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Quantum Computing for Beyond-5G Networks

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*“I think,
I can safely say,
that nobody understands
Quantum Mechanics.”*

Richard P. Feynman

Abstract

The evolution of sixth-generation (6G) wireless networks presents a new paradigm in mobile communications, integrating emerging technologies to address the growing demands for higher data rates, ultra-low latency, and intelligent connectivity. In this context, quantum computing (QC) is recognized as a disruptive enabler, offering novel approaches to solving complex computational problems beyond the capabilities of classical methods. This Thesis explores the intersection of QC and 6G networks, investigating their potential to optimize wireless communication performance in critical areas such as network location, routing optimization, and signal detection.

Although a definitive timeline for 6G remains elusive, projections suggest initial deployments may occur around 2030. Standardization organizations like the 3rd Generation Partnership Project (3GPP) and the International Telecommunication Union (ITU) are likely to define technical specifications in the latter half of the 2020s, once 5G technology has reached full maturity. Recognizing the potential impact of 6G, both academic institutions and industry leaders are conducting foundational research and deploying practical demonstrations to shape this future.

A crucial component of 6G is its alignment with the United Nations' 2030 Agenda, including the Sustainable Development Goals (SDGs). Research indicates that 6G's blueprint for rollout around 2030 is heavily influenced by global sustainability targets. By driving progress in smart cities and connected infrastructures, 6G is expected to play a substantial role in achieving these objectives. Within this framework, the Thesis assesses how QC can influence the sustainability of forthcoming networks by studying Key Value Indicators (KVI) in tandem with emerging quantum hardware, illustrating the ways in which this novel technology might advance human progress.

Regarding practical use cases, this Thesis first tackles the challenge of indoor localization, a persistent issue in wireless environments filled with obstacles. It introduces a quantum-assisted Euclidean distance computation method, leveraging quantum effects to enhance the accuracy of fingerprint-based positioning. Experimental evaluations show that this approach surpasses classical techniques, indicating its potential for high-precision localization in 6G networks.

Next, the research delves into quantum optimization for routing in wireless networks. As network architectures grow increasingly complex and demand real-time traffic management, conventional routing algorithms often struggle

with scalability and efficiency. To address these challenges, this work employs the Quantum Approximate Optimization Algorithm (QAOA) to develop a novel quantum-based routing framework. When quantum hardware matures, this approach promises to significantly reduce computational overhead while simultaneously optimizing key metrics such as latency, energy consumption, and reliability. Performance analyses corroborate the viability of quantum-inspired methods for large-scale, multi-objective optimization in 6G.

Another central contribution is quantum-enhanced signal detection for MIMO-NOMA systems, a technology expected to underpin 6G's high connectivity and spectral efficiency. The Thesis presents a quantum-based Maximum Likelihood Detector (MLD) that tackles the complexity of multi-user interference and symbol detection. By exploiting quantum algorithms, the proposed MLD dramatically reduces computational requirements compared to traditional maximum likelihood detection, paving the way for feasible deployment in massive MIMO scenarios.

The findings of this Thesis underscore the transformative potential of quantum computing in wireless communication networks, demonstrating its capacity to enhance localization accuracy, network optimization, and signal processing. While current quantum hardware remains in the Noisy Intermediate-Scale Quantum (NISQ) era, this research provides a foundation for future developments in quantum-enabled 6G technologies. By bridging quantum mechanics and mobile communications, this work contributes to advancing intelligent, secure, and ultra-efficient wireless networks for the next decade.

Resumen

La evolución de las redes inalámbricas de sexta generación (6G) presenta un nuevo paradigma en las comunicaciones móviles, integrando tecnologías emergentes para satisfacer las crecientes demandas de velocidades de datos más altas, latencia ultrabaja y conectividad inteligente. En este contexto, la computación cuántica (QC, por sus siglas en inglés) se reconoce como un habilitador disruptivo, que ofrece enfoques novedosos para resolver problemas computacionales complejos más allá de las capacidades de los métodos clásicos. Esta Tesis explora la intersección entre la computación cuántica y las redes 6G, investigando su potencial para optimizar el desempeño de las comunicaciones inalámbricas en áreas críticas como la localización de redes, la optimización de rutas y la detección de señales.

Si bien no existe un cronograma definitivo para el 6G, las proyecciones sugieren que los primeros despliegues podrían ocurrir alrededor de 2030. Es probable que organizaciones de estandarización como el 3rd Generation Partnership Project (3GPP) y la Unión Internacional de Telecomunicaciones (UIT) definan especificaciones técnicas en la segunda mitad de la década de 2020, una vez que la tecnología 5G haya alcanzado su plena madurez. Reconociendo el impacto potencial del 6G, tanto las instituciones académicas como los líderes de la industria están llevando a cabo investigaciones fundamentales y demostraciones prácticas para dar forma a este futuro.

Un componente crucial del 6G es su alineación con la Agenda 2030 de las Naciones Unidas, incluidos los Objetivos de Desarrollo Sostenible (ODS). Las investigaciones indican que la hoja de ruta del 6G para su implementación alrededor de 2030 está fuertemente influida por los objetivos de sostenibilidad global. Al impulsar el progreso en ciudades inteligentes e infraestructuras conectadas, se espera que el 6G desempeñe un papel sustancial en el logro de estos objetivos. En este marco, la Tesis evalúa cómo la computación cuántica puede influir en la sostenibilidad de las futuras redes al estudiar los Indicadores Clave de Valor (KVI, por sus siglas en inglés) en conjunto con el hardware cuántico emergente, ilustrando las maneras en que esta novedosa tecnología podría impulsar el progreso humano.

En cuanto a los casos de uso práctico, esta Tesis aborda primero el desafío de la localización en interiores, un problema persistente en entornos inalámbricos llenos de obstáculos. Se introduce un método de cálculo de distancia euclidiana asistido por tecnología cuántica, aprovechando los efectos cuánticos para mejorar la precisión de la localización basada en huellas (fingerprinting). Las

evaluaciones experimentales muestran que este enfoque supera a las técnicas clásicas, lo que indica su potencial para una localización de alta precisión en redes 6G.

Luego, la investigación profundiza en la optimización cuántica para el enrutamiento en redes inalámbricas. A medida que las arquitecturas de red se vuelven cada vez más complejas y requieren gestión de tráfico en tiempo real, los algoritmos de enrutamiento convencionales a menudo enfrentan dificultades en términos de escalabilidad y eficiencia. Para abordar estos desafíos, este trabajo emplea el Algoritmo de Optimización Aproximada Cuántica (QAOA) para desarrollar un nuevo marco de enrutamiento basado en tecnología cuántica. Cuando el hardware cuántico alcance la madurez necesaria, este enfoque promete reducir de manera significativa la sobrecarga computacional, optimizando a la vez métricas clave como latencia, consumo de energía y fiabilidad. Los análisis de desempeño corroboran la viabilidad de los métodos inspirados en la computación cuántica para la optimización a gran escala y con múltiples objetivos en el 6G.

Otra contribución central es la detección de señales mejorada cuánticamente para sistemas MIMO-NOMA, una tecnología que se espera sustente la alta conectividad y eficiencia espectral del 6G. La tesis presenta un Detector de Máxima Verosimilitud (MLD) basado en computación cuántica que aborda la complejidad de la interferencia multiusuario y la detección de símbolos. Al explotar algoritmos cuánticos, el MLD propuesto reduce drásticamente los requisitos computacionales en comparación con la detección clásica de máxima verosimilitud, allanando el camino para su implementación viable en escenarios de MIMO masivo.

Las contribuciones de esta Tesis demuestran el potencial transformador de la computación cuántica en las redes de comunicaciones inalámbricas, demostrando su capacidad para mejorar la precisión de localización, la optimización de redes y el procesamiento de señales. Si bien el hardware cuántico actual permanece en la era Noisy Intermediate-Scale Quantum (NISQ), esta investigación sienta las bases para futuros desarrollos en tecnologías 6G habilitadas por la computación cuántica. Al tender puentes entre la mecánica cuántica y las comunicaciones móviles, este trabajo contribuye al avance de redes inalámbricas inteligentes, seguras y ultraeficientes para la próxima década.

Resum

L'evolució de les xarxes sense fil de sisena generació (6G) presenta un nou paradigma en les comunicacions mòbils, integrant tecnologies emergents per a respondre a les creixents demandes de majors velocitats de dades, latència ultra-baixa i connectivitat intel·ligent. En aquest context, la computació quàntica (QC) es reconeix com un habilitador disruptiu, oferint enfocaments novedosos per a resoldre problemes computacionals complexos més enllà de les capacitats dels mètodes clàssics. Aquesta Tesi explora la intersecció entre la QC i les xarxes 6G, investigant el seu potencial per a optimitzar el rendiment de les comunicacions sense fil en àrees crítiques com la localització de xarxes, l'optimització d'enrutament i la detecció de senyals.

Encara que no existeix un calendari definitiu per al 6G, les previsions suggereixen que els primers desplegaments podrien produir-se cap al voltant de l'any 2030. És probable que organismes d'estandardització com el 3rd Generation Partnership Project (3GPP) i la Unió Internacional de Telecomunicacions (UIT) definisquen les especificacions tècniques en la segona meitat de la dècada de 2020, una vegada la tecnologia 5G haja assolit la seua plena maduresa. Reconeixent l'impacte potencial del 6G, tant les institucions acadèmiques com els líders de la indústria estan duent a terme investigacions fonamentals i demostracions pràctiques per a configurar aquest futur.

Un component crucial del 6G és la seua alineació amb l'Agenda 2030 de les Nacions Unides, incloent-hi els Objectius de Desenvolupament Sostenible (ODS). Les investigacions indiquen que el full de ruta del 6G per al seu desplegament cap a 2030 està fortament influït pels objectius globals de sostenibilitat. En impulsar el progrés en ciutats intel·ligents i infraestructures connectades, s'espera que el 6G tinga un paper substancial en l'assoliment d'aquests objectius. Dins d'aquest marc, la Tesi avalua com la QC pot influir en la sostenibilitat de les pròximes xarxes mitjançant l'estudi dels Indicadors Clau de Valor (KVIs) conjuntament amb el maquinari quàntic emergent, tot il·lustrant de quina manera aquesta tecnologia novedosa podria impulsar el progrés humà.

