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Quantum Computing in Telecommunication—A Survey

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Review

Quantum Computing in Telecommunication—A Survey

Frank Phillipson [1,2]

[1] The Netherlands Organisation for Applied Scientific Research (TNO), 2595 DA The Hague, The Netherlands; frank.phillipson@tno.nl

[2] Department of Quantitative Economics, School of Business and Economics, Maastricht University, 6211 LK Maastricht, The Netherlands

Abstract: Quantum computing, an emerging paradigm based on the principles of quantum mechanics, has the potential to revolutionise various industries, including Telecommunications. This paper explores the transformative impact of quantum computing on the telecommunication market, focusing on its applications in solving computationally intensive problems. By leveraging the inherent properties of quantum systems, such as superposition and entanglement, quantum computers offer the promise of exponential computational speedup and enhanced problem-solving capabilities. This paper provides an in-depth analysis of the current state of quantum computing in telecommunication, examining key algorithms and approaches, discussing potential use cases, and highlighting the challenges and future prospects of this disruptive technology.

Keywords: quantum computing; telecommunications; mobile and fixed networks; optimisation; machine learning

MSC: 81P68; 90-08

1. Introduction

The telecommunications industry faces a growing demand for solving complex computational problems, including network optimisation, data analysis, and resource management. Traditional computing approaches have limitations in handling these large-scale problems efficiently. Quantum computing can exploit quantum phenomena, such as superposition and entanglement, to tackle some of these difficult problems. This section introduces the motivation behind incorporating quantum computing in telecommunication and outlines the scope of this paper.

It is recognised that quantum computing will play an important role in telecommunications [1]. Quantum computing will be an important technology, as acknowledged by the European Commission [2]. Quantum computing can help solving complex computational problems encountered in planning and operation of (future) telecommunication networks. In [1], it is concluded that most of the optimisation problems in the field of telecommunications and ICT are currently solved with algorithms finding suboptimal solutions, because of the excessive cost of finding an optimal solution. An example of these problems includes joint optimisation of several functions, such as radio channel estimation, data detection and synchronisation, and data centre optimisation. Especially in future mobile communication networks (5G and beyond), there is a need for powerful calculations to control and plan the network [3,4]. Henrique [5] stated that 'it is vital to engineer a 6G Radio that is cognitive, fast to predict events, and prevent incidents. For this, 6G Radio must have Artificial Intelligence operating with machine learning with the combined quantum computer superpower to process and harness the incommensurable amount of big data in favour of excellent service level agreements (SLA) and Quality of Experience (QoE)'.

Broad overviews of the current state and possible applications of quantum computing in telecommunications can be found in [6,7]. In [6], the emerging paradigms of machine

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learning, quantum computing, and quantum machine learning and their synergies with communication networks are considered as core 6G enablers. They provide an overview of the application areas, without giving an in-depth overview or analysis of the current research. Furthermore, ref. [7] provided a high-level overview of the playing field and an introduction to the various topics.

This work extends on current literature by giving an overview of existing research on machine learning, optimisation, and search problems using quantum computers and applied to the area of fixed and wireless (ad hoc) telecommunication networks. We discuss how quantum algorithms can address real-world challenges in telecommunication networks, including network congestion management, scheduling, and resource allocation. We do this by discussing the current state-of-the-art quantum machine learning techniques for predictive modelling, anomaly detection, and network optimisation. These quantum algorithms can, in time, improve network performance and enhance operational efficiency. For the performance of the algorithms, we refer to the references provided.

In the remainder of this work, first, an overview is given of examples of applications of optimisation and machine learning in telecommunications in Section 2. Then, in Section 3, some fundamentals of quantum computers are explained. Next, in Section 4, an overview is provided of existing work of quantum computing in optimisation and machine learning for wireless (ad hoc) networks and fixed networks. The last section draws some conclusions and discusses future research.

2. Optimisation and Machine Learning in Telecommunication

Optimisation and machine learning problems in the telecommunication market can be found in many places. Optimisation problems can be found, for example, in network routing optimisation. Telecommunication networks involve the efficient routing of data packets to ensure fast and reliable transmission. Optimisation algorithms are used to determine the best paths, considering factors such as network congestion, latency, and bandwidth allocation. Furthermore, resource allocation is an important area for optimisation. Telecommunication service providers must allocate network resources effectively to meet the varying demands of users. Optimisation techniques are employed here to allocate bandwidth, spectrum, and other resources optimally, ensuring efficient utilisation and maximising network capacity. The third area is network design and planning. Building and expanding telecommunication networks require strategic decisions regarding the placement of base stations, antennas, and network infrastructure. Optimisation methods aid in determining optimal network configurations to minimise costs, maximise coverage, and meet Quality of Service (QoS) requirements. The last example is SLA Management. Telecommunication providers must adhere to SLAs that define quality metrics, such as network availability, latency, and throughput. Optimisation models help in managing SLAs by optimising network resources and ensuring service guarantees are met.

Furthermore, machine learning problems can be found in multiple application areas in telecommunications. In predictive maintenance, machine learning algorithms can analyse real-time data from telecommunication equipment to predict and prevent potential failures. By identifying patterns and anomalies, predictive maintenance models enable proactive maintenance, reducing downtime and improving network reliability. For traffic prediction and network optimisation, machine learning algorithms can analyse historical traffic patterns and user behaviour to predict future traffic demand. This information is then used to optimise network resources, such as routing, bandwidth allocation, and caching, to ensure efficient traffic management and improve overall network performance. Anomaly detection and security has become increasingly important in networks. Machine learning techniques can identify anomalous network behaviour, such as network intrusions or unusual traffic patterns, to enhance network security. By training models on normal network behaviour, anomalies can be detected in real-time, enabling swift response and threat mitigation. Furthermore, on the network (performance) optimisation side, machine learning algorithms can analyse large volumes of network performance data to identify bottlenecks, optimise network parameters, and enhance overall network efficiency. This can involve tasks such as dynamic spectrum allocation, load balancing, and traffic optimisation to improve user experience and network performance. The last area here is more operational. For customer churn prediction, predictive models can analyse customer data to predict the likelihood of customer churn in the telecommunication industry. By identifying factors that contribute to churn, service providers can take proactive measures to retain customers, such as targeted marketing campaigns or personalised offers.

