the cluster head's load distribution. A quadratic loss penalty function was incorporated to convert the constrained optimization problem into an unconstrained one, which enabled the application of a bio-inspired algorithm for optimization. The QPSO algorithm and game theory solved the optimization problem while considering a multi-hop energy transfer technique based on strong magnetic resonant coupling. The proposed QPSO and game theory-based techniques were compared with K-means and Leach algorithms.

Similarly, the operational mode assignment to wireless sensor nodes in wireless sensor networks is an NP-hard problem. Therefore, a Quadri-valent QI gravitational search algorithm was proposed in [80], which considered a heterogeneous computation framework combining the parallel processing capabilities of the central and graphics processing units. The work focused on identifying a network topology that maximized the network lifetime while considering connectivity constraints. The proposed technique enhanced the execution time through the quantum NOT gate and paralleling on the graphics processing unit, where the quantum NOT gate performed the NOT operation on qubits. The benchmark schemes used for comparative analysis included the binary genetic algorithm, binary PSO, improved binary quadri-valent gravitational search algorithm, and QI gravitational search algorithm. The performance metrics included speed, accuracy, network lifespan, and BS energy consumption.

The authors [113] proposed an adaptive virtualization for quantum services using NNs to enable reliable network virtualization and service replication under uncertainty. The objective was to devise a robust system for enhanced resource utilization and minimal delays to achieve customer satisfaction. Linear NNs were used for both virtualization processes and quantum state verification. The proposed technique showed a superior response ratio, processing rate, latency, utilization, and failure. The benchmarks used for comparison included stability and establishment QPSO, energy and performance-efficient task scheduling algorithm, and quantum-aware compositional scheduling framework.

Table XI illustrates various key details of the reviewed papers, including problem objective identification, the considered constraints, the type of problem, the solution approach, and the remarks related to the limitation of the proposed technique or an enhancement for the enrichment of the research work.

Lessons Learnt: The QI techniques can be utilized to further the research of radio resource optimization relating to the IoT and IoV. The research gaps and prospective research directions for IoT and IoV optimization are identified from the reviewed papers and listed as follows:

- ***Communication in Cloud and Edge Computing:*** The challenges in edge computing environments include excessive task processing delays and potential congestion stemming from centralized data centers [67]. Furthermore, the dynamic nature of pervasive edge computing presents obstacles to effective computation and communication [116]. To address these challenges, there is a growing emphasis on energy-efficient collaboration within integrated networks [118], along with incorporating task priority and load balancing into the proposed scheme [121]. Additionally, there is a need to evaluate the feasibility and performance of proposed schemes on a larger scale and in mobile integrated energy system-based wireless sensor nodes [60].
- ***Algorithmic Enhancements and Evaluation:*** The effectiveness of the QPSO technique can be thoroughly examined by evaluating its performance on large-scale problems and exploring its optimization capabilities [68]. Similarly, comparing the QPSO technique with heuristic approaches can yield valuable insights into its efficacy [65]. Moreover, evaluating the proposed techniques across various domains, including large-scale optimization tasks, can provide a comprehensive understanding of their applicability and scalability [72], [80].
- ***Analysis and Scale Evaluation:*** The analysis of average delays for a larger set of vehicles in existing research [117] can provide valuable insights into the applicability of the proposed approach in real-time vehicular networks. Furthermore, evaluating the proposed dynamic resource optimization scheduling scheme considering end user cooperation [70] can lead to a practical assessment of its effectiveness. Additionally, analysis of the proposed scheme through convergence rate analysis in lightweight and complex environments can enhance its adaptability and robustness [122].
- ***Emerging Research Avenues:*** The key areas for future research include big data processing, visualization, and integrating classical optimization with quantum learning [115]. Additionally, the effect of variations in terrain and environment can be explored for the terahertz band, aiming for enhanced communication [69]. Implementing energy-efficient collaborative learning and the trajectory of collaborative learning are considered future enhancements in [119], [120], respectively.

C. Quantum-Inspired Optimization of Reconfigurable Intelligent Surfaces

The intelligent surfaces of tunable meta-materials can significantly enhance wireless communication through coverage extension, improving energy efficiency, mitigating interference, and dynamically adapting to time-varying environments. Fig. 24 illustrates a scenario where an intelligent reflective surface (IRS) mounted on an aerial platform ensures reliable user connectivity by overcoming radio signal blockage from a building, facilitating seamless communication with the base station. These surfaces present various challenges, including deployment, channel estimation, resource allocation, interference, energy efficiency, and scalability. Realizing the benefits