Pel que fa a casos d'ús pràctics, aquesta Tesi aborda en primer lloc el repte de la localització en interiors, un problema persistent en entorns sense fil plens d'obstacles. S'hi presenta un mètode de càlcul de distància euclidiana assistit per tecnologia quàntica, aprofitant els efectes quàntics per a millorar la precisió de la localització basada en empremtes (fingerprinting). Les avaluacions experimentals mostren que aquesta aproximació supera les tècniques clàssiques, cosa que indica el seu potencial per a una localització d'alta precisió en xarxes 6G.

A continuació, la investigació aprofundeix en l'optimització quàntica per a l'enrutament en xarxes sense fil. A mesura que les arquitectures de xarxa es tornen més complexes i exigeixen una gestió del trànsit en temps real, els algorismes d'enrutament convencionals sovint s'enfronten a dificultats d'escalabilitat i eficiència. Per a fer front a aquests reptes, aquest treball empra l'Algorisme d'Optimització Aproximada Quàntica (QAOA) per a desenvolupar un nou marc d'enrutament basat en tecnologia quàntica. Quan el maquinari quàntic assoleixi la maduresa necessària, aquest enfocament promet reduir de manera significativa la càrrega computacional tot optimitzant, alhora, indicadors clau com la latència, el consum d'energia i la fiabilitat. Les anàlisis de rendiment corroboren la viabilitat dels mètodes inspirats en la computació quàntica per a l'optimització a gran escala i multiobjectiu en el 6G.

Una altra contribució destacada és la detecció de senyals millorada quànticament per a sistemes MIMO-NOMA, una tecnologia que s'espera que sustente l'elevada connectivitat i eficiència espectral del 6G. La tesi presenta un Detector de Màxima Versemblança (MLD) basat en computació quàntica que aborda la complexitat de la interferència multiusuari i la detecció de símbols. En aprofitar els algorismes quàntics, el MLD proposat redueix dràsticament els requisits computacionals respecte a la detecció clàssica de màxima versemblança, la qual cosa obri la porta a un desplegament viable en escenaris de MIMO massiu.

Les conclusions d'aquesta Tesi posen de manifest el potencial transformador de la computació quàntica en les xarxes de comunicacions sense fil, demostrant la seua capacitat per a millorar la precisió de la localització, l'optimització de xarxes i el processament de senyals. Tot i que l'actual maquinari quàntic es troba en l'era quàntica de grandària intermèdia i sorollosa (NISQ), aquesta investigació proporciona les bases per a futurs avanços en tecnologies 6G habilitades per la computació quàntica. En connectar la mecànica quàntica amb les comunicacions mòbils, aquest treball contribueix a l'impuls de xarxes sense fil intel·ligents, segures i ultraeficients per a la pròxima dècada.

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Acronyms

1G	First Generation
2G	Second Generation
3G	Third Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
APs	Access Points
ADAM	Adaptive Moment Estimation
AWGN	Additive White Gaussian Noise
AoA	Angle of Arrival
AI	Artificial Intelligence
AR	Augmented Reality
BS	Base Station
B5G	Beyond 5G
BPSK	Binary Phase-Shift Keying
BER	Bit Error Rate
BLE	Bluetooth Low Energy
CSI	Channel State Information
CLOPS	Circuit Layer Operations per Second
CDMA	Code Division Multiple Access
COBYLA	Constrained Optimization By Linear Approximations
CQOA	Constrained Quantum Optimization Algorithm

ACRONYMS

CNN	Convolutional Neural Networks
dBm	decibel-milliwatts
DNN	Deep Neural Networks
DL	Downlink
EPR	Einstein-Podolsky-Rosen
E2E	End-to-End
EE	Energy Efficiency
eMBB	Enhanced Mobile Broadband
FDMA	Frequency Division Multiple Access
GPLK	General-Purpose Linear Programming Kit
GPS	Global Positioning System
HetNets	Heterogeneous networks
HMIs	Human Machine Interfaces
ICT	Information and Communications Technology
IoT	Internet of Things
ISAC	Integrated Sensing and Communication
KPIs	Key Performance Indicators
KVIs	Key Value Indicators
LMMSE	Linear Minimum Mean Square Error
LP	Linear Programming
LoS	Line of Sight
LTE	Long Term Evolution
LoRa	Long Range
ML	Machine Learning
mMTC	massive Machine Type Communications
mMIMO	Massive MIMO
MF	Matched Filter
MLD	Maximum Likelihood Detection
MAE	Mean Absolute Error
mK	miliKelvin
mmW	Millimeter Wave

mW	milliwatts
MMSE	Minimum Mean-Square Error
MIMO	Multiple-Input Multiple-Output
MLP	Multi-layer Perceptron
MOO	Multi-Objective Optimization
MODE	Multi-Objective Differential Evolution
MUSA	Multiuser Shared Access
NDQIO	Non-Dominated Quantum-Inspired Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NP-hard	Non-Deterministic Polynomial-Time
NISQ	Noisy Intermediate-Scale Quantum
NOMA	Non-Orthogonal Multiple Access
NLP	Nonlinear Programming
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
PoA	Phase of Arrival
PUE	Power Usage Effectiveness
QAM	Quadrature Amplitude Modulation
QUBO	Quadratic Unconstrained Binary Optimization
QPSK	Quadrature Phase-Shift Keying
QA	Quantum Annealing
QAOA	Quantum Approximate Optimization Algorithm
QC	Quantum Computing
QEA	Quantum Evolutionary Algorithm
QKD	Quantum Key Distribution
QML	Quantum Machine Learning
QPU	Quantum Processing Unit
QV	Quantum Volume
QoS	Quality of Service
RAN	Radio Access Network
RFID	Radio Frequency Identification

ACRONYMS

RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RIS	Reconfigurable Intelligent Surface
RP_s	Reference Points
SV	Saleh-Valenzuela
SDN	Software-Defined Networking
SISO	Single Input Single Output
SNR	Signal to Noise Ratio
SOO	Single-Objective Optimization
SDK	Software Development Kit
SCMA	Sparse Code Multiple Access
SE	Spectral Efficiency
SD	Sphere Decoding
SIC	Successive Interference Cancellation
SC	Superposition Coding
SVM	Support Vector Machine
SDGs	Sustainable Development Goals
Tbps	Terabit per second
THz	Terahertz
TDMA	Time Division Multiple Access
ToF	Time of Flight
URLLC	Ultra-Reliable and Low Latency Communications
UWB	Ultra-Wideband
UAV	Unmanned Aerial Vehicle
UL	Uplink
UE	User Equipment
VQAs	Variational Quantum Algorithms
VQC	Variational Quantum Classifiers
VQE	Variational Quantum Eigensolver
VRP	Vehicle Routing Problem
VR	Virtual Reality

VLC	Visible Light Communications
WSNs	Wireless Sensor Networks
WWDC	World Wide Developers Conference
XR	Extended Reality
ZF	Zero Forcing
ZigBee	Zonal Intercommunication Global-standard

Notation

This section describes the notation used in this Thesis.

$\mathbf{A}$ (boldface capital letter) and $\mathbf{A}_k$ represent matrices.

$[\mathbf{A}]_{ij}$ is the element of matrix $\mathbf{A}$ in row i and column j .

$[\mathbf{A}]_i$ represents the i -th row of matrix $\mathbf{A}$.

$\hat{\mathbf{A}}$ is a Hermitian matrix operator that acts on quantum states.

$[\mathbf{A}]_{:j}$ represents the j -th column of matrix $\mathbf{A}$.

$\mathbf{A}^H$ denotes the conjugate transpose or Hermitian transpose of $\mathbf{A}$.

$\mathbf{a}$ (boldface lower-case letter) and $\mathbf{a}_k$ represent vectors.

$[\mathbf{a}]_i$ represents the i -th element of vector $\mathbf{a}$.

$\mathbf{A}^T$ denotes the transpose of matrix $\mathbf{A}$.

$\mathbf{a}^T$ denotes the transpose of vector $\mathbf{a}$.

a and A (not boldface italic letters) represent scalars.

$\mathbb{C}$ Complex Numbers.

$\mathbb{R}$ Real Numbers.

$|\psi\rangle$ denotes quantum states.

$|\rangle$ denotes the Dirac notation in quantum states.

$\otimes$ represents the tensor product.

Chapter 1

Introduction

This Thesis examines a cutting-edge technological frontier: the integration of Quantum Computing (QC) with Sixth Generation (6G) wireless networks. The convergence of these two domains represents more than just a technological advancement; it embodies a potential paradigm shift capable of reshaping the telecommunications landscape and redefining the notion of global connectivity.

The vision for 6G, although still in its infancy, is being shaped by unprecedented performance requirements and emerging technological paradigms. Its central objectives include achieving data rates several orders of magnitude beyond those of current systems, supporting massive-scale device connectivity, and ensuring end-to-end latencies on the order of microseconds. To enable such demanding goals, 6G is expected to harness an extensive range of frequency bands, extending from sub-6 GHz to Millimeter Wave (mmW), Terahertz (THz), and even optical spectra. However, these resources also introduce new challenges related to propagation, energy efficiency, and network design.

Beyond physical layer advances, 6G is anticipated to act as a unified fabric for a diverse ecosystem of emerging technologies, including the Internet of Things (IoT), Augmented Reality (AR), and Virtual Reality (VR). Realizing such integration requires unprecedented computational capabilities for network optimization, resource allocation, and intelligent decision making. Conventional classical architectures, while powerful, may struggle to meet these requirements in terms of scalability, efficiency, and complexity. This limitation motivates the exploration of fundamentally new computational models, notably those derived from quantum mechanics [1].

Within this context, the present Thesis investigates the role of QC in enhancing the performance, adaptability, and intelligence of future 6G networks.

Specifically, it addresses how quantum algorithms and paradigms can contribute to critical challenges such as indoor localization, optimization, and detection in beyond-Fifth Generation (5G) scenarios. Chapter 1 introduces the overall scope and framework of the investigation, provides the necessary theoretical background, and outlines the motivations and scientific questions that guide the contributions developed throughout this work.

