

1

Introduction

1.1 Motivation

Owing to the increase in the density and number of different functionalities in wireless networks, there is an increasing need for the use of artificial intelligence (AI) in planning the network deployment, running their optimization, and dynamically controlling their operation. Machine learning (ML) algorithms are used to predict traffic and network state in order to reserve resources for smooth communication with high reliability and low latency in a timely fashion. Big data mining is used to predict customer behavior and pre-distribute (caching) the information content across the network in a timely fashion so that it can be efficiently delivered as soon as it is requested. Intelligent agents can search the Internet on behalf of the customer in order to find the best options when it comes to buying any product online. This book reviews ML-based algorithms with a number of case studies supported by Python and R programs. It discusses the learning algorithms used in decision making based on game theory and a number of specific applications in wireless networks such as channel, network state, and traffic prediction.

We begin the book with a comprehensive survey of AI learning algorithms. These algorithms are used in the prediction of the network parameters for efficient network slicing, customer behavior for content caching across the network, or for efficient network control and management. Subsequently, we focus on network applications with an emphasis on AI-based learning algorithms used for reaching equilibria in games used among different parties in a variety of new business models in communication networks. This includes competition between network operators, service providers, or even users in dynamic network architectures of user-provided networks.

The book also covers in detail a number of specific applications of AI for dynamic readjusting network behavior based on the observation of its state, traffic variation, and user behavior. This includes channel and power level selection in cellular networks, network self-organization, proactive caching, big data learning, graph neural network (GNN), and multi-armed bandit estimators.

Why quantum computing? The ever-reducing transistor size following Moore's law is approaching the point where quantum effects predominate in transistor operation. This specific trend implies that quantum effects become unavoidable, hence making research on quantum computing (QC) systems an urgent necessity. In fact, a quantum annealing chipset is already commercially available from D-Wave1.

Apart from the quantum annealing architecture, gate-based architecture, which relies on building computational blocks using quantum gates in a similar fashion to classical logic gates,

is attracting increasing attention due to the recent advances in quantum stabilizer codes, which are capable of mitigating the de-coherence effects encountered by quantum circuits. In terms of implementation, IBM has initially produced 53-qubits quantum computer [1] and plans to have 1-million qubits by 2030 [2]. D-Wave Two 512 qubit processors [3] are built in Google and NASA quantum computer. With this recent developments, Quantum computing has become a commercial reality and it may be used in wireless communications systems in order to speed up specific processes due to its inherent parallelization capabilities.

Whereas a classical bit may adopt the values 0 or 1, a quantum bit, or qubit, may have the values $|0\rangle$, $|1\rangle$, or any superposition of the two, where the notation $|\rangle$ is the column vector of a quantum state. If two qubits are used, then the composite quantum state may have the values $|00\rangle$, $|01\rangle$, $|10\rangle$, and $|11\rangle$ simultaneously. In general, by employing b bits in a classical register, one out of b^2 combinations is represented at any time. By contrast, in a quantum register associated with b qubits, the composite quantum state may be found in a superposition of all b^2 values simultaneously. Therefore, applying a quantum operation to the quantum register would result in altering all b^2 values at the same time. This represents the parallel processing capability of quantum computing.

In addition to superior computing capabilities, multiple quantum algorithms have been proposed, which are capable of outperforming their classical counterparts in the same categories of problems, by either requiring fewer computational steps, or by finding a better solution to the specific problem. In this book, we will focus on the employment of quantum algorithms in classical communication systems, which is nowadays referred to as quantum-assisted communications.

In the following sections, we revisit the ML methods in the context of quantum-assisted algorithms for ML and the quantum machine learning (QML) framework. Quantum principles based on emerging computing technologies will bring in entirely new modes of information processing. An overview of supervised, unsupervised, and reinforcement learning (RL) methods for QML is presented in this segment of the book.