The intersection of optimisation and machine learning techniques provides powerful tools for addressing complex problems in the telecommunication market. These approaches enable telecommunication providers to enhance network efficiency, improve service quality, optimise resource allocation, and better understand customer behaviour, ultimately driving innovation and competitiveness in the industry. They also require ever-increasing computational power, which can be the reason for introducing quantum computing.

3. Quantum Computing Fundamentals

This section provides a concise explanation of fundamental concepts in quantum computing relevant to the subsequent discussions. It covers topics such as qubits, quantum gates, superposition, and entanglement. Readers will gain a comprehensive understanding of how these concepts underpin the potential computational advantages that quantum computing brings to the telecommunication market. The section explains what quantum computing paradigms there are available and how these systems can represent and manipulate information in ways that surpass the capabilities of classical computing. It also gives description of a general quantum optimisation algorithm and the QUBO (quadratic unconstrained binary optimisation) formulation that is used in many quantum optimisation approaches.

3.1. Fundamental Concepts

Superposition, entanglement, and tunnelling are fundamental concepts in quantum mechanics, which underpin the power of quantum computing. Superposition refers to the ability of a quantum system, such as a qubit, short for quantum bit, which is the fundamental unit of information in quantum computing, to exist in multiple states simultaneously. Unlike classical bits, which can only represent either a 0 or a 1, a qubit can be in a superposition of both states at the same time. Mathematically, a qubit can be represented as a linear combination of the basis states $|0\rangle$ and $|1\rangle$, often denoted as $\alpha |0\rangle + \beta |1\rangle$, where α and β are complex numbers that describe the probability amplitudes of each state. When a measurement is made, the qubit collapses into one of the basis states with a probability determined by the square of the amplitudes. Quantum parallelism is related to superposition. This is the computational advantage gained by using superposition to perform parallel computations on multiple qubits.

Entanglement, on the other hand, describes a strong correlation that can exist between two or more qubits. When qubits become entangled, the state of one qubit becomes intrinsically linked to the state of the other qubits. This entanglement persists even if the qubits are physically separated, leading to a phenomenon often referred to as 'spooky action at a distance'. Entangled qubits can exhibit highly non-classical behaviour and can be used to perform quantum operations that are not possible with classical systems. Superposition and entanglement are fundamental resources in quantum computing, enabling the execution of powerful quantum algorithms and the potential for exponential computational speedup.

Quantum tunnelling is a phenomenon in quantum mechanics where a particle can pass through a potential barrier even when its energy is lower than the energy of the barrier. In classical physics, if a particle does not have enough energy to overcome a barrier, it would be reflected back or stopped by the barrier. However, in the quantum realm, particles such as electrons and protons can exhibit wave-like behaviour and have a non-zero probability of "tunnelling" through the barrier.

3.2. Computing Paradigms

In general, there are two computing paradigms in quantum computing. The first one is gate-based quantum computing or digital quantum computing, a computational paradigm that harnesses the principles of quantum mechanics in a direct sense to perform complex computations. At its core, gate-based quantum computing relies on qubits, the fundamental units of quantum information. As said before, unlike classical bits, which can only represent 0 or 1, qubits can exist in a superposition of states, simultaneously representing multiple values. Through the application of quantum logic gates, which are analogous to classical logic gates, quantum computations are executed. These gates manipulate the quantum states of qubits, enabling operations such as superposition, entanglement, and interference. By leveraging a sequence of carefully crafted gate operations, quantum algorithms can be executed, allowing for the solution of problems that are intractable for classical computers. The precise control and manipulation of qubits, as well as the mitigation of errors due to decoherence, pose significant challenges in the practical implementation of gate-based quantum computing systems.

To give an example, we look at the following. In this work, we are interested in machine learning applications. In many of those applications, one starts with the encoding of the data. Figure 1 shows a quantum circuit for this task. It encodes two data points in two qubits.

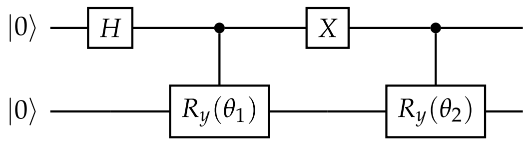

Figure 1. Amplitude encoding: two-qubit circuit for data encoding of two normalised two-dimensional data points.

A quantum circuits must be read from left to right. Each line represents a qubit; in this case, we have two qubits. Each rectangle is a gate operations, operating on one or two qubits. First, a Hadamard gate is applied to the first qubit to bring that qubit in a superposition state. Then, a controlled rotations is used to encode the two data points $x_i = (x_{i0}, x_{i1})$ for $i = 0, 1$ in the amplitudes of the second qubit. The angles of the rotations θ_i are chosen such that $\alpha_i = x_{i0}$ and $\beta_i = x_{i1}$. The initial state is now rotated to the desired state, which can be expressed by:

$$|0\rangle\,|0\rangle \to \frac{1}{\sqrt{2}}\big(\,|0\rangle\,|x_1\rangle + |1\rangle\,|x_2\rangle\,\big). \tag{1}$$

Note that in Equation (1), the first qubit acts as a counter, while the two features of the data point are encoded in the second qubit. Another option is to encode a single data point with four features, using just two qubits. If we want to apply this circuit to a physical layout of a specific quantum computer, quantum programming languages need to be used. Examples of such languages are PyQuil [8], QCL [9], and Q# [10]. These quantum programming languages only focus on that specific part of the quantum software stack [11], whilst tools for other layers are also in development.