This chapter has been divided into the following sections:

- Section 1.1 introduces the technological framework of the Thesis, 6G overview.
- Section 1.2 analyses the state of the art in the field of study of this Thesis.
- Section 1.3 outlines the primary problem that motivates this Thesis and outlines the research hypothesis.
- Section 1.4 defines the research objectives of this Thesis.
- Section 1.5 outlines the structure of the Thesis, summarizing the main content of each chapter.
- Section 1.6 lists the publications related to this Thesis, including journals, conference papers and other related works.

1.1 Background

The rapid advancement of mobile communications has been fueled by evolving user expectations, industrial requirements, and continuous technological innovation. As digital consumption patterns have intensified, so has the demand for higher data rates, lower latency, and more reliable connectivity. In response, the telecommunications industry has maintained a steady cadence of generational updates, introducing a new wireless communication standard approximately every decade to address these growing needs.

Since the deployment of First Generation (1G) mobile networks in the 1980s, each subsequent generation has delivered substantial improvements in multiple dimensions, including spectral efficiency, latency reduction, and support for a wider range of services. 5G represents a pivotal shift, not only advancing mobile broadband performance but also enabling large-scale machine-type communications. It supports emerging paradigms such as the IoT, autonomous vehicles, and AR, offering Ultra-Reliable and Low Latency Communications (URLLC), Enhanced Mobile Broadband (eMBB), and massive Machine Type Communications (mMTC). These capabilities position 5G as a key enabler of digital transformation across multiple sectors.

However, as society moves toward increasingly complex digital ecosystems, even the advanced capabilities of 5G are expected to fall short of future demands. Projections indicate that beyond 2030, new requirements related to ubiquitous intelligence, real-time responsiveness, and seamless integration of physical and digital domains will surpass what current networks can provide [2]. This realization has prompted a global effort to define and develop the next generation of wireless communications, 6G networks.

1.1.1 6G Wireless Communications: A New Horizon

Building on the foundations established by its predecessors, 6G is envisioned as a transformative platform capable of supporting unprecedented levels of connectivity, intelligence, and contextual awareness. Historically, each generational leap in mobile communication has been driven not only by the need to meet current user expectations, but also by the foresight to anticipate and shape emerging technological landscapes. The shift from Third Generation (3G) to Fourth Generation (4G) enabled the widespread adoption of mobile internet, cloud services, and streaming media, while the transition to 5G facilitated ultra-fast, low-latency connections and dense IoT deployments.

In this continued trajectory, 6G is expected to introduce a suite of groundbreaking capabilities. These include native integration of Artificial Intelligence (AI) for real-time network optimization, immersive Extended Reality (XR) applications, and seamless cyber-physical convergence. By bridging the physical, digital and biological worlds, 6G aims to support intelligent environments where data-driven interactions are deeply embedded in everyday life.

The global research community has begun early investigations into 6G architectures and enabling technologies. Leading industry consortia, academic institutions, and international standardization bodies are collaborating to define the vision and requirements of this next generation. While 4G prioritized human connectivity and 5G enabled efficient communication between machines, 6G is poised to unify these domains under a framework of ubiquitous, adaptive, and intelligent communication.

As of 2024, the Third Generation Partnership Project (3GPP) has finalized Release 18, marking a major milestone in the evolution of 5G Advanced. Concurrently, Release 19 is underway, laying the foundation for 6G-related innovations. Standardization efforts for 6G are expected to formally commence with Release 20 and mature in Release 21. These coordinated initiatives reflect the industry's strategic commitment to realize the full potential of 6G, ushering in an era of hyper connected, intelligent, and resilient networks.

6G KPIs and KVIIs

According to the existing literature at the time of writing this Thesis, Key Performance Indicators (KPIs) and Key Value Indicators (KVIs) have been defined to characterize future communication networks, specifically 6G. Table 1.1 summarizes the main KPIs [3].

Table 1.1: 6G Key Performance Indicators (KPIs)

KPI	Description
Data Rate	Expected to reach Terabit per second (Tbps) (both Uplink (UL) and Downlink (DL)) to support high-quality applications like 3D video and VR/AR.
Latency	Aiming for ultra-low latency in the order of microseconds (μs) for real-time applications such as tactile internet and autonomous driving.
Reliability	Ensuring near-perfect network reliability for mission-critical applications.
Energy Efficiency	Significant reduction in energy consumption per bit transmitted.
Geolocation Accuracy	Sub-centimeter level accuracy for applications requiring precise location information.
Connection Density	Supporting massive connectivity with a high number of devices per unit area.
Coverage	Providing global coverage, including hard-to-reach areas through integration with satellite networks.
Spectral Efficiency	Enhancing the efficient use of the available spectrum to achieve higher data rates and network capacity ($1000b/Hz/m^2/s$).

While 6G is expected to introduce transformative capabilities, the current KPIs are insufficient to guide its comprehensive research and development agenda. The complexity and ambition of this next-generation wireless paradigm require an End-to-End (E2E) perspective that transcends traditional performance-based metrics.

To better capture the broader scope of 6G, the concept of KVIs has been introduced. Unlike KPIs, which focus primarily on quantifiable performance outcomes, KVIs emphasize human-centric values and qualitative dimensions. Their formulation often involves deliberative processes and creative thinking, resembling the definition of quality standards. In this 'top-down' approach, the overarching goals of a system or project are established first, followed by the identification of relevant evaluation criteria [4].

KVIs broaden the evaluation framework by incorporating critical societal and ethical dimensions such as sustainability, scalability, digital inclusion, and trustworthiness. By prioritizing these pillars, the 6G vision seeks to achieve a harmonious integration of the physical, digital, and human worlds, laying the foundation for a more equitable and intelligent communication ecosystem.

6G Architecture

A new architectural framework is needed considering the expected developments of 6G. Fundamentally, 6G represents a convergence of technical advancements ready to change our interactions with the surroundings. It has the potential to create a more linked, intelligent, inclusive global society in which the differences between human, physical, and digital spheres blur and signal a new age of invention and opportunities. Including immersive experiences, ubiquitous connection, human-machine interaction, digital twins, healthcare, security, and privacy [5].

Figure 1.1 illustrates the evolving vision of 6G architecture presented by Hexa-X [1], shaped through collaborative efforts between the research community and the leading companies. From an architectural standpoint, the objectives outlined by the authors in [6] include:

- **Specialization:** Incorporating tailored features and functions, sub-networks, and advanced networking capabilities.
- **Programmability:** Utilizing microservices, cloud-agnostic solutions, and programmable hardware to enhance system adaptability.
- **Flexibility:** Allowing for dynamic function placement, scalability, and versatile network topologies.
- **Simplification and Sustainability:** Reducing protocol complexity, simplifying interfaces, and embracing automation to improve system efficiency and longevity.
- **Cloud Platform** Considering public, private, or hybrid cloud platforms and their deployment across various levels, including on-premises, edge, metro, or core, often with integrated acceleration technologies.
- **Robustness and Security:** Ensuring comprehensive network coverage, establish multiple connections, foster trust, improve privacy, and strengthen network resilience.

In the architecture of this new network paradigm, three main layers are expected to be present: the infrastructure and cloud layer, the network service layer, and the application layer.

The infrastructure and cloud layer provides the foundation for 6G. It combines multiple technological enablers to support an ultra-high-speed, reliable, and secure communication system. This layer includes interconnected elements such as IoT and User Equipment (UE) devices, Base Station (BS), small and

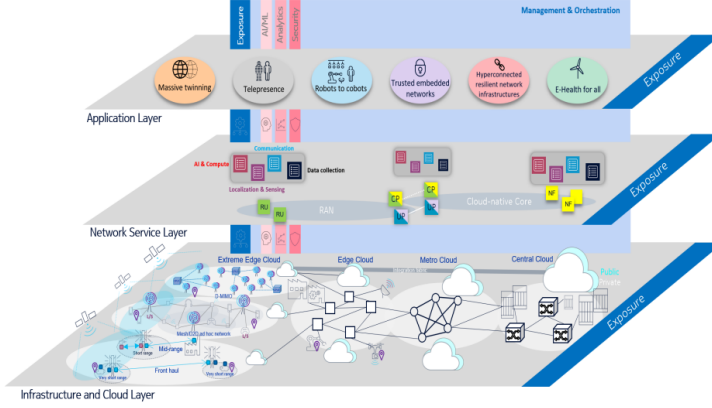


Figure 1.1: Hexa-x E2E architecture [1].

macro cells, access points, and cloud infrastructure. Together, these components ensure seamless data transmission across the system and form the physical backbone of the 6G architecture. In addition, this layer provides the essential resources required to support network services, cloud applications, and the application layer itself [1].

The network service layer is responsible for providing services to end users. It manages network operations and internal services that are not directly visible to users but are critical to ensuring reliability, quality, and security. Beyond traditional communication services, the 6G architecture will also enable new functionalities such as artificial intelligence, computing, data processing, data collection, localization, and sensing. By implementing network functions and services as cloud-native microservices, this layer aims to create a more flexible, intelligent, and efficient network design.

Future network management and orchestration are expected to move towards full automation and closed-loop control, supported by advances in AI and Machine Learning (ML), and potentially incorporating QC. Finally, the application layer directly connects with end-user applications, enabling the exchange of both data and knowledge.

1.1.2 6G Enablers

The expected enablers of 6G technology encompass a range of advanced technological innovations and improvements over 5G, addressing emerging demands for higher performance, efficiency, and new capabilities. 6G is envisioned to be a flexible and heterogeneous network due to the increasing diversity and

complexity of future communication needs and applications. The flexibility of 6G is manifested in its ability to adapt to varying service requirements and network conditions dynamically. This adaptability is achieved through advanced technologies like network slicing, which allows the creation of multiple virtual networks on a shared physical infrastructure, each tailored to specific needs.