TABLE XI
EDGE DEVICES RESOURCE OPTIMIZATION USING QI TECHNIQUES.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[58]	Optimize the energy	Probability of qubit states	NP-hard	QI green communication framework for energy balancing in sensor-enabled IoT systems, QI ant colony optimization	This paper devised a quantum computing-oriented solution to optimize the energy consumption in sensor-enabled IoT environments considering energy-centric solution representation, measurement, and rotation angle.
[60]	Enhance the QoS of wireless sensor network	Intra-cluster distance and BS distance factor	NP-hard	Quantum clone whale optimization algorithm	The paper aimed at enhancing the lifetime of integrated energy system wireless sensor networks by employing a high-performance clustering protocol.
[65]	Maximize energy efficiency	Computation, energy, power, and distance	Mixed integer non-linear programming	QPSO	This work formulated the resource optimization problem as a mixed integer non-linear programming problem and proposed a sub-optimal solution using QPSO algorithm in a device-to-device-assisted edge computing system with hybrid energy harvesting.
[67]	Minimize delay and energy consumption	Local extreme point constraints	Binary programming	Particle swarm-based service migration scheme	The service migration problem was formulated as a non-linear binary programming optimization problem, and particle swarm-based service migration scheme was proposed while considering the queuing delay prediction, delay-aware computation resource optimization, and modified QPSO algorithms.
[68]	Maximize the number of tasks	Deadline and resource capacity	Mixed integer non-linear programming	QPSO	This work formulated a task scheduling problem and proposed QPSO based method identify the solution in reasonable time.
[69]	Maximize energy efficiency	Power and orthogonality of tetra-hertz channels	Non-convex mixed integer non-linear programming	QPSO	This paper formulated the long-term energy efficiency optimization problem for nano-empowered vehicular networks as mixed integer non-linear programming problems over time slots and proposed quantum-behaved particle swarm-based energy efficiency optimization algorithm and improved discrete particle swarm-based energy efficiency optimization algorithm to obtain suboptimal solutions.
[70]	Maximize the total utility of all network coding sets	Service budget and execution time	Statistical fairness measurement model	QPSO and proportional integral model	The paper proposed a dynamic resource optimization algorithm to schedule vehicles in a multi-user IoV system fairly. The QPSO algorithm combined the proportional integral model to achieve the global optimal solution.
[71]	Optimize task offloading and minimize execution time	Tolerance time, continuously connected time and system utility	NP-hard	QPSO for joint offloading	A mobile edge computing-based joint offloading technique for vehicular networks was proposed that utilized the QPSO algorithm to minimize the task delay and energy consumption through tasks offloading to service nodes and roadside units.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[72]	Minimize node energy consumption and assign cluster head's load to nodes	Cluster head load distribution	Quadratic unconstrained optimization	QPSO and game theory	The authors devised a load dividing model for cluster heads in the wireless sensor network to achieve enhanced network lifetime.
[80]	Maximize network secrecy energy efficiency	Connectivity	Operational mode assignment, NP-hard	Quadrivalent QI gravitational search algorithm	The NP-hard problem of operational mode selection for nodes in wireless sensor networks was tackled by employing QI algorithm.
[82]	Optimize bit-rate of video streaming	Buffer size and one-bit-rate	QUBO	Quantum Annealing	This paper focused on adaptive bit-rate control by increasing the average bit-rate and decreasing the rebuffering events for maximal user quality of experience.
[116]	Reduce the energy consumption of VR equipment	Spectrum, computing resources, buffer size and quality of experience	Markov decision process	QI-RL	This paper formulated a joint optimization problem that incorporates viewport rendering offloading, computing, and spectrum resource allocation and aimed to reduce the energy consumed by VR equipment while ensuring a smooth, immersive VR experience. RL-based online learning algorithm integrated with quantum parallelism was employed to find the optimal policy.
[117]	Minimize average task processing latency	Computation, energy and resource cost	Non-convex, NP-hard	QI-RL	This work formulated the uplink resource optimization problem in IoVs as a time-varying Markov decision process, and proposed QI-RL algorithm for edge offloading that allowed vehicles to choose network access mode and offloading strategy flexibly.
[118]	Maximize long-term average revenue	Bandwidth, payment and acquisition mode decision, pre-stored nodes intelligence attainment, one-time block acquisition, delay, and energy	Markov decision process, NP-hard	QI-RL	A non-fungible token-based green intelligence networking scheme was proposed for connected and autonomous vehicles in smart cities enabling efficient networking of intelligence and reduce energy consumption. The core problem was formulated as a discrete Markov decision process and solved using QI-RL algorithm.
[119]	Maximize the sum incomes from all vehicles	Delay, energy, number of master participating vehicles a slave participating vehicle can assist, and master participating vehicle and matching decision value	Markov decision process	Gale-Shapely Algorithm, QI-RL	This work proposed a quantum collective learning and matching game-based scheme for connected autonomous vehicles in the metaverse and used the simulated environment of metaverse to expand the sample size and quantify intelligence diversity for effective learning. The vehicle selection and spectrum allocation problems were formulated as a matching game and Markov decision process, respectively, and solved using Gale-Shapley and QI-RL algorithms to achieve high system revenue.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[120]	Maximize reward (utility of intelligence, acquisition delay, and bandwidth cost)	Bandwidth, delay, energy, only nodes that pre-stored can provide intelligence, and each block is allocated only once	Discrete Markov decision process, NP-hard	Grover algorithm, QI-RL	The paper devised a non-fungible token-based distributed intelligence networking for connected autonomous vehicles by formulating the problem as a discrete Markov decision process and employed QI-RL to identify the optimal policy.
[122]	Accurate node deployment	Offloading decision rate, resource potentiality, channel, qubit state-error probability, and fusion variance	NP-hard	QI online node consolidation, QI-RL	The issue of reliable service deployment was solved through the proposed QI node consolidation algorithm that utilized time-sensitive measurement reinforcement and angular-based node position analysis.
[121]	Minimize task processing delay	Risk, computing capacity and maximum number of offloaded tasks	Markov decision process	Grover iteration, QI-RL	The paper proposed a train-edge-cloud collaborative computing framework to minimize task delays through a risk-sensitive QI-RL algorithm for smart train systems and introduced a novel risk function considering edge intelligent servers load and rail transit characteristics.
[115]	Maximize throughput	Power, energy flow, data rate, and data buffer overflow	Markov decision process	QRL	This work modeled the relay and transmit power selection problem as a Markov decision process and employed QRL algorithm based on Grover iterations to optimize the consumed energy and throughput.
[131]	Minimize expectation of unit cost	Learning in adversarial environment	Multi-armed bandit problem	Quantum amplitude amplification, Grover iterations	The authors solved tasks offloading problem through QI bandit learning, where the client learns the costs of each task by utilizing quantum computing principles.
[143]	Maximize stato-dynamic sensing ability	Sensors in vicinity	Bounded-error quantum polynomial	QI IoT optimization	This work incorporated quantum formalization of sensor-specific parameters in a real-time IoT environment and devised a quantum computing-inspired optimization technique to maximize the data accuracy.

of RIS in communication networks requires advancements in resource optimization plans, hardware design, channel estimate techniques, and optimization algorithms. QI solutions harness the ability to explore multiple configurations simultaneously due to inspiration drawn from quantum computing concepts. It facilitates effectively exploring the solution space through model optimization procedures similar to quantum annealing, creating associations among RIS components, and utilizing fast-converging data-driven ML techniques. These methods provide efficient optimization and ensure flexibility.

IRSs are important in 6G systems due to their energy efficiency. The authors of [30] formulated a combinatorial problem of radio resource optimization for a standalone IRS system. The proposed QUBO formulation provided an energy-saving solution, and it does not require external information, thus eliminating the heavy overheads of channel estimation for each IRS's reflective element, phase shift optimization, and control mechanism. The proposed technique was compared with three methods: A, B, and C. In method A, a sub-set of operators could control the IRS and perform phase shifts. In method B, each operator sequentially gained the right to control the IRS in a single time slot cycle. In method C, simultaneous communication was considered among all operators to optimize phase shift, which caters to maximizing the throughput. There were several constraints, such as traffic for each user equipment, avoiding resource allocation to user equipment excluded in the radio link table in each time slot, upper bound on sub-carriers allocated to each user equipment,

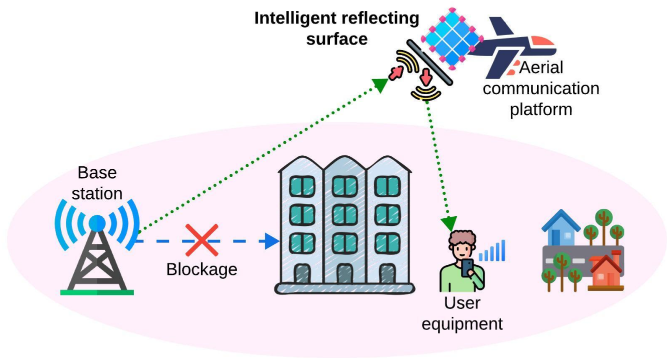

Fig. 24. Intelligent reflecting surface providing reliable connectivity to user.

and the total count of sub-carriers allocated to each user equipment does not exceed the available range if same BS communicated with multiple user equipment in each time slot.