Analogue quantum computing is the second paradigm, where quantum annealing is one of the most used for optimisation and machine learning. Quantum annealing is a specific implementation of adiabatic quantum computing, and is a specialised approach to quantum computing that focuses on solving optimisation problems. It started with the work of Kadowaki and Nishimori [12,13]. In quantum annealing, the computation is guided by a process inspired by the concept of annealing in classical physics. The system consists of qubits, similar to other quantum computing architectures, but in this case, they are organised in a particular way, called a "qubit array"; the most recently used is the "Pegasus graph" [14]. The goal of quantum annealing is to find the lowest energy state, which corresponds to the optimal solution of the given problem. The quantum annealing process starts with the system being initialised in a simple state, typically a uniform superposition of all possible configurations. Then, the system is subjected to a slowly decreasing external field, known as the "annealing schedule". This schedule allows the system to explore different configurations and converge towards the low-energy states that encode the optimal solution. It uses the quantum property tunnelling as is explained in [15]. The physical implementation of quantum annealers, such as those based on superconducting qubits, involves carefully controlling the system's Hamiltonian and the interactions between qubits to achieve the desired annealing behaviour. While quantum annealing is particularly suited for certain optimisation problems, it may be less suitable for other types of computations that require more general-purpose quantum algorithms.

3.3. Grover's Algorithm

Grover's algorithm is a famous quantum search algorithm [16], for a gate-based quantum device, that provides a quadratic speedup over classical search algorithms for unsorted databases. It is one of the earliest and most famous quantum algorithms. The problem Grover's algorithm addresses is the following: Given an unsorted database of N items, we want to find a specific target item with high efficiency. In classical computing, the best algorithm to solve this problem requires O(N) queries to the database in the worst case. However, Grover's algorithm can achieve this with only about $\sqrt{N}$ queries to the database, making it substantially faster for large databases.

The algorithm works as follows:

- Initialisation: Start with a superposition of all possible states. Represent the database items as qubits and put them in an equal superposition of 0 and 1 states.
- Oracle: Create a special quantum oracle that marks the target item. The oracle performs a specific phase inversion on the state corresponding to the target item.
- Amplitude Amplification: Apply a series of operations called amplitude amplification, which consists of two main steps:

  1. Reflection: Reflect the quantum state about the mean of the amplitudes of all items.
  2. Amplification: Amplify the amplitude of the target item by flipping its sign.

  By repeatedly applying the oracle and amplitude amplification operations, the amplitudes of the target item increase, while those of other items tend to cancel each other out. This leads to a higher probability of measuring the target item.
- Measurement: After a sufficient number of iterations (approximately $\sqrt{N}$), perform a measurement. The algorithm outputs the target item with a high probability.

Grover's algorithm is a specific search algorithm and not useful for solving arbitrary problems efficiently. Nevertheless, it demonstrates how quantum computing can provide a substantial speedup over classical algorithms for specific tasks.

3.4. The QAOA Approach for Optimisation

The quantum approximate optimisation algorithm (QAOA) [17] is a basic quantum algorithm designed to tackle combinatorial optimisation problems. It combines classical optimisation techniques with quantum computing to find approximate solutions for such problems. In the QAOA, the problem is encoded into a quantum system using qubits. The algorithm uses a sequence of parameterised quantum gates, known as the QAOA circuit, to manipulate the qubits and search for optimal solutions. The circuit typically alternates between layers of "mixing" and "problem" unitary operations. The mixing operations create superposition among the qubits, while the problem operations encode the problem's objective function.

The QAOA seeks to find the best parameters for the quantum gates to maximise a specific objective function. This is accomplished through classical optimisation techniques, such as variational optimisation, where the parameters are iteratively adjusted to optimise a cost or energy function associated with the problem.

The performance of the QAOA is influenced by the number of layers in the circuit and the choice of the problem and mixing unitary operations. By increasing the number of layers, the algorithm can explore more complex solutions, but requires more quantum resources. The quality of the approximate solution obtained by the QAOA depends on the interplay between the chosen parameters and the structure of the problem at hand.

The QAOA has been applied to a range of optimisation problems, including the Max-Cut problem [18], the Travelling Salesman Problem (TSP) [19], and the Graph Colouring problem [20], among others. While the QAOA provides an avenue for solving optimisation problems with quantum computers, it is important to note that the algorithm's performance depends on various factors, including the size and structure of the problem, the quality of the quantum hardware, and the available classical optimisation techniques.

3.5. QUBO Formulation

A QUBO (quadratic unconstrained binary optimisation) formulation is a mathematical representation of an optimisation problem that is specifically tailored for solving with quantum annealing, QAOA, and classical optimisation algorithms. It represents the problem as a quadratic polynomial of binary variables. It is expressed as follows:

$$\min_{x \in \{0,1\}^n} \quad x'Qx, \tag{2}$$

where x is an n-dimensional vector of binary decision variables, so $x_i \in \{0,1\}\ \forall i$, and has to be set such that, given Q, the expression is minimised. Note that QUBO problems belong to the set of $\mathcal{NP}$-hard problems. The QUBO formulations provide a standardised mathematical representation that allows a wide range [21,22] of optimisation problems to be mapped onto the same framework. This facilitates the development of optimisation algorithms and tools that can be applied across different problem domains, making it easier to utilise quantum annealing or classical optimisation techniques to solve complex optimisation problems efficiently.

The QUBO formulation maps the problem's objective function and constraints into a single quadratic polynomial. The objective function is typically expressed as a combination of linear and quadratic terms, where the coefficients of these terms determine the importance or weight of each variable and their interactions. The constraints of the problem, if any, are also transformed into quadratic terms in the QUBO formulation, using penalty functions.