The heterogeneity of 6G will be evident in its support for a multitude of devices, services, and network environments. 6G networks will interconnect terrestrial, aerial, and satellite networks to provide seamless global coverage. This heterogeneous architecture ensures connectivity in urban, rural, and remote areas, bridging the digital divide. Furthermore, 6G will support a wide range of devices, from smartphones to industrial sensors and autonomous vehicles, each with different connectivity, latency, and power requirements.

The primary enablers that will provide 6G with the necessary flexibility, heterogeneity, and capability to meet its anticipated requirements are presented in [7]. In an ultra-flexible perspective, the categorization of 6G key enablers is encompassing as follows:

Multi-Band Utilization: The shift towards high-frequency bands is driven by the need for higher data rates, increased capacity, and improved network performance to meet the demands of modern and future communication applications. Firstly, the mmW (over 24GHz) band provides a multi-gigabit data rate, higher capacity, and offers hundreds of times more bandwidth compared to the sub-6 GHz bands [8]. Secondly, the THz band is also a promising enabler for 6G, primarily due to its expansive, unused frequency spectrum and the high spatial resolution afforded by its short signal wavelengths and large bandwidth [9]. The vast THz spectrum can accommodate the burgeoning demand for higher data rates and increased capacity, facilitating ultra-fast data transmission and supporting numerous simultaneous connections. In addition, the short wavelengths and broad bandwidth of THz signals enable fine spatial resolution, improving precision in applications such as high-definition imaging, environmental sensing, and advanced positioning systems. These capabilities make the THz band a vital component in realizing the ambitious goals of 6G, driving forward innovations in communication technologies.

Ultra Flexible Phy: Starting with 5G, the term “numerology” refers to the set of parameters that define the physical layer configuration for wireless communication, specifically the structure and characteristics of the radio frame. These parameters encompass subcarrier spacing, symbol duration, cyclic prefix length, and the number of slots per subframe [7], [10]. Numerology is crucial for optimizing network performance, catering to diverse use cases, and efficiently utilizing spectrum resources. For instance, larger subcarrier spacing is utilized in higher frequency bands to manage the wider available bandwidths and reduce

symbol duration. Conversely, in lower frequency bands, a subcarrier spacing of 15 kHz is typically employed, offering good coverage and penetration [11].

Heterogeneous Networks: Heterogeneous networks (HetNets) in the context of 6G refer to a network architecture that combines various cell types, technologies, and spectrum bands to deliver seamless and ubiquitous connectivity. This architecture encompasses macro cells, small cells, pico cells, femto cells, and various access technologies, including cellular, Wi-Fi, and satellite communications. The primary goal of HetNets is to improve network performance, capacity, and coverage by leveraging the advantages of different network components [12].

Intelligent Communications: Communication networks have recently integrated advanced technologies such as AI, ML, holographic Multiple-Input Multiple-Output (MIMO), Reconfigurable Intelligent Surface (RIS), among others, [13–17]. Key characteristics of these intelligent networks include self-optimization, which automatically adjusts parameters to optimize performance by balancing loads, reducing latency, and improving throughput based on real-time data. They also feature self-healing capabilities to detect and respond to faults or failures autonomously, rerouting traffic and adjusting configurations to maintain service continuity and minimize downtime. Adaptive resource management dynamically allocates resources such as bandwidth and computing power to meet changing demands, ensuring efficient utilization and preventing congestion. Additionally, predictive maintenance capabilities allow intelligent networks to analyze patterns and trends to predict potential issues before they occur, enabling proactive maintenance and reducing the risk of unexpected failures.

Integrated Sensing and Communications: The Integrated Sensing and Communication (ISAC) system is a unified platform that combines wireless communication and radar sensing capabilities. ISAC enhances spectrum utilization and addresses spectrum conflicts between radar and communication systems. Furthermore, it reduces the size and energy consumption of the equipment [18]. ISAC can be applied in various domains, including autonomous vehicles (for collision avoidance and navigation), smart cities (for traffic monitoring and infrastructure management), and industrial IoT (for precise monitoring and control).

Green Communications: “Green communication” in the context of 6G refers to the implementation of energy-efficient and environmentally sustainable practices in the design, deployment, and operation of 6G networks. This involves optimizing various aspects of network infrastructure and technology to minimize energy consumption and reduce carbon emissions, thereby promoting environmental sustainability. It has been reported that 5G BS and mobile devices consume significantly more energy than their 4G counterparts . For

instance, a typical 5G BS operating with multiple frequency bands has a power consumption exceeding 11,000 W, compared to less than 7,000 W for a 4G BS. The increased power consumption is primarily attributed to the enhanced power amplification in Massive MIMO (mMIMO) antennas and the processing of large volumes of data. Although the energy consumption per unit of data has decreased substantially, the overall energy cost for 5G cannot be overlooked, as the number of required 5G BS is at least four times greater than that of 4G to achieve equivalent coverage [19].

Quantum Computing: QC is anticipated to play a pivotal role in overcoming the complex challenges associated with the next generation of wireless communication systems, particularly 6G. QC offers the potential to significantly advance various critical areas within 6G networks, including enhanced data processing, optimized resource allocation, bolstered security measures, advanced sensing and localization capabilities, and multi-objective routing optimization. By leveraging the unique computational power of QC, 6G networks can achieve unprecedented efficiency, security, and performance, addressing the demanding requirements of future communication technologies and services.

Secure Communications: Implementing advanced security measures to protect data transmission and ensure privacy in 6G becomes increasingly critical. Trust, security, and privacy are closely related yet distinct components essential for the reliable development of 6G networks, each posing unique multidisciplinary challenges [20]. Trust in 6G requires higher levels of embedded security, demanding new models, policies, and mechanisms, particularly as the physical and digital worlds become increasingly interconnected. Security concerns will intensify as 6G networks expand, necessitating comprehensive architecture planning and addressing the dual-edged nature of security automation. Privacy challenges also persist, especially with the ambiguity in identifying when de-identified datasets become personally identifiable. Addressing these issues through interdisciplinary research is crucial for the successful implementation of 6G technologies.

1.1.3 6G Use Cases

Recent literature has introduced a variety of interesting and novel use cases for 6G technology, showcasing its potential to revolutionize industries and societal functions. These emerging applications underline how 6G can provide ultra-fast communication, assist AI-driven automation, and enable developments in fields such as remote healthcare, smart cities, and immersive experiences via XR. These use cases will probably change the global digital scene as technology develops, so 6G is a necessary framework for future innovation and connection much beyond the capacity of its 5G predecessor.

For example, the study in [21] offers a detailed overview of 6G technology, stressing its possible uses in the IoT and the difficulties it could encounter in the future. Among the notables mentioned are smart cities, intelligent healthcare, and immersive experiences made possible by holographic technologies. Other studies also point out important developments in 6G including industrial automation, XR, and necessary communications for critical infrastructure.

Figure 1.2 shows a simple representation of the most creative application scenarios anticipated for 6G. Among these, sustainable development in 6G is absolutely essential to solve world problems and reach the UN Sustainable Development Goals (SDGs). Advanced features include AI, IoT, and energy-efficient architectures help 6G technologies maximize resource usage, lower environmental impact, and so support sustainability. Key uses are spectrum management for effective resource use, rural development through improved connectivity, and the building of smart, sustainable cities. Making 6G a necessary instrument to promote economic and social development while minimizing its environmental impact, these technologies seek to bridge the digital divide, enabling green infrastructure, and supporting new applications such as remote healthcare and smart agriculture, thus bridging the digital divide.

In AR and VR, 6G will enable more immersive and responsive experiences through ultra-low latency and higher data rates. Industry 4.0 will benefit from improved automation, real-time monitoring, and AI-driven manufacturing processes powered by 6G's robust connectivity. Autonomous vehicles will utilize 6G for faster, safer, and more reliable vehicle-to-vehicle and vehicle-to-infrastructure communication. In eHealth, 6G will support remote surgeries, telemedicine, and real-time patient monitoring with unprecedented precision. Additionally, holographic communications will evolve, allowing lifelike 3D interactions for remote work, education, and entertainment, creating new dimensions of collaboration and connectivity.

1.2 State of the Art Analysis

The current state of the art in 6G technology is comprehensively reviewed in this section, and each consecutive chapter presents an independent review of the state of the art specific to its respective subject matter.

The advancement of 6G technology, as emphasized by both academic research and industry experts, is not just an incremental enhancement over 5G; rather, it is designed to solve the inherent limitations and unmet requirements of its predecessor. Although 5G has indeed advanced network capabilities, its performance in areas such as energy efficiency, ultra-low latency, and seamless global coverage has not met initial expectations. As a result, the develop-

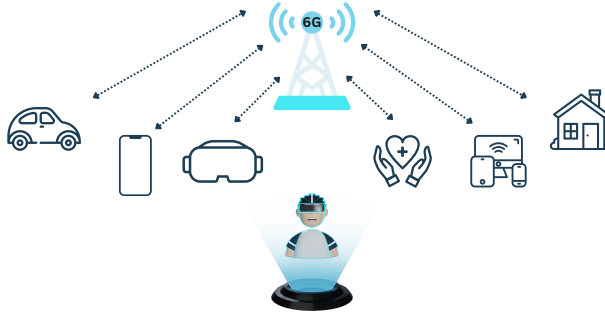


Figure 1.2: 6G Use Cases.

ment of 6G is being focused on the resolution of the critical deficiencies of 5G, as well as the improvement of network intelligence, reliability and feasibility. This change underscores the necessity for a more significant transformational leap in telecommunications technology, as opposed to a simple evolutionary progression.

A series of white papers has been published, which provide a comprehensive overview of the main advancements, requirements, and future orientations of 6G technology. The fundamental research issues for the next generation of communication networks are addressed by the authors in [20]. They emphasize the significance of privacy, security, and trust as distinct, yet interconnected components that are essential for the establishment of a reliable 6G network. Addressing inherited and novel security threats in a network that will support 100 billion IoT devices, designing post-quantum cryptography to accommodate the emergence of QC, utilizing ML for security automation, and investigating physical layer security for ultra-sensitive applications such as human body communications are among the primary challenges. Given the anticipated convergence of confidential, sensitive, and contextual data, privacy concerns are also of the utmost importance.