Currently, 5G networks have entered into the commercialization phase, which makes it appropriate to launch a strong effort to conceptualize the future vision of the next generation of wireless networks. The increasing size, complexity, services, and performance demands of communication networks necessitate planning and consultation for envisioning new technologies to enable and harmonize future heterogeneous networks. An overwhelming interest in AI methods is seen in recent years, which has motivated the provision of essential intelligence to 5G networks. However, this provision is limited to the performance of different isolated tasks of optimization, control, and management. The recent success of quantum-assisted and data-driven learning methods in communication networks has led to their candidature as enablers of future heterogeneous networks. This section reviews a novel framework for 6G/7G networks, where quantum-assisted ML and QML are proposed as the core enablers along with some promising communication technology innovations.

The relevance of the research fields integrated throughout this book can be easily recognized within the National Science Foundation (NSF) list of research priorities in science and technology: These 10 areas specified by NSF include (i) AI and ML; (ii) high performance computing, semiconductors, and advanced computer hardware; (iii) quantum computing and information systems; (iv) robotics, automation, and advanced manufacturing; (v) natural or anthropogenic disaster prevention; (vi) advanced communications technology; (vii) biotechnology, genomics, and synthetic biology; (viii) cybersecurity, data storage, and data management technologies; (ix) advanced

energy; and (x) materials science, engineering, and exploration relevant to other key technology areas. The 10 areas would be revisited every four years.

1.2 Book Structure

The first part of the book covers selected topics in ML, and the second part presents a number of topics from QC relevant for networking.

Chapter 2 (Machine Learning Algorithms): This chapter presents an introductory discussion of many basic ML algorithms that are often used in practice and not necessary directly related to networking problems. However, they will present a logical basis for developing more sophisticated algorithms that are used nowadays to efficiently solve various problems in this field. These algorithms include linear regression, logistic regression, decision tree (regression trees vs. classification trees), and working with decision trees [4] in R and Python. In this chapter, we answer the questions: What is bagging? What is random forest? What is boosting? Which is more powerful: GBM or XGBoost? We also explain the basics of working in R and Python with GBM, XGBoost, SVM (support vector machine), Naive Bayes, kNN, K-means, random forest, dimensionality reduction algorithms [5, 6], gradient boosting algorithms, GBM, XGBoost, LightGBM, and CatBoost [7, 8].

Chapter 3 (Artificial Neural Networks): We are witnessing the rapid, widespread adoption of AI [9] in our daily life, which is accelerating the shift toward a more algorithmic society. Our focus is on reviewing the unprecedented new opportunities opened up by using AI in deploying and optimization of communication networks. In this chapter, we will discuss the basis of artificial neural networks (ANNs) [10] including multilayer neural networks, training and backpropagation, finite-impulse response (FIR) architecture spatial temporal representations, derivation of temporal backpropagation, applications in time series prediction, auto-regressive linear prediction, nonlinear prediction, adaptation and iterated predictions as well as multiresolution FIR neural-network-based learning algorithm applied to network traffic prediction. Traffic prediction is important for timely reconfiguration of the network topology or traffic rerouting to avoid congestion or network slicing.

Chapter 4 (Explainable NN): Even with the advancements of AI described in the previous chapter, a key impediment to the use of AI-based systems is that they often lack transparency. Indeed, the black-box nature of these systems allows powerful predictions, but they cannot be directly explained. This problem has triggered a new debate on explainable AI (XAI) [11–14].

XAI is a research field that holds substantial promise for improving the trust and transparency of AI-based systems. It is recognized as the main support for AI to continue making steady progress without disruption. This chapter provides an entry point for interested researchers and practitioners to learn key aspects of the young and rapidly growing body of research related to XAI. Here, we review the existing approaches regarding the topic, discuss trends surrounding related areas, and present major research trajectories covering a number of problems related to Explainable NN. This, in particular, includes such topics as using XAI: the need and the application opportunities for XAI; explainability strategies: complexity-related methods, scoop, and model-related methods; XAI measurement: evaluating explanations; XAI perception: human in the loop; XAI antithesis: explain or predict discussion; toward more formalism; human-machine teaming; explainability methods composition; other explainable intelligent systems; and the economic perspective.