The Ising formulation is an alternative formulation, which is closely related to the QUBO formulation. The Ising formulation originates from statistical physics and is commonly used to describe the behaviour of magnetic spins in a physical system. In the Ising model, binary variables $\{+1, -1\}$, representing spins, interact with each other through pairwise interactions, and the goal is to find the spin configuration that minimises the total energy of the system. The relationship between the QUBO and Ising formulations lies in their mathematical equivalence. Given an Ising model, it is possible to convert it into an equivalent QUBO problem, and vice versa. This conversion involves mapping the variables and interactions of one formulation onto the other in a way that preserves the optimisation objective. This mapping can be achieved by employing appropriate linear and quadratic transformations. The equivalence between QUBO and Ising formulations has practical implications for solving optimisation problems using quantum annealing or classical optimisation algorithms. Quantum annealers, such as those provided by D-Wave Systems, primarily operate on QUBO problems. However, they can also solve Ising problems by converting them into the QUBO form. Similarly, many classical optimisation algorithms that work with QUBO problems can also be applied to Ising problems through the same conversion process. This interchangeability allows researchers and practitioners to leverage existing tools and techniques developed for one formulation to solve problems in the other formulation.

3.6. Simulated and Digital Annealing

Simulated annealing, introduced in [23], and digital annealing [24] are optimisation algorithms used to solve complex problems. Although they are not quantum methods, they play an important role in the transition to, especially, quantum annealing. Simulated annealing is inspired by the process of annealing in metallurgy, where a material is heated and gradually cooled to reduce defects and reach a low-energy state. In the context of optimisation, simulated annealing starts with an initial solution and explores the solution space by allowing occasional uphill moves to escape local optima. As the algorithm progresses, it gradually decreases the probability of accepting worse solutions over time, simulating the cooling process. This probabilistic acceptance of worse solutions allows for a more extensive exploration of the solution space and increases the chances of finding a global optimum.

On the other hand, digital annealing is a technique employed by quantum-inspired annealers, such as Fujitsu's Digital Annealer. Digital annealing does not rely on the physical properties of materials in the same way that simulated annealing does, but rather uses a digital circuit to emulate the behaviour of quantum bits (qubits). It leverages concepts from quantum annealing to solve combinatorial optimisation problems. Digital annealing can rapidly explore a vast number of possible solutions by manipulating the digital qubits and applying operations that simulate quantum effects. By using a digital approach, digital annealing can provide efficient and scalable solutions to optimisation problems, making it an attractive option for various applications.

Both simulated annealing and digital annealing offer powerful techniques for optimisation. Simulated annealing is a classical optimisation algorithm that can be applied to a wide range of problems, while digital annealing brings quantum-inspired methods to tackle combinatorial optimisation problems. The choice between the two depends on the specific problem at hand and the available computational resources.

4. Quantum Computing in Telecommunication Application Areas

In this section, we provide an overview of the existing literature on the use of quantum computing approaches specifically tailored for fixed and wireless telecommunication. The literature review focuses on exploring how quantum computing techniques have been leveraged to address challenges and enhance various aspects of telecommunication systems. This literature review provides a comprehensive overview of the current state of research and highlights the key findings, trends, and gaps in the use of quantum computing approaches for fixed and wireless telecommunication. Understanding the existing body of knowledge, researchers, engineers, and decision makers can help us gain insights into the potential impact of quantum technologies on telecommunication systems and pave the way for future advancements in this rapidly evolving field.

4.1. General Problems and Their Quantum Approach

Before looking into the specific literature on problems in telecommunications, we can identify some general problems in telecommunication networks that have quantum approximation approaches. As those problems are computationally hard (NP-hard), quantum computers do not give efficient exact solvers. For example, both quantum annealing and QAOA can be regarded as heuristic approaches. The complexity of QAOA depends on several factors, including the number of qubits used, the depth of the quantum circuit (number of layers), and the structure of the optimisation problem being addressed. Generally, as the number of qubits and the depth of the quantum circuit increase, the algorithm's performance and accuracy can improve. The complexity of quantum annealing is typically analysed in terms of the annealing time, which is the time taken for the quantum system to reach its ground state. The time to find the ground state depends on the energy gap between the ground state and the first excited state of the quantum system. If the energy gap is small, the annealing process might take longer, leading to longer computation times.

The graph colouring problem is the first important problem for telecommunications. It has practical applications in various areas of network design and optimisation. The graph colouring problem involves assigning colours to the vertices of a graph such that no two adjacent vertices have the same colour. In the context of telecommunications, the vertices of the graph can represent different elements, such as cell towers, antennas, or channels, while the edges represent the connections or interference between these elements. One key application of graph colouring in telecommunications is in frequency assignment for wireless communication systems. In wireless networks, different channels or frequency bands need to be assigned to different base stations or antennas to avoid interference. By representing the network as a graph and applying graph colouring algorithms, it becomes possible to find a suitable assignment of frequencies to minimise interference and maximise the overall capacity and performance of the network. Graph colouring is also relevant for optimising other aspects of network design, such as channel allocation, resource allocation, and scheduling. By appropriately colouring the graph representing the network, it becomes possible to efficiently allocate resources, schedule transmissions, and manage network resources to minimise congestion, improve efficiency, and enhance overall network performance. Furthermore, the graph colouring problem is closely related to the concept of chromatic numbers, which quantifies the minimum number of colours needed to colour a graph. The determination of chromatic numbers is valuable in network planning and optimisation, as it provides insights into the requirements and limitations of a given network configuration. Quantum solutions can be found for example in [25], which is based on quantum annealing. In [26], a hybrid quantum-classical approach based on the traditional column generation approach is given. Furthermore, [20] gives a hybrid approach based on the QAOA algorithm. Hybrid quantum-classical computing refers to a computational approach that combines the strengths of both classical computing and quantum computing to solve complex problems. It leverages the computational power of quantum computers for specific tasks while utilizing classical computing for other aspects of the problem-solving process [27].