The white paper [22] investigates the technological opportunities and challenges associated with the implementation of 6G communications, which are intended to facilitate Tbps data rates by 2030. It emphasizes the convergence

of communications and sensing, thereby addressing the necessity for energy efficiency, multi-use scalability, and ultra-low power solutions. The complexity of attaining these objectives is underscored in the paper, which takes into account the trade-offs between the necessity for novel solutions and the limitations of existing RF technologies, as well as the narrowing gap between radio and optical communications. In order to confront the critical obstacles and cultivate cross-disciplinary collaboration for the development of the future of 6G, it concludes by posing sophisticated questions to the RF community and associated stakeholders.

In [23], the challenges and requirements for establishing connectivity in rural and remote areas through 6G technology are examined. It underscores the fact that a significant number of regions worldwide lack sufficient connectivity, resulting in a burgeoning digital divide. These regions are less attractive for network investment due to factors such as low population density and low income. The authors suggest that the first mobile generation, specifically designed to reconcile this digital divide, could be 6G. The paper offers a comprehensive examination of international targets and standards related to rural connectivity, as well as technical solutions that can be employed to overcome these obstacles. Each section concludes with a list of research topics that are specific to 6G and must be addressed in order to achieve this objective.

Furthermore, [24] investigates subjects such as sensing and localization. It identifies critical technological enablers, addresses the associated challenges, and suggests potential solutions for these advancements. The business models and ecosystems that are based on 6G are discussed in [25]. The paper explores the disruption of conventional business models, which will result in the introduction of new roles for digital service operators, cloud operators, and resource brokers. It investigates the potential for innovative, sustainable business models that incorporate long-tail services and customized performance attributes. The paper generates twelve scenarios that concentrate on the interactions between key trends and uncertainties in the 6G ecosystem through qualitative scenario planning. Addressing privacy, security, governance, decentralized business models, and user empowerment are critical factors in the development of successful business strategies in 6G.

The literature has extensively investigated other topics that are related to 6G, including ML [26], IoT [27], SDGs [28], and mMTC [29]. The future of 6G technology is significantly influenced by these subjects, which have the potential to revolutionize connectivity, enable intelligent networks, and support a diverse array of applications. The integration of ML in 6G will enable intelligent network management, while IoT advancements will facilitate the further expansion of the connectivity among devices. In the same vein, the emphasis on the SDGs is consistent with the necessity of developing 6G with a focus on

social impact and sustainability. Additionally, mMTC will be crucial for facilitating the exponential expansion of connected devices. Consequently, these subjects are essential for the comprehension and development of the capabilities and applications of 6G.

1.3 Problem and Thesis Scope

The incorporation of quantum mechanics into future mobile communication systems represents a disruptive technological advancement and is expected to play a pivotal role in enabling 6G networks. This integration spans two principal domains: QC, which addresses computational challenges that exceed classical processing capabilities, and quantum communication, which leverages quantum states to enable inherently secure information transmission and the development of robust quantum networks. Together, these fields signal a paradigm shift in how information is processed, transmitted, and secured, offering transformative potential for wireless communications.

The increasing convergence of quantum mechanics and wireless technologies is reflected in the growing body of academic literature and emerging research initiatives. While theoretical studies and comprehensive reviews have explored the advantages of quantum integration in wireless systems, practical implementations and concrete use cases remain relatively scarce. This gap highlights the early-stage maturity of QC, which continues to face technical barriers such as qubit decoherence, gate errors, external noise, and underdeveloped error correction protocols. These limitations currently hinder the deployment of robust quantum frameworks suitable for real-world wireless communication scenarios.

This doctoral research addresses these challenges by focusing on the practical application of QC within the wireless domain, specifically in the context of the Noisy Intermediate-Scale Quantum (NISQ) era. By developing novel frameworks that align with current hardware constraints, this work aims to bridge the gap between quantum theory and implementable wireless solutions.

A comprehensive literature review has revealed several promising use cases where QC could serve as a transformative enabler for next-generation wireless systems. Independently, both QC and wireless communication exhibit the potential to meet the increasingly stringent requirements for performance, scalability, and security. One compelling scenario involves indoor localization, particularly in environments involving massive data and multiple antennas. This raises fundamental questions: How efficiently can classical systems handle such large-scale datasets? Could quantum algorithms, for instance, be employed to compute Euclidean distances more efficiently for fingerprinting applications?

CHAPTER 1. INTRODUCTION

These questions underscore the latent power of quantum-enhanced solutions for complex wireless tasks.

Another key application area lies in optimization problems, which are ubiquitous across wireless networks and grow increasingly intractable as system complexity scales. Quantum optimization techniques, powered by principles such as superposition and entanglement, offer a novel computational paradigm for exploring large solution spaces efficiently. Algorithms like the Quantum Approximate Optimization Algorithm (QAOA) have already demonstrated their ability to tackle combinatorial problems previously considered impractical on classical machines.

For example, the well-known Traveling Salesman Problem (TSP), long studied in both classical and quantum computing, provides a useful analogy. Its structural similarity to wireless routing optimization problems, involving the selection of optimal paths under multiple constraints, makes it an ideal candidate for quantum treatment. The successful application of QAOA to TSP, like problems reinforces the promise of using quantum approaches to improve network performance in terms of latency, load balancing, and energy efficiency.

In alignment with these insights, this research proposes the following hypotheses:

- Hypothesis 1: Despite its current technological limitations, QC has already demonstrated potential as an enabler for emerging 6G applications. Proof-of-concept implementations exploiting quantum advantages could catalyze further research and provide foundational blocks for future wireless systems.
- Hypothesis 2: The Euclidean distance, a fundamental computational building block in many localization and classification tasks, can be effectively computed using quantum algorithms. Quantum-based implementations may offer performance advantages over classical methods, particularly in high-dimensional or large-scale scenarios.
- Hypothesis 3: Routing optimization in wireless networks can benefit significantly from quantum optimization techniques. Algorithms such as QAOA could improve key performance indicators like Quality of Service (QoS) and throughput. While full-scale deployment remains constrained by NISQ-era limitations, small-scale demonstrators can provide critical insight and validation.
- Hypothesis 4: Technologies such as MIMO and Non-Orthogonal Multiple Access (NOMA) are expected to play a central role in 6G evolution. However, advanced detection techniques like Maximum Likelihood Detection (MLD), although optimal in terms of Bit Error Rate (BER), remain

computationally prohibitive for classical processors. Quantum computing may provide the necessary processing power to make MLD feasible in practice, paving the way for more robust and efficient communication systems.

1.4 Thesis Objectives

The global research objective of this Ph.D. thesis is to investigate the latest advancements and foundational principles of quantum mechanics and QC, with the aim of identifying quantum-based solutions to potential challenges in 6G wireless communication. This includes proposing and developing QC applications tailored for 6G networks. To achieve this broad objective, the research has been subdivided into the following specific objectives:

- Conduct a comprehensive review of the state-of-the-art QC to identify potential applications that align with the requirements of 6G technology.
- Analyze and select appropriate systems and tools, such as IBM (Qiskit), Google (Cirq), D-Wave, PennyLane, and others.
- Propose candidates and suitable applications considering the 6G main features.
- Design and develop proactive, efficient, and practical applications leveraging QC for 6G and beyond.

1.5 Thesis Outline

The Thesis is structured into six distinct chapters. It begins with an introductory chapter and concludes with a final chapter that summarizes the findings and outlines potential directions for future research. A concise overview of the remaining chapters is provided as follows:

Chapter 2 provides a comprehensive overview of QC, encompassing the foundational postulates of quantum mechanics, the basics of quantum computation, and the advances in quantum technologies up to the time of this Thesis. The central focus of the chapter is a state-of-the-art analysis of the integration of QC within 6G networks from a research perspective. Additionally, the SDGs in the context of the evolution of quantum and wireless technologies are examined.

Chapter 3 introduces an innovative indoor localization method leveraging QC and the Euclidean distance. The chapter provides an overview of indoor localization techniques and technologies alongside a review of the relevant literature on quantum technologies.

Chapter 4 presents a quantum routing optimization framework based on the QAOA. The chapter systematically outlines the methodology, including the construction of the network graph, problem formulation, development of the Quadratic Unconstrained Binary Optimization (QUBO) model, the implementation of the QAOA, and the quantum circuit. To assess the framework's performance, both single-objective and multi-objective case studies are provided and thoroughly analyzed.

Chapter 5 introduces the MLD framework for MIMO and NOMA utilizing QC. The chapter elaborates on the integration of MIMO-NOMA and its synergy with QC, highlighting the advantages of this use case in the context of 6G.

1.6 Thesis Publications

The work developed during this Thesis made the following publications possible.

Journals

- [J1] **Helen Urgelles**, Pablo Picazo-Martínez, David García-Roger and J. F. Monserrat, “Multi-Objective Routing Optimization for 6G Communication Networks Using a Quantum Approximate Optimization Algorithm,” *Sensors 2022*, vol. 22, no. 19: 7570, Oct. 2022.
- [J2] **Helen Urgelles**, Shivam Maheshwari, Swaraj Shekhar Nande, Riccardo Bassoli, Frank H.P. Fitzek, J. F. Monserrat, “In-Network Quantum Computing for Future 6G Networks”, *Advanced Quantum Technologies*. 2024, 2300334.
- [J3] **Helen Urgelles**, David García-Roger and J. F. Monserrat, “Quantum-Based Maximum Likelihood Detection in MIMO-NOMA Systems for 6G Networks,” *Quantum Reports 2024*, vol. 6, no. 4, Oct. 2024.

Conferences

- [C1] **Helen Urgelles**, Pablo Picazo-Martínez and J. F. Monserrat, “Application of Quantum Computing to Accurate Positioning in 6G Indoor Scenarios,” *ICC 2022 - IEEE International Conference on Com-*

munications, Seoul, Korea, Republic of, 2022, pp. 643-647, doi: 10.1109/ICC45855.2022.9838523.