Chapter 5 (Graph Neural Networks): Graph theory is a basic tool for modeling communication networks in the form $G(N,E)$, where N is the set of nodes and E the set of links (edges) interconnecting the nodes. Recently, the methodology of analyzing graphs with ML have been attracting

increasing attention because of the great expressive power of graphs; that is, graphs can be used to represent a large number of systems across various areas including social science (social networks) [15, 16], natural science (physical systems [17, 18] and protein–protein interaction networks [19]), knowledge graphs [20], and many other research areas [21] including communication networks, which is our focus in this book. As a unique non-Euclidean data structure for ML, graph analysis focuses on node classification, link prediction, and clustering. GNNs are deep-learning-based methods that operate on graph domain. Due to its convincing performance and high interpretability, GNN has recently been a widely applied graph analysis method. In this chapter, we will illustrate the fundamental motivations of GNNs and demonstrate how we can use these tools to analyze network slicing. The chapter includes GNN modeling, computation of the graph state, the learning algorithm, transition and output function implementations, linear and nonlinear (non-positional) GNN, computational complexity, and examples of Web page ranking and network slicing.

Chapter 6 (Learning Equilibria and Games): A comprehensive network optimization also includes the cost of implementing specific solutions. More generally, all negative effects caused by a certain decision in the choice of network parameters such as congestion, power consumption, and spectrum misuse, can be modeled as a cost. On the other hand, most economic theory relies on equilibrium analysis, making use of either Nash equilibrium or one of its refinements [22–31]. One justification of this is to argue that Nash equilibrium might arise as a result of learning and adaptation. In this chapter, we investigate theoretical models of learning in games. A variety of learning models have been proposed, with different motivations. Some models are explicit attempts to define dynamic processes that lead to Nash equilibrium play. Other learning models, such as stimulus response or reinforcement models, were introduced to capture laboratory behavior. These models differ widely in terms of what prompts players to make decisions and how sophisticated players are assumed to behave. In the simplest models, players are just machines who use strategies that have worked in the past. They may not even realize they are in a game. In other models, players explicitly maximize payoffs given beliefs that may involve varying levels of sophistication. Thus, we will look at several approaches including best response dynamics (BRD), fictitious play (FP), RL, joint utility and strategy learning (JUSTE), trial and error learning (TE), regret matching learning, Q-learning, multi-armed bandits, and imitation learning.

Chapter 7 (AI Algorithms in Networks): Finally, at the end of Part I of the book, in this chapter we present an extensive set of examples of solving practical problems in networks by using AI. This includes a survey of specific AI-based algorithms used in networks, such as for controlled caching in small cell networks; channel and power level selection; controlling network self-organization; proactive caching; big data learning for AI-controlled resource allocation; GNN for prediction of resource requirements; and multi-armed bandit estimators for Markov channels.

In particular, we consider AI-based algorithms for traffic classification, traffic routing, congestion control, resource management, fault management, Quality of Service (QoS) and Quality of Experience (QoE) management, network security, ML for caching in small cell networks, Q-learning-based joint channel and power level selection in heterogeneous cellular networks, stochastic non-cooperative game, multi-agent Q-learning, Q-learning for channel and power level selection, ML for self-organizing cellular networks, learning in self-configuration, RL for SON coordination, SON function model, RL, RL-based caching, system model, optimality conditions, big data analytics in wireless networks, evolution of analytics, data-driven networks optimization, GNNs, network virtualization, GNN-based dynamic resource management, deep reinforcement learning (DRL) for multioperator network slicing, game equilibria by DRL, deep Q-learning for latency limited network virtualization, DRL for dynamic VNF migration, multi-armed bandit estimator (MBE), and network representation learning.

Chapter 8 (Fundamentals of Quantum Communications): During the last few years, the research community has turned its attention to quantum computing [32–36] with the objective of combining it with classical communications in order to achieve certain performance targets, such as throughput, round trip delay, and reliability targets at a low computational complexity. As we will discuss in more detail in this chapter, there are numerous optimization problems in wireless communications systems that may be solved at a reduced number of cost function evaluations (CFEs) by employing quantum algorithms. Although we do not attempt to cover the problems of quantum computer design itself, in this chapter we will discuss the basics of QC technology in order to understand better how this technology can enable significant improvements in the design and optimization of communication networks. These fundamentals include discussions on the qubit system, algebraic representation of quantum states, entanglement, geometrical (2D, 3D) representation of quantum states, quantum logical gates, tensor computing, the Hadamard operator H , and the Pauli and Toffoli gates.