The IRS-based improved energy utilization in 6G networks refers to achieving the same throughput with a reduced transmission power and frequency bandwidth. In [86], the IRS allocation scheduling was formulated as a QUBO problem, and quantum computing was used to solve the combinatorial optimization problem. The objective was to identify the ground state to minimize the Hamiltonian. The ground state of the Ising model was identified through the adiabatic theorem. The system considered two user pieces of equipment communicating with a BS through a single IRS. The reflection coefficient of each IRS was adjusted to maximize the array gain for the user having the IRS assigned. D-Wave Advantage and hybrid solver were used to solve the formulated problem. The constraints included traffic, user equipment assignment to the IRS, traffic reduction avoidance due to interference, and prevention of IRS allocation in case of non-availability of wireless links. The performance of the proposed technique was compared with orthogonal frequency division multiple access and frequency sharing under various conditions such as IRS array gain, traffic reduction due to interference, and signal-to-noise ratio variations.

A larger IRS leads to limited improvements in performance. Hence, Zhang et al. proposed a flexible and secure intelligently mixed reflecting and relaying surface-aided communication system in [79] where the designed fast intelligent reflective elements working mode selection technique enabled individual intelligent reflecting elements to select their working modes, such as reflection or relaying. The network secrecy energy efficiency maximization task was formulated analytically, and secure energy-efficient communication was ensured by employing fast intelligent reflective elements working mode selection and secure dynamic hybrid resource optimization. Specifically, the QI bald eagle search algorithm was proposed to solve the secure dynamic hybrid resource optimization problem. There was a constraint on the target secrecy rate and power allowed by each BS and intelligent reflecting element antenna. The computational complexity of the QI bald eagle search algorithm was $O(iP_s(3n+2))$, where i, P_s, and n refer to the number of iterations, quantum bald eagle population, and dimensions, respectively. The performance of the proposed secure dynamic hybrid resource optimization based bald eagle search technique was compared with other heuristic and classical algorithms such as secure dynamic hybrid resource management-PSO, secure dynamic hybrid resource management-Dinkelbach, passive-IRS, active-IRS, and direct transmission.

Phase optimization is necessary in RISs to obtain the desired reflected wavefront. Hence, the authors of [85] transformed the beamforming problem into an NP-hard problem of identifying the target Ising Hamiltonian's ground state. The formulated problem had an exponential solution space. Two sub-Hamiltonians relating to energy and enforcing weighing constraints simplified the formulation due to multiple spin-spin interactions. There were constraints on RIS array size, material thickness, and beam weight. The proposed RIS-Ising-quantum annealing technique was compared with two benchmark schemes: simulated annealing provided by the D-Wave neal package and branch and bound solver of IBM's complex linear programming expert optimizer. However, the proposed quantum annealing can solve relatively smaller-sized problems due to a mismatch between the fully connected graph generated by RIS Ising models and the sparse Pegasus graph used in D-Wave quantum processing unit hardware. Therefore, a hybrid quantum annealing scheme was proposed to mitigate the mismatch of quantum annealing.

Table XII provides the key details of the reviewed sub-set of papers related to the resource optimization of RIS. The tabulated information includes objectives, constraints, problem type, solution, and remarks.

Lessons Learnt: The research gaps and future directions listed below have been identified from the dataset used for the literature review. The QI approaches can be explored to address these appealing research pathways to enrich the radio resource optimization of RIS.

- ***IRS Deployment and Optimization:*** Current research can be improved by focusing on three key areas: optimizing the placement of IRS alongside BSs, refining patterns in phase shift and switching, and integrating a control technique for managing multiple BSs and IRSs [30]. Similarly, real-time optimization of large-scale RIS structures can be investigated [85].
- ***Evaluation of Secrecy Energy Efficiency:*** The proposed technique's effectiveness in maintaining secrecy energy efficiency in scenarios with imperfect channel state information can be assessed [79].
- ***Throughput Maximization:*** To maximize throughput, simultaneous optimization can be conducted for each base station's transmission power, transmission precoding, and IRS reflection coefficient [86].

D. Quantum-Inspired Spectrum Sensing and Localization

Spectrum sensing optimization aims to better identify and manage the radio frequency spectrum for improved wireless communication. Similarly, in localization, the position of a device or user is determined through signal strength measurements or GPS. Fig. 25 illustrates integrated spectrum sensing and localization of target objects within the coverage area of

TABLE XII
RIS OPTIMIZATION USING QI TECHNIQUES.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[30]	Optimize the energy	Traffic, and sub-carriers	Complex combinatorial optimization problem	QUBO	The authors applied quantum computing for radio resource optimization of the proposed standalone IRS and alleviated the concerns of impractical overhead in designing phase shift for IRSs.
[79]	Maximize network secrecy energy efficiency	Target secrecy rate and power	Secure dynamic hybrid resource optimization	QI bald eagle search	Increasing the number of elements in IRS leads to minor improvement in performance, hence a fast reflecting element's working mode selection method was devised based on QI algorithm.
[85]	Identify the ground state of target Ising Hamiltonian	RIS array size, material thickness and weighing of beams	NP-hard	Hybrid quantum annealing	This paper solved the problem of optimizing the phase configuration of RIS.
[86]	Maximize the array gain	Traffic, user equipment assignment to IRS, traffic reduction avoidance due to interference, and prevention of IRS allocation in case of non-availability of wireless links	Combinatorial optimization problem	QUBO	The optimization of IRS allocation scheduling was considered while limiting the number of users and IRS array gain was maximized by configuring the reflection coefficients.

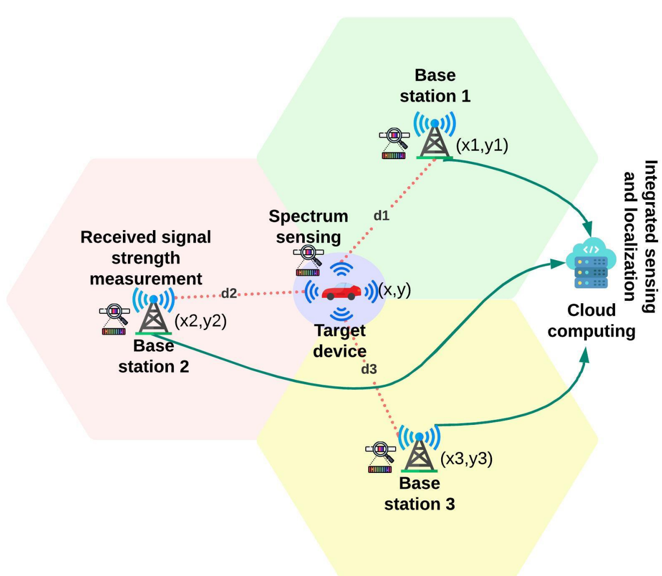

Fig. 25. Spectrum sensing and localization of target objects [144].

a wireless network. It shows three base stations, a smart car positioned at the intersection of their coverage areas, two-dimensional coordinates (x, y), distance measurements (di) from each base station, and a cloud platform to coordinate the sensing and localization tasks across all stations. Key challenges include adaptability to heterogeneous environments, coordinated spectrum sensing, detection accuracy, energy efficiency optimization, interference, and security against malicious attacks. Resolving these issues is crucial to optimizing spectrum use and improving the general performance of communication networks. Technological advancements in signal processing, AI, and ML aid in overcoming these obstacles and enhancing spectrum sensing abilities.