- [C2] **Helen Urgelles**, Swaraj Shekhar Nande, Domenico Scotece, J. F. Monserrat, Riccardo Bassoli, Luca Foschini and Frank H. P. Fitzek “Quantum-Enhanced Software-Defined Networking: A Communication Perspective,” *IEEE INFOCOM 2025-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, 2025. p. 1-6.*, doi: 10.1109/INFOCOMWKSHPS65812.2025.11152794.

Related Works

- [R1] Pablo Picazo Martínez, J. F. Monserrat and **Helen Urgelles**, “Applications of Quantum Computing to 6G Wireless Networks”, *Master Thesis*, 2021, Universitat Politècnica de València.
- [R2] **Helen Urgelles**, “Calculate Quantum Euclidean Distance with Qiskit”, Qiskit Medium Blog-IBM Quantum, October 12, 2022.
- [R3] **Helen Urgelles**. GitHub repository related to thesis use cases.
Available at:
github.com/helenup/quantum-computing-wireless-networks

Chapter 2

Quantum Computing and its Applications in 6G

Richard Feynman noted that certain quantum mechanical phenomena pose challenges for efficient simulation using classical computers [30]. This observation, conversely, prompted speculation regarding the possibility of improving computational efficiency by harnessing these quantum effects. However, constructing a system grounded in quantum mechanics presents difficulties due to its inherent unpredictability and probabilistic behavior.

In the early 1990s, significant progress was made in Quantum Computing (QC) research. In 1993, C.H. Bennett and colleagues demonstrated Quantum Teleportation, showcasing how quantum information could be transmitted over long distances using entanglement [31]. Subsequently, in 1994, Peter Shor proposed the Las Vegas Algorithm for solving discrete logarithms and factoring integers on quantum computers, which were foundational problems in cryptosystems [32]. The following year, Shor and A. Steane introduced Quantum Error Correction Codes, while DiVincenzo outlined the essential physical requirements for constructing quantum computers. Quantum computation, which revolves around information processing governed by quantum mechanics, emerged as a field of study [33]. A pivotal moment occurred in 2001 when the IBM Almaden Research Center and Stanford University achieved the execution of Shor's Algorithm, demonstrating its capability to factorize the number 15 using qubits in nuclear spin [34], [35].

After D-Wave introduced the first commercial quantum computer in 2010, QC has witnessed rapid and extensive advances. In 2016, for example, IBM reached a milestone by enabling the implementation of quantum circuits, marking the emergence of gate-based quantum computers. Presently, IBM's cloud-

based systems offer access to hundreds of qubits. Nonetheless, these systems suffer from excessive noise, which prevents them from exceeding classical computers in performance. At the time of writing this thesis, the current stage is referred to as Noisy Intermediate-Scale Quantum (NISQ), where the presence of noise in quantum gates will impose restrictions on the size of quantum circuits that can be executed reliably [36]. Although NISQ systems can perform tasks with imperfect reliability, their inherent quantum mechanical properties (such as superposition and entanglement) enable them to achieve capabilities beyond those of classical computers. Additionally, sufficient progress in the field is believed to usher in a new era of fault-tolerant quantum computing. QC signifies a groundbreaking shift in information processing, utilizing the tenets of quantum mechanics to conduct computations fundamentally distinct from classical computers.

This chapter seeks to establish a comprehensive foundational understanding of QC and the fundamental principles of quantum mechanics, which are essential to comprehend the use cases discussed in this thesis. Furthermore, it presents an overview of the leading quantum technologies that have been developed at the time of writing, accompanied by a review of the current state of quantum hardware. Finally, a detailed summary of the state-of-the-art in QC for Sixth Generation (6G) networks is provided, along with an analysis of the impact of utilizing quantum technologies on the Sustainable Development Goals (SDGs). Therefore, it is divided as follows:

- Section 2.1 presents an overview of the fundamentals of QC giving a broad overview from the postulates of quantum mechanics to the current quantum technologies and hardware.
- Section 2.2 analyzes the integration of quantum technologies and 6G wireless communications according to the literature.
- Section 2.3 outlines the 6G Key Value Indicators (KVIs) related to QC focused on the SDGs.
- Section 2.4 provides the conclusions of the chapter.

2.1 Basics of Quantum Computing

QC is a type of computing based on quantum mechanics. Unlike classical computing, at its core, QC relies on the unique properties of quantum bits, or qubits, which can exist in superposition states and exhibit entanglement, enabling exponential parallelism and the solution of computational problems that are intractable for classical computers. This occurs when the solutions

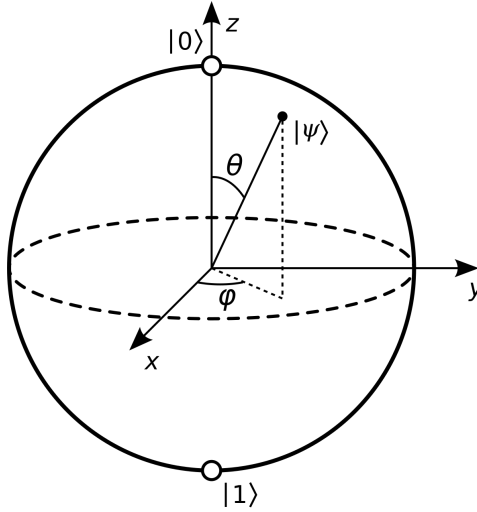


Figure 2.1: Bloch sphere qubit representation.

to these problems exhibit exponential scaling in computing time on classical machines [37].

A qubit is a unit vector in a two-dimensional complex vector space called the Hilbert space of the system, which forms a linear combination of the states $|0\rangle$ and $|1\rangle$:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad (2.1)$$

where α and β are complex numbers and $|\rangle$ represents the Dirac notation. The measurement of a qubit in a superposition state results in its collapse to one of its basis states, either $|0\rangle$ or $|1\rangle$. The probabilities of obtaining $|0\rangle$ or $|1\rangle$ as the measurement outcome are given by $|\alpha|^2$ and $|\beta|^2$, respectively.

A qubit is geometrically represented using the Bloch Sphere, as illustrated in Fig. 2.1. The Bloch sphere is a unit sphere in a three-dimensional space, with each point on its surface corresponding to a possible pure state of a qubit [38]. While pure states are depicted as points on the sphere's surface, mixed states, combinations of pure states with varying probabilities, are represented within the sphere.

2.1.1 Postulates of Quantum Mechanics

“Quantum Mechanics: Real Black Magic Calculus”

- Albert Einstein

Quantum mechanics is a fundamental branch of physics that explores the behavior of particles, including atoms, electrons, and photons. It provides a mathematical framework for describing and understanding nature at the sub-atomic level, where matter behaves differently from macroscopic objects in classical physics. In this regard, the theory of quantum mechanics is based on some fundamental postulates derived from the work of Von Neumann [39].

- **Postulate 1 - State Space:** The state of an isolated physical system is represented by a state vector $|\psi\rangle$ in a complex Hilbert space (see (2.1)).
- **Postulate 2 - Evolution:** The time evolution of a closed quantum system is governed by Schrödinger’s equation, which dictates that the quantum state evolves in a unitary manner.

$$i\hbar \frac{\partial |\psi\rangle}{\partial t} = \mathbf{H}|\psi\rangle, \quad (2.2)$$

where $\hbar$ is the Planck’s constant whose value must be experimentally determined, H is a Hermitian operator known as the Hamiltonian of the closed system, and t is the time.

- **Postulate 3 - Quantum Measurement:** A physical observable is represented by a Hermitian operator. Measuring observable results in one of its eigenvalues, with the probability determined by the projection of the normalized state vector onto the eigenspace of that eigenvalue. Unlike Postulate 2, this measurement process leads to a loss of natural quantum coherence, generally causing an irreversible loss of information and the destruction of superposition across eigenspaces [40].
- **Postulate 4 - Physical quantities:** In quantum physics, observables are related to mathematical operators $\hat{\mathbf{A}}$ acting on the vector $|\psi\rangle$ as $\hat{\mathbf{A}}|\psi\rangle$. In the quantum matrix formalism, $\hat{\mathbf{A}}$ is a Hermitian (linear) matrix operator that acts on the state vector $|\psi\rangle$ to evaluate the quantized or continuous physical properties of quantum objects [37]. Postulates 2 and 3 are also related to Hermitian operators.

Apart from the main postulates mentioned above, other features of quantum mechanics are essential and distinguish it from classical mechanics:

- **Superposition:** As previously mentioned, superposition is one of the key properties of quantum mechanics. It asserts that a quantum system, described by a wave function, can exist as a linear combination of multiple states (2.1), [38].
- **Entanglement:** Entanglement is a peculiar yet useful phenomenon where quantum states are maximally interconnected. This means that two or more qubits are linked and dependent on each other, regardless of their physical separation. When entangled, these qubits share the same state and can be evaluated simultaneously. Consequently, measuring the state of one entangled qubit instantly determines the states of the remaining qubits [38].
- **Wave - Particle Duality:** This refers to the fact that quantum objects, such as electrons or photons, exhibit wave-like and particle-like properties. Their behavior changes based on the type of observation. In some experiments, these quantum objects act like classical waves, are not localized in space, and produce interference patterns when combined, similar to how colors (photons) and sounds (acoustic waves) can mix. In other experiments, they behave as classical particles, can be localized in space, and possess kinetic momentum and mass [37].
- **Uncertainty Principle:** Formulated by Heisenberg, this principle states that certain pairs of physical properties of particles, such as position and momentum, cannot be precisely known simultaneously. The more accurately one property is measured, the less accurately the other can be determined [38].
- **Quantum Tunneling:** According to classical mechanics, it is an impossible phenomenon. However, in quantum mechanics, tunneling occurs due to the wave nature of matter. Particles, such as electrons or atoms, are able to pass through a potential energy barrier [41].
- **Quantization of Energy:** In classical mechanics, physical properties like distances are continuous. However, in quantum mechanics, quantities such as energy, momentum, and angular momentum are quantized, meaning they can only assume discrete values rather than a continuous range. For instance, the energy levels of the electrons in an atom are quantized [40].