Chapter 9 (Quantum Channel Information Theory): Quantum information processing exploits the quantum nature of information. It offers fundamentally new solutions in the field of computer science and extends the possibilities to a level that cannot be imagined in classical communication systems. For quantum communication channels, many new capacity definitions were developed in analogy with their classical counterparts. A quantum channel can be used to achieve classical information transmission or to deliver quantum information, such as quantum entanglement. In this chapter, we review the properties of the quantum communication channel, the various capacity measures, and the fundamental differences between the classical and quantum channels [37–43]. Specifically, we will discuss the privacy and performance gains of quantum channels, the quantum channel map, the formal model, quantum channel capacity, classical capacities of a quantum channel, the quantum capacity of a quantum channel, quantum channel maps, and capacities and practical implementations of quantum channels.

Chapter 10 (Quantum Error Correction): The challenge in creating quantum error correction codes lies in finding commuting sets of stabilizers that enable errors to be detected without disturbing the encoded information. Finding such sets is nontrivial, and special code constructions are required to find stabilizers with the desired properties. We will start this section by discussing how a code can be constructed by concatenating two smaller codes. Other constructions include methods for repurposing classical codes to obtain commuting stabilizer checks [44–47]. Here, we will outline a construction known as the surface code [48, 49]. The realization of a surface code logical qubit is a key goal for many quantum computing hardware efforts [50–54]. The codes belong to a broader family of so-called topological codes [55]. In this framework, within this chapter we will discuss stabilizer codes, surface codes, the rotated lattice, fault-tolerant gates, fault tolerance, theoretical framework, classical error correction, and the theory of quantum error correction in addition to some auxiliary material on binary fields and discrete vector spaces, and noise physics.

Chapter 11 (Quantum Search Algorithms): The appetite for faster, more reliable, greener, and more secure communications continues to grow. The state-of-the-art methods conceived for achieving the performance targets of the associated processes may be accompanied by an increase in computational complexity. Alternatively, degraded performance may have to be accepted due to the lack of jointly optimized system components. In this chapter, we investigate the employment of quantum computing for solving problems in wireless communication systems. By exploiting the inherent parallelism of quantum computing, quantum algorithms may be invoked for approaching the optimal performance of classical wireless processes, despite their reduced number of CFEs cost-function evaluations. In Chapter 8, we have already discussed the basics of quantum computing using linear algebra, before presenting here the operation of the major quantum algorithms that have been

proposed in the literature for improving wireless communications systems. Furthermore, in the following chapters, we will investigate a number of optimization problems encountered both in the physical and network layer of wireless communications, while comparing their classical and quantum-assisted solutions. More specifically, in this chapter we will discuss the following: quantum search algorithms (QSAs) for wireless communications such as the Deutsch algorithm, the Deutsch–Jozsa algorithm, Simon’s algorithm, Shor’s algorithm, the quantum phase estimation algorithm, Grover’s QSA, the Boyer–Brassard–Høyer–Tapp QSA, the Dürr–Høyer QSA, quantum counting algorithm, quantum heuristic algorithm, quantum genetic algorithm, Harrow–Hassidim–Lloyd algorithm, quantum mean algorithm, and quantum-weighted sum algorithm.