Next, the travelling salesman problem (TSP) and routing problems are crucial in the field of telecommunications due to their relevance in optimising network efficiency, resource allocation, and overall system performance. The TSP involves finding the shortest possible route that a salesman can take to visit a set of cities and return to the starting point, while visiting each city only once. In the context of telecommunications, this problem translates into finding the most efficient routing paths for data packets or signals to traverse through a network of interconnected nodes, such as routers or switches. Efficient routing is essential in telecommunications to minimise latency, reduce congestion, and optimise the utilisation of network resources. By solving TSP-like problems or employing routing algorithms inspired by TSP concepts, telecommunications companies can design more efficient network architectures, plan optimal routing paths for data transmission, and improve the overall performance and reliability of communication networks. Routing problems, including TSP variants such as the Vehicle Routing Problem (VRP) and the Capacitated Vehicle Routing Problem (CVRP), are particularly relevant in logistical aspects of telecommunications, such as the deployment of service technicians, the delivery of equipment or resources, or the optimisation of fleet management. Efficient routing algorithms and optimisation techniques can help telecommunication companies reduce operational costs, improve service delivery times, enhance network scalability, and ensure the efficient utilisation of available resources. Moreover, in the era of expanding communication networks and emerging technologies such as 5G and Internet of Things (IoT), the ability to solve routing problems becomes even more critical for managing the complex and dynamic flow of data within these networks. An elaborated overview of quantum approaches for the TSP and other routing problems can be found in [28]. More detailed quantum (approximate) TSP solvers can be found in [29–31].

The Maximum Weighted Independent Set (MWIS) problem holds significant importance in the field of telecommunications. The MWIS problem involves finding a subset of nodes in a network, such that no two nodes in the subset are directly connected, and the total weight of the selected nodes is maximised. In the context of telecommunications, where network resources are often limited and need to be efficiently utilised, solving the MWIS problem becomes crucial. By identifying the maximum weighted independent set, telecommunication operators can optimise resource allocation, such as assigning channels or frequencies, scheduling transmissions, or allocating bandwidth. The MWIS problem aids in mitigating interference, improving network efficiency, and enhancing overall system performance. It plays a vital role in tasks such as spectrum allocation, network planning, and resource management, making it an indispensable tool for achieving optimal utilisation of telecommunication resources while ensuring reliable and high-quality communication services. Quantum solutions for the MWIS problem can be found for the gate-based computer [32], the quantum annealer [33], and even the photonic device [34].

The Maximum Weighted k-Clique problem holds great significance in the field of telecommunications. It involves finding a subset of k nodes in a network that form complete subgraphs (cliques), where every node within a clique is directly connected to every other node. In telecommunications, identifying the maximum weighted k-cliques has several crucial applications. It aids in understanding network topology, identifying densely connected regions, and detecting communities or clusters of nodes with strong interconnectivity. By analysing maximum weighted k-cliques, telecommunication operators can gain insights into the underlying structure of their networks, which can inform various tasks, such as network design, routing optimisation, traffic engineering, and fault detection. Moreover, maximum weighted k-cliques provide valuable information for resource allocation, capacity planning, and network resilience, allowing for more efficient and robust telecommunications systems. A clique finding approach using Grover's search on a gate-based device can be found in [35]. In [36], a hybrid quantum approach combining parallel quantum annealing with graph decomposition is shown, allowing for solving larger clique problems accurately.

The scheduling problem holds significant importance in the field of telecommunications. Efficient scheduling is crucial for optimising the utilisation of network resources and ensuring the smooth operation of communication systems. In telecommunications, various tasks require effective scheduling, such as allocating transmission slots, managing bandwidth allocation, coordinating channel access, and prioritising traffic. By solving scheduling problems, telecommunication operators can minimise latency, maximise throughput, and enhance the overall quality of service. Effective scheduling algorithms and techniques contribute to improved network efficiency, reduced congestion, and better utilisation of available resources. Additionally, in emerging technologies such as 5G and beyond, scheduling plays a vital role in supporting diverse applications with varying quality-of-service requirements, enabling the coexistence of different services and efficiently utilising the available spectrum. Therefore, solving the scheduling problem is essential for optimising the performance, capacity, and reliability of telecommunications networks. A quantum annealing approach for scheduling problems can be found in [37] and a QAOA approach in [38].

4.2. Optimisation in Wireless Networks

One area where quantum computing shows great promise is in wireless networks, which play a crucial role in modern communication systems. Optimising wireless networks involves addressing challenges in radio resource management such as spectrum allocation, resource management, signal interference mitigation, and network planning, all of which are inherently complex and computationally demanding. This section explores the potential of quantum computing in tackling optimisation problems in wireless networks.

4.2.1. Scheduling Problems

In [39], the scheduling of the activation of the air links for maximum throughput, subject to interference avoidance near network nodes in wireless networks, is modelled as a maximum weighted independent set problem. This is solved on the quantum annealer, where they make the annealer error insensitive by a novel Hamiltonian extra penalty weight adjustment that enlarges the gap and substantially reduces interference resulting from inevitable spin bias and coupling errors.

The work in [40] also looks at a scheduling problem, here to avoid interference in the very specific Dirichlet protocol in wireless networking. The authors compare the optimisation results from the quantum annealer with the results from simulated annealing.

Another scheduling problem is that of resource allocation for the situation that a swarm of unmanned aerial vehicles serves a set of sensor nodes in [41]. For this combinatorial problem, a QUBO representation is formulated. Since state-of-the-art quantum annealers have a limited number of qubits and limited inter-qubit connectivity, the scheduling plan is obtained by employing a hybrid quantum-classical approach using a quantum annealer and compared to two classical solvers.

In [42], a wireless network's scheduling problem is again formulated as a maximum weighted independent set formulation, where the weight is defined as the queue-backlog to be transmitted over wireless channels. The paper proposes a quantum approximate optimisation for scheduling (QAOS) algorithm, inspired by the QAOA approach. The designed Hamiltonian is converted into a unitary operator and implemented as a quantum gate operation. After that, the iterative QAOS sequence solves the wireless scheduling problem.