2.1.2 Quantum Computing Technologies

We are presently experiencing the second quantum revolution, a significant scientific and technological advancement building upon the foundational principles established during the first quantum revolution in the 20th century. This contemporary revolution seeks to translate the theoretical underpinnings of quantum mechanics (2.1.1) into practical and transformative applications. By harnessing the unique phenomena of quantum mechanics, such as superposition, entanglement, and quantum tunneling mentioned above, this era aims to revolutionize various fields, including computing, cryptography, communication, and sensing. The second quantum revolution focuses on the development and implementation of new quantum technologies that promise to surpass the limitations of classical systems and lead to unprecedented advancements in both science and industry [42].

As of this thesis, QC technologies are distinguished by the types of qubits they use that refer to their physical implementations, the methods for constructing and maintaining these qubits, and the computational approaches developed by quantum hardware. Various tech giants, such as IBM, Google, and Microsoft, each employ different technologies. An overview of these aspects is presented below.

Qubit Types

Various technologies are currently used to develop qubits, each employing unique methods for creating and manipulating them. As a result, the design and construction of quantum devices are tailored to the specific type of qubits they utilize. At the highest level of qubit classification, they are divided into two distinct categories [5]:

- **Stationary Qubits:** As the name implies, these qubits remain largely stationary during operations. This category encompasses a variety of qubits, such as trapped ions, cold atoms, electron spins, and superconducting loops.
- **Flying Qubits:** Usually represented by photons, these qubits are dynamic, transmitting quantum information across different distances.

Stationary Qubits

Trapped Ions: These are individual ions (atoms with net charge) confined by electromagnetic fields. Their quantum states are precisely manipulated using targeted laser beams [43]. Various elements can be used as

ion qubits, but ytterbium, calcium, barium, and strontium are the most popular choices. Used by companies like IonQ and Honeywell.

Cold Atoms: These atoms are cooled to temperatures approaching absolute zero, enabling precise control over quantum operations by reducing thermal interference. Rubidium or Cesium atoms are examples [37] used in research by institutions like Harvard and MIT.

Electron Spins: Quantum information is encoded and processed by isolating and manipulating the intrinsic spin of electrons. This approach offers precise control at atomic levels [44]. Used in research by institutions like Intel and various academic groups.

Superconducting Loops: When cooled to extremely low temperatures and carrying electric current without resistance, qubits can be entangled and manipulated using microwave pulses [45]. One example is the Transmon qubits, used by companies like IBM, Google, and Rigetti.

Flying Qubits

Photonic Qubits: Central to quantum communication, photonic qubits use photons to carry quantum information over extensive distances [46]. Explored by companies like Xanadu and PsiQuantum.

Quantum Hardware

David P. DiVincenzo is particularly renowned for formulating the DiVincenzo criteria, which outline the essential requirements for constructing a practical quantum computer. These criteria have significantly influenced the direction of research and development in QC.

According to DiVincenzo in [47], the ultimate physical theory of the world is not Newtonian mechanics, and there is no reason to assume that machines governed by the laws of quantum mechanics would have the same computational power as classical machines. Because Newtonian mechanics is a particular case of quantum mechanics, quantum machines inherently have greater computational power than classical ones. Motivated by this, DiVincenzo and his colleagues outlined five requirements for the implementation of quantum computation and two additional requirements for quantum communication:

2.1.3 Criteria for Quantum Computation

A well-defined and scalable physical qubit system: A qubit represents a fundamental two-level system, realizable through various physical con-

structs such as an electron’s spin states (up or down), a photon’s polarization states (horizontal or vertical, or alternatively at $+45^\circ$ or -45°), superconducting currents circulating in opposite directions, and numerous other paired energy levels. Precisely characterizing a qubit entails comprehensive knowledge of its intrinsic Hamiltonian, eigenstates, and interactions with external influences and neighboring qubits. Such meticulous characterization facilitates precise qubit control and manipulation, crucial for reliable quantum computation.

Additionally, qubits with distinctly separated energy levels mitigate unintended state transitions, thereby enhancing computational stability. Scalability is another critical aspect—essential for solving complex problems, leveraging the exponential growth in computational capability with increased qubit count, enabling robust error correction, and fostering the advancement of quantum algorithms and applications.

Initialization of the Qubit Register: Before computation commences, the qubit register must be initialized to a well-defined state, typically the logical zero state. In superconducting qubits, this corresponds to the system’s lowest energy level, commonly referred to as “ground state” [37]. Qubit initialization can be achieved through two principal approaches: passive cooling, where the system naturally relaxes into its Hamiltonian ground state, or active initialization, wherein a measurement projects the system into a desired state that can subsequently be transformed as needed [47].

Decoherence Time: The interaction of qubits with their surrounding environment governs their coherence properties. Decoherence time quantifies the duration over which a qubit retains its quantum state before transitioning into a mixed state due to external perturbations. This phenomenon results from both amplitude damping and phase fluctuations induced by interactions with surrounding quantum systems. Additionally, inter-qubit decoherence plays a pivotal role in error correction protocols, as correlated errors can impede fault-tolerant operations. Implementing quantum error correction codes that encode logical qubits across multiple physical qubits is an effective strategy to extend the computational coherence time [37, 47].

Implementation of Universal Quantum Gates: The capability to execute a universal set of quantum gates is contingent on the underlying qubit technology. A universal gate set comprises elementary single-qubit operations, enabling arbitrary rotations on the Bloch sphere, supplemented by at least one entangling two-qubit gate. The hardware in-

frastructure must support these operations with high fidelity to enable scalable quantum computation.

Qubit Measurement: Extracting computational outcomes requires the ability to measure individual qubits with minimal disturbance to the remaining system. Ideally, measurement operations should be highly reliable, with error rates significantly below 0.1%, ensuring the integrity of quantum information processing.

2.1.4 Criteria for Quantum Communication

Qubit Interconversion: A fundamental requirement for quantum communication is the ability to coherently convert between stationary and mobile qubits. Typically, flying qubits, such as photons, facilitate long-range quantum information transfer, whereas stationary qubits, such as trapped ions or superconducting qubits, serve as computational and memory nodes. Achieving efficient and loss-resistant conversion between these two modalities is essential for networked quantum systems.

Qubit Transmission: Reliable long-distance qubit transmission underpins quantum networking, distributed quantum computation, and secure quantum communications. Establishing robust channels for qubit transfer enables advanced applications such as blind QC, which allows remote quantum processing while preserving privacy and data security.

Quantum Computing Classification

QC encompasses a diverse range of system architectures, rather than being confined to a singular technological paradigm. A fundamental distinction must be drawn between gate-based quantum computers and analog quantum devices, the latter including quantum annealers such as those developed by D-Wave. Figure 2.2 provides a classification of the main categories within QC and identifies the key industry players advancing these technologies.

In parallel, quantum emulators and quantum-inspired systems leverage principles derived from QC without fully implementing quantum mechanical processes. Quantum emulators are classical platforms designed to simulate the behavior of quantum systems, thereby enabling the development and testing of quantum algorithms without the need for quantum hardware. Quantum-inspired systems, by contrast, apply quantum-derived concepts to classical algorithms and architectures, offering performance enhancements despite not performing genuine quantum computations.

CHAPTER 2. QUANTUM COMPUTING AND ITS APPLICATIONS IN 6G

Quantum annealers are specialized devices aimed at solving complex optimization problems. These systems operate based on the quantum adiabatic theorem, wherein a network of qubits evolves slowly under a controlled Hamiltonian to remain in its ground state. Unlike classical annealing, which relies on thermal fluctuations, quantum annealing exploits quantum tunneling to explore the energy landscape and identify optimal solutions.

Universal gate-based quantum computers represent the most general-purpose and programmable class of quantum systems. They are capable of executing any quantum algorithm by applying a universal set of quantum gates to manipulate qubits. However, these systems are currently limited by noise and decoherence, which compromise computational accuracy. As a result, logical qubits, constructed from multiple physical qubits through quantum error correction, are necessary for fault-tolerant quantum computation. Presently, we operate in the NISQ era [36, 37], characterized by devices that lack full error correction but are sufficient for exploring near-term quantum algorithms.

Today’s quantum hardware, offered by companies such as IBM, Google, Rigetti, and Honeywell, demonstrates varying degrees of compliance with the DiVincenzo criteria. For example, IBM’s superconducting qubit systems exhibit scalable arrays with improving coherence times and gate fidelities. Google’s Sycamore processor is notable for its high-fidelity gate operations, essential for implementing quantum error correction protocols. Honeywell’s trapped-ion architecture is distinguished by its high connectivity and low error rates, contributing to precise qubit initialization and readout. While no single platform fully satisfies all criteria, collective advancements across these systems reflect substantial progress toward realizing practical QC.

In contrast, Quantum Annealing (QA) meets several of these criteria in a non-universal but effective manner. Although QA systems do not employ a universal gate set, they efficiently initialize and manipulate qubits within their coherence time to solve specific optimization problems. The annealing process itself constitutes a viable computational paradigm for certain problem classes within QC.

Figure 2.3 provides a comparative overview of the leading quantum hardware systems in mid-2025, categorized by qubit type. Each horizontal bar represents the approximate number of physical qubits (or equivalent entities, such as photonic modes or annealing qubits) reported by vendors, arranged in ascending order. The color coding reflects the underlying qubit technology. It is important to note that the notion of a “qubit” varies among hardware platforms; thus, the data should be interpreted in terms of relative rather than absolute scale. The information shown is based on publicly available disclosures current to the time of this writing.