Chapter 12 (Quantum Machine Learning): In this chapter, we provide a brief description of quantum machine learning (QML) and its correlation with AI. We will see how the quantum counterpart of ML is much faster and more efficient than classical ML. Training the machine to learn from the algorithms implemented to handle data is the core of ML. This field of computer science and statistics employs AI and computational statistics. The classical ML method, through its subsets of deep learning (supervised and unsupervised), helps to classify images, recognize patterns and speech, handle big data, and many more. Thus, classical ML has received a lot of attention and investments from the industry. Nowadays, due to the huge quantities of data with which we deal every day, new approaches are needed to automatically manage, organize, and classify these data. Classical ML, which is a flexible and adaptable procedure, can recognize patterns efficiently, but some of these problems cannot be efficiently solved by these algorithms. Companies engaged in big databases management are aware of these limitations, and are very interested in new approaches to accomplish this. They have found one of these approaches in quantum ML. However, the interest in implementing these techniques through QC is what paves the way for quantum ML. QML [56–59] aims to implement ML algorithms in quantum systems by using quantum properties such as superposition and entanglement to solve these problems efficiently. This gives QML an edge over the classical ML technique in terms of speed of functioning and data handling. In the QML techniques, we develop quantum algorithms to operate classical algorithms using a quantum computer. Thus, data can be classified, sorted, and analyzed using the quantum algorithms of supervised and unsupervised learning methods. These methods are again implemented through models of a quantum neural network or support vector machine. This is the point where we merge the algorithms discussed in Parts I and II of this book. In particular, we will discuss QML algorithms, quantum neural network preliminaries, quantum, classifiers with ML: near-term solutions, the circuit-centric quantum classifier, training, gradients of parameterized quantum gates, classification with quantum neural networks, representation, learning, the quantum decision tree classifier, and the model of the classifier in addition to some auxiliary material on matrix exponential.

Chapter 13 (Quantum Computing Optimization): Convexity naturally arises in many segments of quantum information theory; the sets of possible preparations, processes, and measurements for quantum systems are all convex sets. Many important quantities in quantum information are defined in terms of a convex optimization problem, such as quantifying entanglement [60, 61]. Since the set of separable or unentangled states is convex, a measure of entanglement may be defined for entangled states outside of this set, given a suitable “distance” measure, such as the minimum distance to a state inside. Perhaps the most well known of these quantities is the relative entropy of entanglement. In addition, in the chapter we discuss a number of optimization algorithms including optimization for hybrid quantum-classical algorithms, the quantum approximate optimization algorithm (QAOA), convex optimization in quantum information theory, relative entropy of entanglement, quantum algorithms for combinatorial optimization problems, QC for linear systems of equations, a design example (QC for multiple regression), and a quantum algorithm for systems of nonlinear differential equations.

Chapter 14 (Quantum Decision Theory): The classical decision-making process is mostly based on expected utility theory, and its performance significantly degrades in scenarios involving risk and uncertainty [62]. In most of the classical decision-making processes, the possibility of making correct predictions can be strongly affected by the nature of the surrounding environment such as the unknown stochastic or varying environment. Furthermore, in scenarios having incomplete or partially reliable information or incomplete preference relations, any prediction is likely to be just partial and qualitative. To address this, quantum decision theory (QDT) seems to be a promising approach and has been already investigated in the existing literature [62, 63]. Also, the process of representing all steps of a decision process mathematically in order to allow quantitative prediction is significant not only for the decision theory but also for developing artificial quantum intelligence, which can work only for the operations defined in mathematical terms [64].

With the recent advances in quantum information and QC, there has been a trend of formulating classical game theory using quantum probability amplitudes toward analyzing the impact of quantum superposition, entanglement, and interference on the agents' optimal strategies [65]. Quantum game theory (QGT) in general replaces the classical probabilities of game theory with quantum amplitudes by creating the possibility of new effects arising from entanglement or superposition. The main difference between the classical game and the quantum game is that classical games perform calculations in the probability space, whereas quantum games operate in the Hilbert space. Quantum game theoretic techniques can be utilized for investigating suitable solutions in quantum communication [66] and quantum information processing [67]. In this regard, an article [65] provided an introduction to quantum theory along with some related works and discussed some well-known quantum games including the quantum penny flip, Eisert's quantum prisoners' dilemma, and quantum Parrondo games. Furthermore, a recent article [68] analyzed the existing works on quantum games from three perspectives, namely, co-authorship, co-occurrence, and co-citation, and also reviewed the main quantum game models and applications. Under this umbrella, the chapter discusses QGT, definitions, quantum games, a design example (quantum routing games), quantum game for spectrum sharing, QDT, a model (QDT), predictions in QDT, utility factors, and classification of lotteries by attraction indices.