The Radio Access Network can been virtualised and disaggregated into different functions whose location is best defined by the requirements and economics of the use case. This virtualised RAN (vRAN) architecture separates network functions from the underlying hardware. In [43], the scheduling problem of 5G vRAN with mid-haul network capacity constraints is modelled as a combinatorial optimisation problem and translated to a QUBO problem.

In [44,45], the use of quantum annealing for cellular baseband processing is evaluated on power consumption, computational throughput and latency, spectral efficiency, operational cost, and deployment timelines surrounding quantum technology. They analyse and project the quantitative performance targets future quantum annealing hardware must meet in order to provide a computational and power advantage over current hardware, while matching its whole-network spectral efficiency.

The work in [46] explores the boundary between two types of computation, classical–quantum hybrid processing for optimisation problems in wireless systems based on quantum annealing, to envision how wireless networks can simultaneously leverage the benefit of both approaches. Preliminary results on a low-latency, large MIMO system envisioned in the 5G New Radio roadmap are encouraging.

4.2.2. Routing and Assignment Problems

Another problem is the Physical Cell Identifier (PCI) assignment problem. In 4G cellular networks, the PCI assignment problem refers to the challenge of assigning unique PCI values to each cell in the network while minimising interference and maintaining efficient communication. The PCI is a fundamental parameter that identifies a specific cell within a cellular network. It is used by mobile devices to synchronise with and access a particular cell for communication. The PCI is crucial for proper cell identification, handover procedures, and interference mitigation. However, in a dense cellular network deployment, where a large number of cells are in close proximity, assigning unique and interference-free PCI values becomes challenging. This is because neighbouring cells with similar or overlapping PCI values can cause interference, leading to decreased network performance, reduced signal quality, and potential communication issues for mobile devices. The PCI problem involves finding optimal PCI assignments that minimise interference and maximise network efficiency and can be seen as a map colouring problem with additional constraints. In [47], a heuristic decomposition algorithms is given to solve this PCI problem, modelled in a QUBO formulation, suitable to run on an annealer or using the QAOA algorithm.

The next generation (6G) technology focuses on global coverage, massive spectrum usage, complex new applications, and strong security. In [48], it is concluded that these features may require computation capabilities that are beyond those of classical computers. The paper focuses on routing optimisation in wireless mesh networks using the QAOA approach.

In many networks, multiple quality-of-service requirements can be conflicting. To enable decision makers to make a good trade-off between different aspects, Pareto optimal solutions may be calculated. In a Pareto optimal solution, it is impossible to make any individual (requirement) better off without making another worse off. In other words, a situation is Pareto optimal if there is no feasible way to improve the well-being of any objective without adversely affecting another objective. However, this comes at the cost of increased complexity owing to searching through the extended multi-objective search-space. In [49–51], a quantum-assisted dynamic programming optimisation framework is proposed, which is capable of circumventing this problem. They use a so-called evolutionary quantum Pareto optimisation (EQPO) algorithm, which is capable of identifying most of the optimal routes at a near-polynomial complexity versus the number of nodes.

Quantum computing architecture that are based on neutral atoms are becoming increasingly interesting for both short- and long-term quantum applications. These quantum devices are particularly well suited to solve problems that are of interest in telecommunication, such as the independent set problem, as the combinatorial constraints can be naturally encoded in the low-energy Hilbert space due to the Rydberg blockade mechanism. In [52], applications are shown for the antenna placement problem, 5G ad hoc networks coverage, ad hoc network routing problems, and telecommunication network loss optimisation.

A problem from a satellite network, which could be of interest for wireless networks, is the coverage problem. In [53], they look at the optimisation problem of splitting a set of satellites into further small groups, which is a Weighted K-Clique Problem. The goal is to find the assignment of each satellite to a subgroup such that the total coverage of a designated Earth region is maximised. To be able to solve bigger problems, they present a hybrid computing stack that combines annealing and classical machine learning.

4.2.3. Power Optimisation and Optimal Coding

In wireless communication systems, the transmitted signal typically undergoes modulation and amplification before being transmitted through the wireless channel. PAPR (Peak-to-Average Power Ratio) refers to the ratio between the peak power and the average power of the transmitted signal. High PAPR values can lead to several issues in wireless systems, including nonlinear distortion, (low) power efficiency, and the need of enlarged dynamic range. To mitigate these issues, PAPR minimisation techniques are employed. These techniques aim to reduce the difference between the peak and average power of the transmitted signal, thereby improving system performance and efficiency. In [54], a PAPR minimisation scheme with the 3GPP EVM requirement as a constraint is run on the D-Wave Systems' quantum annealer.

Vector Perturbation Precoding (VPP) is a technique used in wireless communication systems, particularly in Multiple-Input Multiple-Output (MIMO) systems, to improve the performance and capacity of the system. In MIMO systems, multiple antennas are used at both the transmitter (base station) and receiver (user devices) to transmit and receive multiple data streams simultaneously. Precoding techniques are employed at the transmitter to optimise the signal transmission and exploit the spatial diversity offered by the multiple antennas and multi-path wireless channels. VPP is a specific type of precoding technique that aims to improve the capacity of the MIMO system while maintaining a low-complexity implementation. Finding an optimal perturbation in VPP is known to be an NP-hard problem, demanding heavy computational support at the base station and limiting the feasibility of the approach to small MIMO systems, meaning MIMO systems with limited computation capability. In [55], a quantum-annealing-based approach is proposed, to enable the applicability of VPP to large MIMO systems. They reduce the VPP to a QUBO form, which can be solved by annealing.

4.3. Machine Learning in Wireless Networks

Leveraging the power of machine learning, wireless networks can enhance performance, adapt to changing conditions, and provide intelligent decision-making capabilities. However, as wireless networks grow in complexity, traditional computing resources may struggle to handle the computational demands of advanced machine learning models. Quantum computing for these applications can be found on multiple places in the literature. We see applications in scheduling problems, classification, and prediction.