Incorporating quantum principles into classical computing approaches enables QI techniques to optimize spectrum sensing effectively. These techniques improve spectrum sensing parameter optimization efficiency by exploring numerous solutions simultaneously through quantum annealing, superposition, and parallelism. Spectrum sensing techniques get coherence and data-driven adaptation from quantum entanglement and ML algorithms. These methods effectively handle the complexity of spectrum sensing optimization in communication networks and provide flexibility in response to changing spectrum conditions. While QI methods on classical computers help improve spectrum sensing capabilities, real quantum computers may offer further benefits.

Cognitive wireless medical sensor networks are also beneficial in healthcare systems for remote transmission of information and monitoring purposes. However, the classical static spectrum allocation technique limits the wireless sensors' communication using a single channel and could cause packet loss or interference issues. Addressing these issues, a cognitive spectrum allocation technique binary quantum-behaved elite PSO algorithm was proposed in [73], which followed the bird colony behavior. The objective was to optimize network revenue and spectrum allocation. The designed interference matrix had a constraint called non-interference. An undirected graph denoted the network, and the spectrum allocation was modeled as a graph coloring problem. Genetic and classical PSO algorithms were considered benchmarks, and the performance metrics included network reward and spectrum allocation efficiency.

The spectral efficiency can be achieved in 5G networks through co-frequency self-interference cancellation techniques. However, the cross-link interference is a performance-limiting factor. Therefore, the authors in [88] devised a two-loop technique to maximize spectral efficiency. The objective was to optimize duplex mode selection and secrecy transceivers jointly. It was a non-convex mixed integer problem that incorporated binary variables and was regarded as an NP-hard problem. A QI tabu search algorithm was proposed for duplex mode enhancement in the outer loop. A successive convex approximation was employed in the inner loop to optimize transceivers and artificial noise. QI tabu search diversified and aimed to identify solutions through intensive search. The successive convex approximation and QI tabu search algorithms showed fast convergence within ten to fifteen and ten iterations, respectively. The colluding and non-colluding eavesdroppers were considered, and the constraints included antenna operational mode, transmission power, and uplink receivers. The benchmark schemes used for comparison included greedy search, network-assisted full duplex with fixed duplex mode, and time-division duplex. The overall complexity of the proposed technique was $O(C(V_a^{2.5}C_o^2 + V_a^{3.5}))$, where C, V_a, and C_o refer to the count of possible solutions, scalar variables, and constraints respectively.

Considering the need for resource optimization in a 6G network scenario, power-domain non-orthogonal multiple access (NOMA) developing on RL-inspired QNN was proposed in [145] for user grouping and meeting spectral efficiency. The objective was to maximize the user sum rate while incorporating constraints on power. The proposed RL-QNN and QNN approaches had a time complexity of $O(n_{layer}n_{neuron})$, which was superior to the conventional NN's time complexity of $O(n_{layer}(n_{neuron})^2)$, where n_{layer} and n_{layer} represent the number of neurons and neural layers, respectively.

Sensor errors, noise, and multipath effects usually impact the accuracy of indoor localization. In [107], a hybrid quantum deep NN model was proposed to achieve accelerated learning through quantum computing and handle complex data through deep NN. The proposed scheme showed superior localization through received signal strength and time of flight metrics, compared to benchmark techniques, including a Euclidean-based K-nearest neighbor, a classical deep NN with and without dropout. Furthermore, the complexity of the proposed scheme was reduced by decreasing the number of variational parameters. Therefore, the QI techniques have the potential to address complex localization tasks.

Table XIII presents key details, including the objectives, constraints, problem, type, solution, and remarks for the sub-set of research papers focused on resource optimization techniques related to spectrum sensing.

Lessons Learnt: The research gaps and prospective research directions based on the dataset used for the spectrum sensing optimization literature review are listed below:

- ***Integration with Emerging Technologies:*** The cognitive wireless medical sensor networks can be integrated with emerging technologies such as 6G networks, edge computing, and the IoT, aiming to enhance spectrum allocation, improve network performance, and design new healthcare applications [73].
- ***Imperfections in Channel State Information and Noise:*** Analysis of integrating imperfect channel state information into massive MIMO systems can lead to enhancing performance and reliability [88]. Decentralized QNN can be considered for resource optimization while catering to the performance-related challenges posed by noise [145].

E. Quantum-Inspired Resource Optimization in UAV-Assisted Networks

UAVs are indispensable components of wireless communication networks, providing an economical and flexible solution for emergency deployments. Fig. 26 illustrates a UAV-assisted emergency coverage scenario, emphasizing the need for an optimized flight path. The UAV starts at a hovering point within a cell with intact network resources and a control center, then follows an optimal trajectory towards an emergency-struck area, previously served by a base station, while accounting for obstacles such as buildings. Trajectory planning optimizes UAV flight routes in communication networks, enhancing communication capabilities. Some challenges include avoiding obstacles, adapting to different environments, optimizing energy efficiency, ensuring good communication range and quality, maintaining network connections, using complex path planning algorithms, and accounting for weather conditions. The QI techniques simultaneously explore multiple trajectory options, simulate quantum annealing-like optimization, create associations between planning elements, employ data-driven ML algorithms, explore solution space effectively, and provide novel hybrid approaches. They offer effective optimization methods and guarantee flexibility in dynamic environments. The UAV trajectory planning process is improved by QI techniques, allowing for efficient and safe navigation in dynamic communication networks.

Specifically, trajectory planning can be performed in a cellular-connected UAV environment to minimize flight time while ensuring satisfactory wireless transmission quality. In [126], the UAV's flight path was formulated as a Markov decision process, and optimized flight direction within each time slot was identified through a deep RL-based approach. The trajectory planning problem was too sophisticated to be solved through standard optimization techniques. Hence, a QI experience replay framework was proposed, which inter-linked the experienced transition to the associated qubit and applied Grover's technique iteratively for amplitude amplification. The

TABLE XIII
SPECTRUM SENSING AND LOCALIZATION USING QI TECHNIQUES.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[73]	Optimize network revenue and spectrum allocation	Non-interference	Graph coloring problem	Binary quantum-behaved elite particle swarm algorithm	This paper addressed the problem of efficient spectrum allocation in cognitive medical wireless sensor network through quantum computing algorithm.
[88]	Maximize secrecy spectral efficiency	Antenna operational mode, transmission power, and uplink receivers	NP-hard	Successive convex approximation, QI tabu search	This paper addressed the joint optimization of duplex mode selection and secrecy transceivers to maximize overall secrecy spectral efficiency.
[107]	Minimize mean square error	None	Indoor localization	Hybrid quantum deep NN	The paper aimed at minimizing the localization error in a real environment by using low-cost devices for received signal strength measurements and limited time of flight.
[145]	Maximize user sum rate	Power	Grouping of users	Quantum NN	The paper uses quantum NN to achieve the required spectral efficiency of next-generation wireless communication.