Chapter 15 (Quantum Computing in Wireless Networks): In this chapter, we discuss several examples of wireless network design based on the tools enabled by quantum computing. Both satellite and terrestrial networks are considered. Traditional security techniques mostly focus on the encryption of communication, where security depends on the mathematical complexity. However, encryption methodologies are becoming less reliable as eavesdroppers and attackers are gaining powerful computing ability. As already discussed in Chapters 8 and 11, quantum cryptography is a new cryptographic technology for generating random secret keys to be used in secure communication. Quantum cryptography can provide communication security based on the laws of quantum physics (e.g., the no-cloning theorem and uncertainty principle). However, the quantum key has to be distributed over the communication network to be used by the senders and receivers.

Reference [69] demonstrated the feasibility of quantum key distribution (QKD) over optical networks. Such a QKD network can be constructed by distributing end-to-end secret (quantum) keys through trusted repeaters (e.g., based on the point-to-point BB84 protocol). References [70, 71] also reported such optical-fiber-based QKD networks, used to secure metropolitan and backbone networks. Recent studies discussed about the integration of QKD and classical networks, such as QKD over wavelength division multiplexing (WDM) networks [72, 73] and QKD-enabled software-defined networks (SDN) [74]. While implementing QKD in terrestrial optical networks, distributing secret keys over a long distance (e.g., across the globe) is challenging. Single-photon signals

transmitted over long-distance optical fiber suffer from high losses and depolarization. Hence, carrying the keys using optical fiber over long distances (e.g., 1000 km) is not an effective solution [75].

To address these limitations, an experimented free-space QKD has been studied in recent years. In contrast to optical fibers, the free-space photon will experience negligible loss in vacuum, making it feasible to distribute secret keys over thousands of kilometers. Although the optical beam of a satellite-to-ground link can suffer from atmospheric loss, most of the space is empty, which makes the channel loss less than that for a long fiber [75, 76]. The quantum satellite *Micius*, launched in 2016 for quantum communication experiments, has successfully demonstrated satellite-to-ground QKD using single-photon source [77]. In 2017, a ground free-space QKD experiment was conducted using telecom wavelength in daylight and demonstrated the feasibility of inter-satellite QKD in daylight [78, 79]. Therefore, satellite-based QKD is a promising method for distributing quantum keys between two ultra-long-distance parties on the ground.

Since the coverage and flyover time of one satellite is limited, a group of quantum satellites can be used as trusted repeaters to serve ground stations. Recently, researchers have proposed a “network of quantum satellites” to realize global-scale quantum communications [80, 81]. The authors of [78] proposed a QKD satellite networks architecture based on quantum repeaters. The researchers also proposed the trusted-repeater-based satellite QKD scheme [79–83]. Their scheme is based on BB84 protocol since quantum repeaters are still far from being implemented. Reference [84] investigates the possible schemes of free-space QKD using inter-satellite links and analyzed the properties of satellite-ground links. These studies motivated the concept presented here [85], which is a contribution toward the advancement of the state of the-art in satellite-based QKD networks.

Prior studies envision that a quantum-capable satellite constellation can be formed to construct global QKD (similar to traditional satellite constellations such as IRIDIUM [86]). In recent proposals, quantum satellites will use a low earth orbit (LEO) to benefit from its low channel loss. But a LEO satellite can access a particular ground station for a limited time of the day [87]. This limited coverage may lead to a shortage of secret keys between satellite and ground. By contrast, geostationary earth orbit (GEO) satellites can access ground stations continuously, all day. However, their signal can suffer from high channel loss and a limited key generation rate.