In [56], the NP-hard URLLC (ultra-reliable and low-latency communication) task offloading optimisation problems in 6G is solved. Classical limitations of machine learning capabilities make it challenging to achieve stringent 6G URLLC requirements. For this, they demonstrate the use of the QAOA. Considering the security and privacy issues, as well as computational-resource overheads in federated learning, distributed quantum computation in blind and remote fashions is further investigated for quantum-assisted federated learning.

In [57], an overview of (supervised) quantum machine learning techniques to be used for user indoor-outdoor detection in wireless networks is given. The three approaches are: (1) a gate-based hybrid quantum variational classifier, (2) a gate-based quantum distance-based classifier, and (3) a quantum annealing-based support vector machine.

The work in [58] analyses the the statistical characteristics of a wireless 5G communication system with an L-branch selection combining receiver. In the paper, the channel capacity (CC) of the signal-to-interference ratio at the output of the SC receiver is estimated. In closed form, the results for CC is presented for the ratio of fading power and interference and the CC value is leveraged among the inputs of quantum predictive model for QoS level estimation.

4.4. Optimisation in Fixed Networks

Optimising fixed telecommunication networks is a critical task to ensure efficient and reliable communication services. These networks encompass a vast array of interconnected components, including switches, routers, optical fibres, and transmission links. As these networks continue to grow in complexity, traditional optimisation methods may struggle to handle the scale and intricacy of the optimisation problems involved. However, the emergence of quantum computing brings new possibilities for tackling these challenges head-on. This section explores the potential applications of quantum computing in optimising fixed telecommunication networks.

In optical networks, the wavelength assignment problem arises in the context of wavelength-division multiplexing (WDM) technology. WDM enables the transmission of multiple optical signals simultaneously over a single optical fibre by using different wavelengths of light as carriers for each signal. The wavelength assignment problem involves determining which wavelengths (also known as channels) should be assigned to each connection or communication request in the network. This assignment needs to be done in a way that minimises conflicts and ensures efficient utilisation of the available wavelengths. The goal is to assign wavelengths to connections in such a manner that there is no interference or crosstalk between them. Interference occurs when two or more connections share the same wavelength and their signals overlap, leading to signal degradation or loss. To avoid interference, each connection should be assigned a unique wavelength or a non-overlapping set of wavelengths. The wavelength assignment problem becomes more challenging as the network size and traffic demand increase. Efficient wavelength assignment strategies are required to optimise network performance, minimise signal degradation, and maximise the number of connections that can be supported. Solving industry relevant cases is exponentially hard. In [59], a quantum-inspired algorithm for solving the wavelength assignment problem is proposed. The basis of the work is a translation of the problem into the QUBO form. Then, a quantum-inspired technique for solving QUBO is benchmarked against classical heuristic and industrial combinatorial solvers and opens the way of solving this on real quantum hardware.

Another problem in fixed communication networks is that of resource assignment for transporting data over networks. The work of [60] looks for a quadratic optimisation model on top of Segment Routing concepts. The validity of the model is proven for different cost and reliability targets. Using a real-life dataset, this was solved by digital annealing. Digital annealing refers to a computational approach that mimics the annealing process from classical physics but implemented using dedicated classical digital hardware rather than physical quantum systems. However, it can be a step towards applying the problem on real quantum hardware. They show that the quality of the results is comparable to classical optimisation methods, while the new approaches outperform those in computation time and have potential for a higher number of demands.

For all networks, date compression is an important aspect of bandwidth-efficient data transfer for computer vision applications. In [61], a quantum-enabled lossy 3D point cloud compression pipeline is proposed, based on the constructive solid geometry model representation. Key parts of the pipeline are mapped to NP-complete problems and translated to a Ising formulation, which can be directly translated into a QUBO (and vice versa). It uses existing Ising formulations for the maximum clique search problem and the smallest exact cover problem.

In the near future, a new quantum technology based key distribution, Quantum Key Distribution (QKD), system may be exploited. In [62], a classical and a quantum annealing approach to compute the minimum deployment of QKD hardware is given. The ensemble of QKD systems needs to be able to exchange as many encryption keys between all network nodes in order to encrypt the data payload, which is defined by traffic demand matrices. Redundancy and latency requirements add additional boundary conditions.

Generally in networks, the shortest path problem is of interest. Furthermore, [63] looks at a single-source, single-destination shortest path problem and algorithms to run on quantum annealing hardware. Three distinct approaches are presented. In all the three cases, the shortest path problem is formulated as a QUBO with can be solved by quantum annealing. The first implementation builds on existing quantum annealing solutions to the travelling salesman problem, and requires the anticipated maximum number of vertices on the solution path to be provided as an input. The second implementation adapts the linear programming formulation of the shortest path problem. The third implementation is designed exclusively for undirected graphs. Scaling factors for penalty terms, complexity of coupling matrix construction, and numerical estimates of the annealing time required to find the shortest path are made explicit in the article.

4.5. Machine Learning in Fixed Networks

Furthermore, quantum machine learning can bring new possibilities in operating fixed telecommunication networks. However, almost all work found in the literature concentrates on detection of intrusion in cyber networks.

In recent years, we have seen an increase in computer attacks through our communication networks worldwide. A lot of work has been performed on (automated) detection of intrusion and attacks in cyber networked systems. Furthermore, here, it is expected for quantum machine learning applications to have improvements in capacity and learning efficiency over classical machine learning methods. A literature review of research performed on this topic between 2017 and 2022, concentrating on gate-based quantum machine learning, is given in [64]. A broader overview of quantum machine learning in cybersecurity can be found in [65]. Examples include the hybrid quantum-classical neural network approach in [66], the quantum support vector machine and quantum convolution neural network approach in [67], and the hybrid variational quantum circuit and classical machine learning strategy in [68]. Furthermore, work exists that uses annealing. Older work presents approaches based on simulated annealing, such as the improved simulated annealing neural network in [69] and the simulated annealing and fuzzy c-means clustering approach in [70]. Fuzzy c-means is a data clustering technique in which a dataset is grouped into N clusters with every data point in the dataset belonging to every cluster to a certain degree. This methods can be translated to quantum annealing. In [71], a restricted Boltzmann machine on a quantum annealer is trained. As a last example, in [72], an efficient and high-performance intrusion detection system based on quantum annealing is presented which aims on identifying attacks in an IoT environment such as Smart Home. They use Qboost, an iterative training algorithm in which a subset of weak classifiers is selected by solving a hard optimisation problem in each iteration.