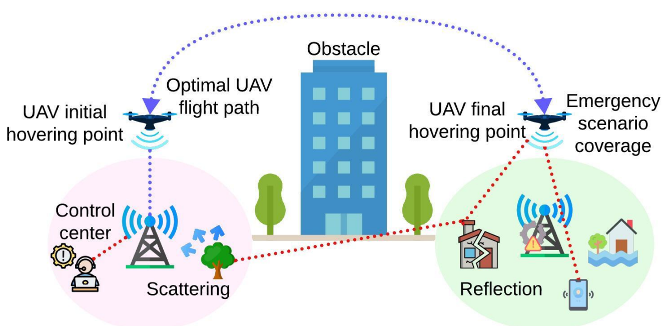

Fig. 26. UAV-assisted networking scenario.

objective was to minimize each UAV's flight time cost and corresponding expected ergodic outage duration. The constraints included sector association, UAV location, flying direction, mobility, normalization, and priorities. The proposed approach was compared with several other deep RL-based benchmarks, such as standard experience relay, prioritized experience replay, deep curriculum RL, and simultaneous navigation and radio mapping. The performance metrics included an average weighted sum of ergodic outage duration and time cost.

In contrast to terrestrial networks, UAVs are considered a favorable means of wireless service provisioning due to their movability and on-demand deployment. The authors of [123] performed UAV's flight trajectory planning, aiming at maximizing the ground users' expected sum uplink transmission rate. A QI-RL technique was proposed to optimize the UAV's trajectory without knowing user information, such as location, channel state information, and transmit power. There were constraints on flying distance between arbitrary adjacent time slots, the UAV's trajectory was within a feasible area, maximum exploration time was constrained by onboard power capacity, and the sum of individual ground user bandwidths must not exceed available bandwidth. Classical optimization approaches cannot solve such a problem due to the unavailability of environmental information. Model-free RL methods can be incorporated to solve such problems by employing the "trial and error" method. The proposed technique was compared with two conventional RL benchmarks, such as Q-learning with ϵ-greedy and the Boltzmann exploration technique.

The authors of [76] proposed a UAV path planning model and multi-objective QI seagull optimization algorithm based on decomposition. They devised a logic to disintegrate the multi-objective task into multiple scalar optimization tasks. The concept of neighbors was incorporated into the proposed algorithm to enhance the connection between seagulls. There was a constraint on the independent variable's feasible region, and flight height has upper and lower bounds. The performance metrics included convergence, distributivity, and extensiveness, which were evaluated through parameters such as hypervolume and spread. The benchmark algorithms used for comparison included multi-objective PSO, non-dominated sorting genetic algorithm II, multi-objective evolutionary algorithm based on decomposition, multi-objective vortex search algorithm, multi-objective artificial algae algorithm, and multi-objective spotted hyena optimizer. The standard test function sets from Congress on evolutionary computation-2009, Deb-Thiele-Laumanns-Zitzler, and Zitzler-Deb-Thiele were used for performance evaluation of the aforelisted techniques and incorporated properties such as convex, concave, disconnected, and linear. The time complexity of the proposed technique was approximated as $O(P_s^2)$, where P_s refers to the population size (and count of weight vectors).

The UAV path planning is usually decomposed into two steps, including viable path identification between two points and trajectory optimization. Fernandes et al. proposed an enhanced diversity PSO technique in [74] aimed at efficient and safe path identification, energy wastage avoidance, and system integrity. The proposed scheme was evaluated in two-dimensional static and dynamic environments. The cost function was devised based on the route length, terrain crossed, and obstacle avoidance. The stochastic ranking was used for invalid paths, such as crossing through obstacles. Such paths were considered constraints and treated with a death penalty, which referred to assigning a high value to the collision parameter. The performance of the proposed technique was evaluated in comparison to various benchmark algorithms, such as enhanced evolutionary PSO, cooperative multi-objective PSO, grey wolf optimizer PSO, adaptive genetic PSO, global and cooperative PSO, QPSO, PSO, genetic algorithm, and cuckoo search. The metrics used for performance evaluation included the reciprocal of Pareto sets proximity, reciprocal of hypervolume, inverted generational distance in decision space, and inverted generational distance in objective space. The aforementioned metrics were evaluated through the Congress on evolutionary computation benchmarking suite, comprising 22 functions with different characteristics. In particular, the QPSO algorithm showed a higher average convergence cost than the enhanced diversity PSO algorithm.

A motion-encoded PSO algorithm was proposed in [146] to identify a fast-moving target through UAVs. The objective of the NP-hard optimization task was to maximize the cumulative probability of target detection. The search trajectory was encoded as a sequence of UAV motion paths while preserving the cognitive and social coherence of the swarm. The problem considered the target's last known location and employed a normal probability distribution function through a grid mapping called a belief map. There was a constraint, such that the UAV could move in one out of eight directions during each step. The QPSO algorithm was used as a benchmark and showed inferior performance compared to the proposed technique in identifying the fitness value of accumulated detection probability.

Similarly, the UAV target tracking control can provide intelligent consciousness remotely due to its major role in patrolling, surveillance, and target monitoring. Ma et al. proposed a QI experience relay deep deterministic policy gradient technique based on deep RL framework for vertical take-off and landing aircraft in [147]. The tracking control problem was formulated as a Markov decision process. The aim was to learn an optimal tracking control policy without prior knowledge for autonomous tracking of a target in flight through UAVs. The reward function for UAVs comprised two tasks: effectively reaching the desired position in less time and providing high precision target tracking guidance. The average reward of the proposed QI experience relay deep deterministic policy gradient technique increased more quickly with an effective sampling of high-priority samples and fewer fluctuations, compared to the benchmark techniques such as prioritized experience replay deep deterministic policy gradient and deep deterministic policy gradient.

Table XIV shows the objectives, constraints, problem, type, solution, and remarks for the sub-set of research papers focused on resource optimization techniques related to UAV trajectory.

Lessons Learnt: The UAV trajectory path planning research can be enriched by considering the following research gaps

TABLE XIV
QI RESOURCE OPTIMIZATION IN UAV-ASSISTED NETWORKS.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[74]	Efficient and safe path identification, energy wastage avoidance, and ensuring system integrity	Collisions, paths with obstacles	Trajectory planning problem for autonomous mobile robots	Enhanced diversity PSO	This paper solved mobile robotic vehicles trajectory planning problem for static and dynamic environments.
[76]	Multi-target optimization	Feasible region of independent variable, upper and lower bound on flight height	Multi-objective problem	Multi-objective QI seagull optimization algorithm based on decomposition	The proposed technique transformed multi-objective problem into several scalar sub-problems and tested its effectiveness for UAV path planning.
[126]	Minimize UAV flight time and expected ergodic outage duration	Sector association, UAV location, flying direction, mobility, and priorities	Markov decision process	Grover iteration based amplitude amplification, Deep RL	The authors formulated a UAV navigation approach to address the problem of minimizing the weighted sum of time cost and expected outage duration.
[123]	Maximize expected sum uplink transmission rate through UAV flight trajectory planning	Flying distance, power and bandwidth	Markov decision process	QI-RL	The authors solved trajectory planning problem of UAV through QI-RL to optimize expected sum uplink transmission rate.

and directions identified from the dataset of papers used in this survey.