In 2017, German researchers successfully measured quantum signals that were sent from a GEO to a ground station [88]. Italian researchers have also demonstrated the feasibility of quantum communications between high-orbiting global navigation satellites and a ground station [89]. The Chinese Academy of Sciences has future projects to launch higher-altitude satellites [77–79]. According to the researchers, the future quantum satellite constellation will comprise satellites in high and low orbits [90]. Thus, combining both GEO and LEO satellites to build QKD networks is a research direction worth exploring. Within this scope, in this chapter we will address the following problems: quantum satellite networks, satellite-based QKD system, quantum satellite network architecture, a routing and resource allocation algorithm, QC routing for social overlay networks, social overlay networks, a multiple-objective optimization model, QKD Networks, QoS in QKD overlay networks, adaptive QoS-QKD networks, and a routing protocol for QKD networks.

Chapter 16 (Quantum Network on Graph)

To fully benefit from the advantages of quantum technology, it is necessary to design and implement quantum networks [91, 92] that are able to connect distant quantum processors through remote quantum entanglement distribution. However, despite the tremendous progress of quantum technologies, efficient long-distance entanglement distribution remains a key problem, due to the exponential decay of the communication rate as a function of distance [93, 94]. A solution to counteract the exponential decay loss is the adoption of quantum repeaters [95, 96]. Instead of distributing entanglement over a long link, entanglement will be generated through

shorter links. A combination of entanglement swapping [97] and entanglement purification [98] performed at each quantum repeater enables the entanglement to be extended over the entire channel. Now a simple question arises: “when does a repeater ensure higher entanglement distribution over the direct long link?”

Different from classical information, quantum information (e.g., qubits) cannot be copied due to the no-cloning theorem [99, 100]. Hence, quantum networks rely on the quantum teleportation process (Chapter 8), [101] as a unique feasible solution, transmitting a qubit without the need to physically move the physical particle storing the qubit. The quantum teleportation of a single qubit between two different nodes requires (i) a classical communication channel capable of sending two classical bits and (ii) the generation of a pair of maximally entangled qubits, referred to as Einstein–Podolsky–Rosen (EPR) pair, with each qubit stored at each remote node. In the following, the generation of an EPR pair at two different nodes is referred to as remote entanglement generation. Under this umbrella, in this chapter we discuss the following specific problems: optimal routing in quantum networks, network model, entanglement, optimal quantum routing, quantum network on symmetric graph, quantum walks, discrete quantum walks on a line (DQWL), Performance study of DQWL, multidimensional quantum walks, the quantum random walk, *Channel Entropy*, quantum random walks on general graphs, continuous time quantum random walks, and searching large-scale graphs.

Chapter 17 (Quantum Internet): Finally, in this chapter we discuss current progress in building up a quantum Internet [91, 102–104] intended to enable the transmission of quantum bits (qubits) between distant quantum devices to achieve the tasks that are impossible using classical communication. For example, with such a network we can implement cryptographic protocols like long-distance QKD [105, 106], which enables secure communication. Apart from QKD, many other applications in the domain of distributed computing and multi-party cryptography [107] have already been identified at different stages of quantum network development [108].

Like the classical Internet, a quantum Internet consists of network components such as physical communication links, and eventually routers [2, 109–111]. However, due to fundamental differences between classical and quantum bits, these components in a quantum network behave rather differently from their classical counterparts. For example, qubits cannot be copied, which rules out retransmission as a means of overcoming qubit losses [112]. To nevertheless send qubits reliably, a standard method is to first produce quantum entanglement between a qubit held by the sender and a qubit held by the receiver. Once this entanglement has been produced, the qubit can then be sent using quantum teleportation [112, 113]. This requires, in addition, the transmission of two classical bits per qubit from the sender to the receiver. Importantly, teleportation consumes the entanglement, meaning that it has to be re-established before the next qubit can be sent. When it comes to routing qubits in a network, one hence needs to consider routing entanglement [102, 114–117]. In this chapter, we discuss the Internet system model, routing algorithms, the quantum network on general virtual graph, the quantum network on ring and grid graph, quantum network on recursively generated graph (RGG), recursively generated virtual graphs, the quantum network protocol stack, preliminaries, the quantum network protocol stack, Layer 3 – reliable state linking, and Layer 4 – region routing.

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