4.6. Searching Problems in Wireless Networks

A slightly different task that quantum computers do well is searching, thanks to the famous Grover's algorithm, as shown in Section 3.3. Although this algorithm can be used for optimisation, in this section, a specific overview of using this algorithm is given.

Clustering is an effective topology control approach that evenly distributes loads across sensor nodes, enhances network scalability, and increases the lifetime in wireless sensor networks. In [73], a novel energy-efficient weighted cluster head selection approach is proposed that improves the overall performance of the network and increases energy efficiency. They use a quantum search algorithm for choosing the cluster head, which has a quadratic speed-up advantage.

In [74,75], an overview is given of the use of quantum searching techniques to solve optimisation problems encountered both in the physical and network layer of wireless communications. Application areas that are designated are multi-user detection, joint channel estimation and data detection, multi-user transmission, multi-objective Routing, indoor localisation, and big-data analysis. The topic of indoor localisation is further elaborated in [76] by the same author.

5. Conclusions and Outlook

Overall, the unique computational capabilities of quantum computing, such as superposition, entanglement, tunnelling, and quantum parallelism, hold the potential to address complex optimisation and machine learning problems in telecommunication wireless and fixed networks. Leveraging quantum algorithms can lead to more efficient network operations, improved performance, enhanced resource utilisation, and ultimately, better user experiences in telecommunication networks. Examples are spectrum management, channel estimation, resource optimisation, routing and network planning, fault diagnosis, and energy management. A multitude of examples in the literature have been given earlier in this article and are summarised in Table 1. Implementing quantum computing in telecommunication, however, faces significant challenges related to hardware limitations, error rates, and scalability. To fulfil the promises, we will need a great amount of research efforts and currently still unimaginable developments in quantum hardware technology. To fully utilise the benefits, industry stakeholders and regulatory frameworks should align and strategic collaborations are needed to shape the future landscape of quantum computing in telecommunication.

Table 1. Overview of the work discussed earlier. In Boev [59], no paradigm is used. The work only describes a QUBO representation that can be solved by QAOA and annealing approaches. The work in Engel [60] uses digital annealing. Digital annealing refers to a computational approach that mimics the annealing process from classical physics but implemented using dedicated classical digital hardware rather than physical quantum systems. It is a method for solving combinatorial optimisation problems by leveraging the principles of simulated annealing, a classical optimisation technique.

Work	Paradigm	Topic	Network
Alanis [51]	gate-based	routing	wireless
Alanis [49]	gate-based	routing	wireless
Alanis [50]	gate-based	routing	wireless
Barillaro [47]	annealing	planning	wireless
Barletta [72]	annealing	classification	cyber
Bass [53]	annealing	coverage	satellite

Table 1. *Cont.*

Work	Paradigm	Topic	Network
Bern [54]	annealing	power optimisation	wireless
Boev [59]	QUBO	Assignment	fixed
Botsinis [75]	gate-based	searching	wireless
Botsinis [76]	gate-based	searching	wireless
Botsinis [74]	gate-based	searching	wireless
Choi [42]	gate-based	scheduling	wireless
Dixit [71]	annealing	classification	cyber
Engel [60]	digital annealing	flow problem	fixed
Feld [61]	annealing	compression	data
Gao [69]	annealing	classification	cyber
Godar [62]	annealing	planning	fixed
Gong [68]	gate-based	classification	cyber
Griol [77]	gate-based	classification	wireless
Kalinin [67]	gate-based	classification	cyber
Kasi [44]	annealing	scheduling	wireless
Kim [46]	annealing	scheduling	wireless
Kim [45]	annealing	decoding	wireless
Krauss [63]	annealing	shortest path	general
Milic [58]	gate-based	prediction	wireless
Nicesio [64]	gate-based	classification	cyber
Payares [66]	gate-based	classification	cyber
Phillipson [57]	annealing+gate-based	classification	wireless
Roy [73]	gate-based	searching	wireless
Saravanan [43]	annealing	scheduling	wireless
Urgelles [48]	gate-based	routing	wireless
Vista [41]	annealing	scheduling	IoT
Wang [39]	annealing	scheduling	wireless
Wang [40]	annealing	scheduling	wireless
Wu [70]	annealing	classification	cyber
Wurtz [52]	gate-based	routing	wireless
Zaman [56]	gate-based	scheduling	wireless

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Abbreviations

The following abbreviations are used in this manuscript:

3GPP	3rd Generation Partnership Project
5G, 6G	The fifth- and sixth-generation mobile networks
CC	channel capacity
CVRP	Capacitated Vehicle Routing Problem
EQPO	Evolutionary Quantum Pareto Optimisation
EVM	Error Vector Magnitudes
ICT	Information and Communication Technology
IoT	Internet of Things
MIMO	Multiple-Input Multiple-Output
MWIS	Maximum weight independent set
PAPR	Peak-to-Average Power Ratio
PCI	Physical Cell Identifier
QAOA	Quantum Approximate Optimisation Algorithm
QAOS	Quantum Approximate Optimisation for Scheduling
QKD	Quantum key distribution

QoE	Quality of Experience
QoS	Quality of Service
QUBO	Quadratic Unconstrained Binary Optimisation problem
RAN	Radio Access Network
SLA	Service Level Agreement
TSP	Travelling Salesman Problem
URLLC	ultra-reliable and low-latency communication
VPP	Vector Perturbation Precoding
VRP	Vehicle Routing Problem
WDM	Wavelength-Division Multiplexing

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