- ***GPS and UAV Navigation:*** The research can consider integrating GPS technology to enhance the navigation capabilities of UAVs, enabling more accurate and reliable positioning, trajectory planning, and overall flight control [126]. Additionally, Deep RL-based formation control in GPS-denied environments can be explored to address challenges UAVs face, such as maintaining formation and performing coordinated tasks effectively [147].
- ***Transmission Rate Optimization:*** A feasible direction worth exploring is maximizing the expected sum uplink transmission rate for ground users in multi-UAV scenarios [123]. This involves optimizing the system to achieve higher average data transmission rates from multiple users to the BS or access point, enhancing uplink performance and overall throughput.
- ***Power Systems Dispatch:*** A prospective area for future research is applying the proposed technique to power systems dispatch [76]. It can aid in optimizing power resource allocation, leading to enhanced efficiency and improved performance in power grids.
- ***Complexity Reduction:*** The research can evaluate the proposed technique for multiple mobile robots and reducing computational complexity [74]. This involves optimizing coordination and control by developing algorithms and techniques to ensure efficient and effective operation.

F. Quantum-Inspired Power Control Optimization

Optimal power control is crucial in wireless networks to extend the battery life of edge devices and ensure reliable data transmission. Fig. 27 illustrates a base station with dynamic transmission power allocation. The system optimizes communication with three UAVs, each providing coverage to their respective zones. UAVs cohesively account for multiple power-affecting parameters, including transmission, flight, and data processing power, while managing their battery status to maintain coverage in their respective zones.

The MIMO systems employ optimal power control to achieve high transmission quality and reduced computational complexity through linear processing, but the security of transmitted information is a significant concern. Therefore, a secure co-time co-frequency massive MIMO network was designed in [78] that considered passive eavesdroppers and aimed to improve time-frequency resource utilization while ensuring physical layer security. The proposed joint antenna selection and power allocation problem was NP-hard. The objective was to maximize the secrecy capacity and energy efficiency. The optimized joint antenna selection and power allocation scheme was obtained through hybrid optimization functions through a QI backtracking search algorithm that had a computational complexity of $O(i(5P_s+4P_sn)$, where i, P_s, and n refer to iterations, population size, and dimension (of quantum individuals), respectively. There were constraints on power, uplink, and downlink transmission rates. The proposed technique was compared with benchmarks including PSO, Discrete PSO, artificial physics optimization, and backtracking search optimization algorithm.

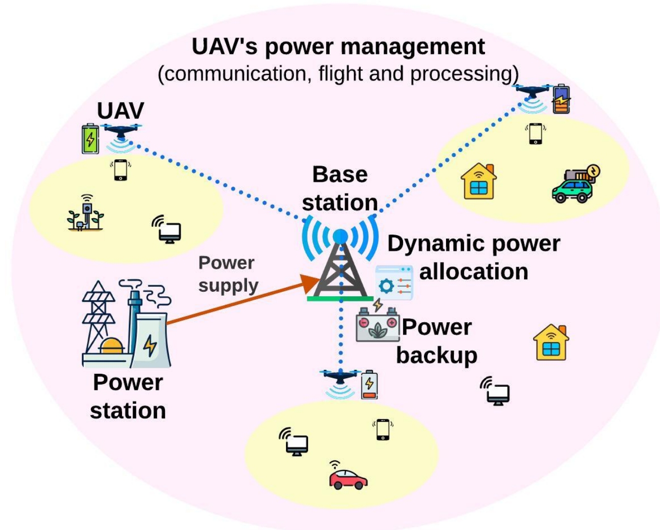

Fig. 27. Scenario depicting the necessity of optimized power allocation.

The multicarrier communication system performance depends on the peak-to-average power ratio. Selected mapping significantly reduces the peak-to-average power ratio without losing spectrum resources. Hou et al. proposed a QI evolutionary technique in [62] to solve this NP-hard problem through combinatorial optimization of angle increment updating and characteristics information ranking. The objective was to minimize the maximum signal of discrete-time transmitted orthogonal frequency division multiple access signal, and the sign sequence was constrained. The proposed scheme had a computational complexity of $P_s \times G \times O(N_c \log N_c)$, where P_s, G, and N_c are population size, generation value, and sub-carriers, respectively. The benchmark techniques used for comparison included artificial bee colony selected mapping, cross-entropy selected mapping, and selected mapping. The performance metrics included average peak-to-average power ratio, bit error rate, and raw cubic metric.

The authors of [77] proposed an efficient power allocation and antenna selection technique called continuous QI termite colony optimization algorithm. It ensured reliable communication in a co-frequency full duplex massive MIMO system. The precoding and reception at the base station were done through maximum ratio transmission and maximum ratio combination. The simultaneous transmission and reception lead to self-interference, and the degree of self-interference cancellation ranged from 0 to 1, where 0 meant no self-interference. The aim was to maximize the transmission capacity and energy efficiency. It was a non-convex NP-hard problem. The number of transmitting antennas and the uplink transmission power of each user were discrete and continuous variables, respectively. They belonged to different optimization domains and were transformed into a continuous optimization problem. There were constraints on the transmission rate, power, and search range of quantum termites. The benchmarks used for comparison included backtracking search optimization, half-power random resource allocation, PSO, and termite colony optimization. The computational complexity of the continuous QI termite colony optimization algorithm was $O(i(5P_s + 3P_s n)$, where i, n, and P_s represent iterations, dimensions, and population size (of quantum termites), respectively.

The optimization of achievable data rate and network coverage in wireless communication were considered key performance metrics in [106]. A QNN employing parallel training was proposed to optimize transmit precoding and power allocation in NOMA with MIMO. The objective was to maximize the sum rate of edges while incorporating the constraints on power allocation range and transmit precoding. The slope of the sum rate of edges decreased with respect to the transmit signal-to-noise ratio due to inter-user interference. The proposed parallel training QNN scheme was compared with the conventional gradient-descent-based approach and static power allocation-maximum rate precoding. The overall complexity of the feed-forward process and unsupervised parallel training for QNN was $O(N_{shot} N_{layer} N_{neuron})$, which was found to be superior to the conventional approach having overall complexity of $O(N_{edge} \cdot (N_{shot} N_{layer} N_{neuron} + N_{shot} N_{layer}^2 N_{neuron}^2))$, respectively. N_{edge}, N_{layer}, N_{neuron}, and N_{shot} denote the number of edges, layers in NN, neurons in NN, and quantum measurements, respectively. The drawback of the proposed approach lied in higher memory utilization for the parallel training process.

VR videos impose significantly greater power requirements than other video types due to viewport rendering. The key techniques for wireless VR include content-correlation-based computation offloading, quality of experience-aware content transmission, and buffer-aware content caching. Therefore, Lin et al. proposed a joint intelligence framework in [124] considering content correlation such as caching, computing, and transmission. The three-layered framework comprised reality access, user access, and a virtual environment layer. A QI-RL scheme was proposed to solve the multidimensional resource provisioning problem by jointly optimizing the streaming. In the proposed technique, the agent performed online learning and decided about task offloading and multidimensional resource allocation decisions relating to computation, spectrum, and storage. The environment was referred to as a time-varying channel and was modeled as a Markov decision process. The policy referred to rewards, such as energy consumption and quality of experience of VR equipment. The objective was to minimize the energy consumption of VR equipment. There were constraints on resource capacity, flow stability, offloading capacity, and resource utilization assurance.

Table XV shows the objectives, constraints, problem, type, solution, and remarks for the sub-set of research papers focused on resource optimization techniques related to optimized power control.

Lessons Learnt: The research related to optimal power allocation can be enriched by considering the following research gaps and directions identified from the dataset of papers used in this survey.

- ***Ultra-Dense Scenarios and Heterogeneous Networks:*** The proposed technique can be evaluated for ultra-dense scenarios and heterogeneous networks in the presence of many eavesdroppers [77] and [78]. As a future direction, optimization enhancements can be made to the existing research, such as MIMO-NOMA user-pairing and integration of the parallel training QNN approach with support vector regression and distributed deep learning [106]. The practical assessment of the proposed peak-to-average power ratio reduction technique and the impact of system parameters variation can be explored [62].
- ***VR Streaming Services:*** While targeting joint optimization of streaming services in VR, the security concerns can be considered a future direction [124].

VI. Use Case: Quantum-Inspired Vertical Farming

The 6G networks will deal with compute-intensive and dense sensor environments, offering new opportunities for integrating QI optimization into smart farming practices, including vertical and digital farming. These practices optimize urban spaces by using multi-layered structures within controlled environments, such as unused buildings or repurposed warehouses, to boost crop productivity and reduce the carbon footprint [148]. For example, a vertical farming setup spanning $50\ m^2$ might include crop stacks arranged in rows, each featuring five vertical layers with five sensors installed in each layer that monitor plant health, soil moisture, and environmental conditions. Each row, measuring $1\ m$ in width and spaced $1\ m$ apart, extends $24\ m$ in length. This setup will result in approximately $1,250$ sensors, many of which would be in hard-to-reach positions.

The sensors in such an environment generate tasks with low computational complexity and flexible latency requirements. However, managing a high density of sensors in large farms necessitates robust and scalable mobile edge computing techniques to handle data influx and provide wireless energy harvesting, thereby maximizing sensor lifetime. Fig. 28 illustrates the effectiveness of QI optimization in vertical farms for efficiently managing the extensive network of IoT sensors, ensuring effective monitoring of environmental conditions and plant health. UAVs can utilize the QI algorithms to dynamically optimize flight paths for real-time data acquisition and edge processing, enhancing data collection efficiency and energy harvesting. Additionally, agricultural robots and IoV for the transportation of goods to and from the farm can benefit from QI optimization for automated resource management and maintenance tasks, ensuring efficient scheduling and routing.

QPSO is particularly effective in balancing exploration and exploitation with minimal computational overhead, making it ideal for managing high-dimensional sensor data and dynamic farming environments [67], [71]. It integrates seamlessly with IoT and edge computing systems, ensuring robust resource allocation. The QI simulated annealing is well-suited for real-time environmental adjustments, though it may exhibit slower convergence in highly dynamic scenarios [136]. QI-RL can enhance IoV systems for agricultural robots and vehicles [117], while the QI Genetic algorithm addresses complex, multi-objective problems such as UAV flight path optimization. However, its higher computational demands and hardware requirements may limit its real-time applicability, making it preferable where high precision is prioritized over speed [11].

TABLE XV
POWER ALLOCATION OPTIMIZATION USING QI TECHNIQUES.

Ref.	Objective	Constraints	Problem	Solution	Remarks
[62]	Minimize the maximum signal of discrete-time transmitted orthogonal frequency division multiple access signal	Sign sequence is constrained	NP-hard	QI evolutionary algorithm	This paper solved the problem of high peak-to-average power ratio through selected mapping technique.
[77]	Maximize transmission capacity and energy efficiency	Transmission rate, power and search range of quantum termites	Non-convex, NP-hard	Continuous QI termite colony optimization algorithm	A QI algorithm was proposed for energy-efficient resource optimization while aiming to achieve a balance among energy consumption, system resource utilization, and overall transmission capacity.
[78]	Maximize secrecy capacity and energy efficiency	Power, uplink, and downlink transmission rates	NP-hard	QI backtracking search algorithm	The authors aimed at joint optimization of antenna selection and power allocation in co-time co-frequency full duplex MIMO network.
[106]	Maximize edge sum rate	Power and transmit precoding	NP-hard	Parallel training QNN	The wireless resources optimization was achieved by requiring the edges to transmit only statistical parameters.
[124]	Minimize energy consumption of VR equipment	Resource capacity, flow stability, offloading capacity, and resource utilization assurance	Markov decision process	QI-RL	This paper tackled multidimensional resource provisioning issues in wireless VR through a joint framework comprising of computation, storage and communication resources.

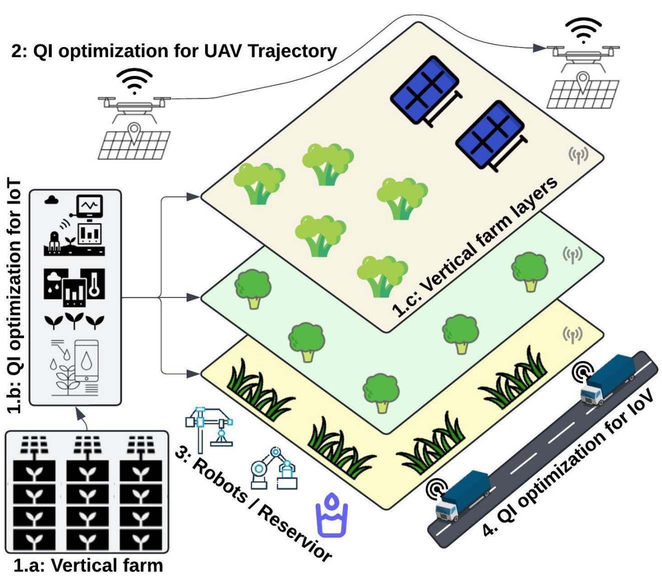

Fig. 28. Vertical farming system model for QI optimization.

Therefore, the selection of the QI optimization technique depends on the system's specific requirements and available resources. Conclusively, these QI optimization techniques offer seamless integration into classical networks, eliminating the need for specialized infrastructure.

VII. FUTURE RESEARCH DIRECTIONS AND CHALLENGES

Considering the exponential increase in communication devices, there is a dire need for novel optimization techniques to achieve the desired communication network performance through efficient resource optimization and resilience to noise. This section organizes future directions to offer clear insights from the reviewed dataset of QI optimization papers.

*1) **Applications in 6G networks**:* The quantum technology is favorable to addressing various communication problems, including cryptosystems for blockchain, hybrid algorithms, IoT and IoV optimization, multimedia processing, satellite communication, and UAV trajectory planning [12]. The vehicular routing problem addressed by the proposed scheme inspired by quantum computing can also integrate objectives such as minimizing distributed network latency and ensuring the authenticity and security of the quantum platform [143]. The quality of service enhancing clustering technique proposed in [60] can be applied to large-scale and mobile integrated energy system-based wireless sensor nodes. The marine predators algorithm with crossover proposed in [149] can be reformulated and evaluated in a QI scenario while hybridizing with fuzzy logic or artificial NNs. The QPSO can show slow convergence in large-scale scenarios. Therefore, it is necessary to reduce the convergence time for the proposed QPSO technique for multi-hop wireless power transfer in [72]. The dynamic resource optimization scheduling technique proposed in [70] developing on QPSO and proportional integral can be employed on a large-scale and in cooperative user scenarios. Analyzing how individual user response patterns influence scheduling decisions helps identify discrepancies between service requests and resource allocation, enhancing dynamic resource optimization scheduling performance.

*2) **Complexity Reduction Techniques**:* The QI optimization techniques offer significant speedups compared to classical optimization approaches. Further reducing the complexity of QI optimization algorithms is a favorable domain [8]. The gradient-free optimization technique can optimize the circuit parameters of the quantum approximate optimization algorithm [150]. The hybrid classical-quantum optimization approaches, such as QUBO and higher-order unconstrained binary optimization, lead to tractable solutions, which may not be possible through classical approaches. Therefore, analyzing the possibility of further enhancements involves integrating the bits, neurons, and qubits [6].

The quantum energy balancing technique for IoT sensors proposed in [58] can be compared with other QI metaheuristics techniques for green communication in IoT networks. The algorithms proposed for maximizing energy efficiency, such as QPSO and improved discrete PSO in [69], can consider evaluation in complex terrain and terahertz bands. The QPSO technique proposed for energy efficiency maximization in [65] only considers one relay unit. Considering multiple relay units for transferring computational tasks can enhance the system. Similarly, the iteration process significantly influences the clustering performance of proposed single-objective cat swarm optimization and multiple objective cat swarm optimization techniques in [110]. Implementing alternate progressive optimization techniques can further enhance the running speed. The QI evolutionary algorithm proposed in [61] aims to optimize caching and user association jointly. Enhancing the techniques involves considering additional parameters, such as user association in adaptive bit-rate scenarios, resource allocation, and UAV deployment strategies.

*3) **Machine Learning-based Approaches**:* Quantum learning-based green computing is an appealing technique for connected vehicular networks, big data processing, visualization, and integration of classical optimization with quantum learning [115]. In the IoV scenario, the QI-RL framework presented in [117] can facilitate self-adaptive resource optimization on a broader scale, allowing for the evaluation of average delays. Similarly, researchers can extend the QI-RL technique proposed for optimizing a single UAV trajectory path in [123] to simultaneously optimize the trajectory paths of multiple UAVs, aiming to maximize the aggregate uplink rate. Expanding the QI experience replay technique proposed in [126] involves extending it into deep RL-based models, such as deep deterministic policy gradient, soft-actor centric, and Rainbow. The multi-party quantum devices can harness benefits from a collective utilization of federated and transfer learning-based techniques [105]. Examining the proposed QI support vector machine algorithm and error propagation process can help reduce complexity and tighten error bounds [151].

*4) **Peak-to-average Power Reduction**:* The 3rd generation partnership project establishes stringent standards for telecommunication networks, particularly for error vector magnitude. It is a metric that assesses the accuracy of transmitted signals by measuring the deviation from their ideal form, and a lower value is crucial for robust data transmission. However, the challenge arises with the peak-to-average power ratio, highlighting the variation between the peak signal power and its average power. Its high value can lead to signal distortion and inefficient transmission, severely affecting communication quality [62].

Classical optimization methods, such as mixed integer programming, will struggle to address the complexity of 6G networks, such as real-time, dynamic datasets on a massive scale. Quantum annealing solves large-scale combinatorial problems by simulating quantum behaviors like tunnelling to escape local optima. This capability enables it to explore numerous solutions simultaneously. It offers an efficient way to minimize the peak-to-average power ratio while complying with the error vector magnitude constraints set by 3rd generation partnership project. Therefore, quantum annealing can optimize network performance to meet the increasingly complex demands of future 6G standards, outperforming classical methods in both speed and accuracy [152].

*5) **Quantum Key Distribution and Entangled pairs**:* The medoids-based clustering technique proposed in [49] for distributing quantum keys over a fiber optic network can undergo evaluation in a QI wireless network scenario. Furthermore, exploring the effect of inter-network connectivity, extension of key distribution territory, and physical features on QKD quality is also possible. The dynamic programming-based algorithm proposed in [32] only targets latency minimization of entangled pairs; analyzing aggregated trees, pipelining, purification, and multimode memories can also be performed. The technique proposed in [31] for optimized entanglement generation distribution can extend to a large-scale network incorporating quantum repeaters. Incorporating security provisioning for highly mobile IoT devices, maximizing the integration of narrowband IoT systems, and evolving machine-type communications can enhance the quantum-resistant access authentication and data distribution technique for IoT devices proposed in [153].

*6) **Resilience to Noise**:* Investigating the noise performance of the photonics-inspired recurrent NN proposed in [154] is possible through its implementation on photonic hardware.

*7) **Transitioning from Classical to Quantum Infrastructure**:* The transition to quantum infrastructure in networking necessitates the development of hybrid architectures to maintain service continuity during the transition phase. Recent advancements in routing optimization for 6G networks, particularly through applying QML approaches, necessitate adaptive and intelligent network management protocols capable of dynamically adjusting to the complexities of quantum communication [155]. As scalability remains a significant challenge, ensuring that quantum hardware can support large-scale networks is crucial for a successful transition.

*8) **Challenges**:* Realizing a quantum-integrated communication networking scheme requires addressing several key challenges, which include learning QML models, decoherence, noise, and classical-quantum system integration [22]. The secret-key flow model proposed in [47] considers fiber optic networks where infrastructure upgrades are necessary for QKD integration while accounting for the distance limitations for QKD transmission. The fiber optic-based scalable and reconfigurable quantum network architecture proposed in [34] for photon-pair distribution would encounter challenges related to quantum resource constraints, such as the availability and generation of entangled photon pairs, quantum noise and loss, and compatibility with existing infrastructure. The quantum frequency processors categorized in [156] target full process tomography, and their experimental characterization would give rise to several challenges, such as non-ideal models for integrated platforms that potentially undermine the open-box assumptions, the computational complexity of black-box methods, and longer integration time due to noise.

VIII. Conclusion

As the number of devices increases and the demand for reliable communication grows, optimizing communication networks is becoming increasingly complex. The large-scale optimization tasks inherently require more time to identify the optimal solution, leading to increased latency. The classical optimization techniques also tend to get stuck in local optima due to inefficient exploration of the solution spaces. URLLC is crucial in 6G, enabling services like AR, VR, intelligent transportation, and remote surgery. This importance drives the use of QI optimization techniques in communication networks. The reviewed research papers demonstrate that QI meta-heuristics, ML and specialized techniques outperform classical benchmark techniques by providing faster and more efficient solutions. The QI techniques for optimizing radio resources leverage quantum physics principles but do not require quantum hardware. Classical entities imitate quantum principles like entanglement, superposition, and tunneling through transformations. This technique enables a faster convergence of meta-heuristics, ML and specialized optimization approaches compared to their classical counterparts. Furthermore, continually exploring and refining such techniques is essential in addressing the dynamic and evolving optimization tasks relating to communication networks.

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