2.1 Basics of Quantum Computing

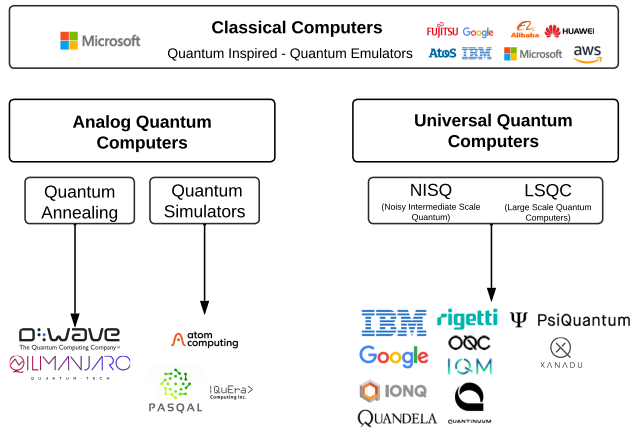


Figure 2.2: Quantum Computing Technologies. Adapted from [37]

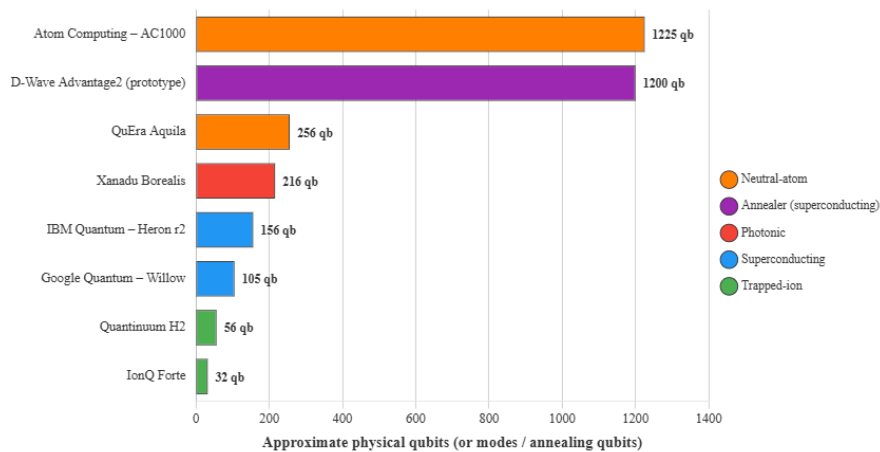


Figure 2.3: Quantum hardware snapshot showing physical qubit counts by technology (2024-2025 data).

2.1.5 Quantum Gates

The unitary evolution postulate is related to quantum gates. This postulate asserts that the time evolution of a closed quantum system is governed by a unitary operator. In QC, this implies that the transformations (or operations) applied to quantum states are represented by unitary matrices, known as quantum gates. Table 2.1 presents the principal quantum gates and their matrix representations and functionalities.

Quantum gates harness the principles of quantum mechanics, such as superposition and entanglement, to perform complex, parallel computations, and reversible operations on qubits. In contrast, classical gates rely on deterministic, irreversible Boolean operations on bits. The unique properties of quantum gates allow quantum computers to potentially solve specific problems much faster than classical computers, which rely on classical gates.

Table 2.1: Principal Quantum Gates

Gate	Matrix Representation	Description
Hadamard	$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$	Creates superpositions of states
Pauli-X (NOT)	$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$	Flips the state between $ 0\rangle$ and $ 1\rangle$
Pauli-Y	$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$	Applies a bit-flip and phase-flip
Pauli-Z	$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$	Applies a phase flip
Phase (S)	$\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}$	Applies a phase shift of $\pi/2$
T-Gate	$\begin{bmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{bmatrix}$	Applies a phase shift of $\pi/4$
CNOT (Controlled-NOT)	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$	Flips the target qubit if the control qubit is $ 1\rangle$
SWAP	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$	Exchanges the states of two qubits
Toffoli (CCNOT)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$	A three-qubit gate that flips the target qubit if both control qubits are $ 1\rangle$

2.2 Quantum Technologies for 6G and beyond

Integrating quantum technologies into future wireless communications signifies a major paradigm shift, primarily in terms of quantum communication and

QC. On the one hand, **quantum communication** uses quantum states to transmit information, leveraging quantum mechanics to achieve secure communication, enhanced capacity and other aspects. These technologies provide unbreakable encryption, secure key distribution, and advanced authentication mechanisms, safeguarding data against both current and future threats, including those posed by quantum computers. As quantum technology continues to evolve, its integration into communication networks promises to redefine the standards of security and privacy in the digital age.

Quantum Key Distribution (QKD), the core technology, ensures that encryption keys are shared with theoretically unbreakable security, as any eavesdropping attempt alters the quantum states and reveals the intrusion. This technology promises to revolutionize secure communications by providing unparalleled data transmission security, making it crucial for applications in finance, government, and other sectors that require robust data protection. Moreover, quantum communication lays the foundation for the future Quantum Internet, enabling secure, long-distance quantum information transfer and connecting quantum computers globally.

Quantum Teleportation was initially proposed by Charles H. Bennett and his colleagues in 1993. Their research illustrates that Einstein-Podolsky-Rosen (EPR) correlations can enable the “teleportation” of a complete quantum state from one location to another, allowing a sender to transmit the state without having knowledge of either the state itself or the receiver’s location [31]. Since the actual information does not traverse the space between sender and receiver, it is inherently more secure against interception and eavesdropping. Moreover, quantum teleportation supports long-distance quantum communication by leveraging entanglement as a resource, potentially enabling communication over vast distances.

Another quantum communication protocol that relies on entanglement is Superdense Coding. This protocol focuses on the efficient transmission of classical information using qubits. In superdense coding, the sender transmits two classical bits to the receiver by sending only one qubit, utilizing pre-shared entanglement between the parties [48]. In addition to enhancing security, this protocol can boost network capacity by increasing the amount of classical information transmitted with fewer qubits [49].

In the realm of quantum communication protocols, the terms “quantum network” and “quantum internet” have emerged as promising candidates poised to revolutionize the world [50], [51]. Defining a quantum network architecture is still premature due to its complexity, diversity, and inherent nature. However, some research has been conducted, and proposals have been made. For instance, to maintain the same logistics as classical networks, a layered view of network functionalities based on a vertical protocol stack has been sug-

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gested. Another proposed implementation of a quantum network involves using quantum channels to distribute entangled quantum systems between parties, enabling communication via teleportation [40]. In this setup, classical networks run in parallel to transmit the results of the measurements in the teleportation protocol from a source to a destination. The necessary entangled quantum systems can be generated either through direct interaction or indirectly via entanglement swapping. Additionally, in this context and comparing traditional networks and communications with their quantum counterparts, the authors in [52] propose a quantum network architecture where drones and satellites act as flexible quantum repeaters, extending nodes to achieve global wide-area coverage.

On the other hand, since **quantum computing** uses qubits to perform computations and can solve complex problems more efficiently than classical computers, it is considered one of the potential enablers for 6G.

In the literature, various perspectives depict QC as a key enabler for 6G technology. Quantum-assisted approaches enhance or support classical systems using quantum technologies without entirely replacing them. Quantum-inspired methods develop advanced classical algorithms and systems based on principles derived from quantum mechanics without utilizing quantum hardware. Quantum-hybrid techniques integrate both quantum and classical computing systems, leveraging the strengths of each to tackle complex problems. The quantum-enhanced perspective uses quantum techniques to improve specific aspects of classical systems, similar to quantum-assisted systems but often focuses on particular enhancements.

For example, quantum-assisted approaches are presented in [49] for radio access networks, non-terrestrial networks, data centers, and blockchains. The authors highlight opportunities to leverage quantum technologies for 6G networks. They discuss Quantum Internet management and control as the ability to manage quantum network resources, including quantum memory, entangled qubits, and quantum channels.

Quantum-inspired Machine Learning (ML) applications are discussed in [53] in the context of resource allocation and network security. Quantum Markov Chain theory is suggested for resource allocation due to the significant impact of stochastic behavior and time-varying wireless conditions on system performance in random environments. These factors affect the accuracy of predictions for high-dimensional data in dynamic, large-scale settings. Furthermore, future directions and research challenges include quantum-inspired multimedia processing, satellite communications, network optimization for Internet of Things (IoT) applications, and secure connected vehicle communications.

In [54], a thorough review of the current advancements in QC and Quantum Machine Learning (QML) is provided, highlighting their potential benefits,

challenges, and applications within Beyond 5G (B5G) networks. The authors introduce an innovative QC-assisted and QML-based framework designed for 6G communication networks, addressing its associated challenges and exploring enabling technologies across network infrastructure, network edge, air interface, and user end. Their analysis is categorized into two main areas: Network Infrastructure and Edge, which covers intelligent proactive and mobile edge computing, multi-objective and routing optimization, massive IoT, and Big Data analytics; and Air-Interface and User-End, which includes configurable multi-antenna systems, optical, Millimeter Wave (mmW), and Terahertz (THz) communications, tiny-cells and cell-free communications, as well as user-side learning, among other topics. Other reviews covering diverse applications, such as joint channel estimation, quantum cryptography, resource allocation, and spectrum management, include [55], [56].

Following the comprehensive review of the literature, the primary use cases and applications that stand to benefit significantly from QC in the context of 6G and future communication technologies are delineated below:

Multi-user detection has become more challenging as the number of users has increased due to heightened interference, higher user density, complex signal processing requirements, varied signal characteristics, dynamic network conditions, and resource constraints. These factors necessitate the development of more advanced and efficient techniques to ensure reliable communication in increasingly crowded wireless environments. Since the advent of Third Generation (3G), quantum solutions have been proposed for multi-user detection. Notably, the authors in [57] introduced an innovative solution utilizing a quantum rotation algorithm for a quantum channel. In [58], a quantum multi-user detector based on discrete coherent states is introduced. This technique evaluates the performance of higher-dimensional signal sets in the presence of noise and determines the optimal performance for a wide range of signals under noisy conditions.

Channel estimation in wireless communication systems, especially in the context of 6G, faces several key challenges. High mobility environments cause rapid channel variations and Doppler shifts, complicating accurate and timely estimation. Massive MIMO (mMIMO) systems introduce significant complexity due to the large number of antennas and associated parameters. Utilizing mmW and THz frequencies adds difficulties with severe path loss and susceptibility to blockages, requiring sophisticated models. Non-stationary and time-variant channels demand dynamic estimation techniques to adapt to changing conditions. Additionally, interference, noise, and resource constraints pose further hurdles, necessitating robust, efficient, and adaptive estimation methods to ensure reliable communication. Integrating QC introduces potential benefits but also new challenges related to quantum noise and scalability. [59] initiates

a discussion on the potential use of QC-based algorithms for solving linear systems of equations to assist in fundamental operations of the transceiver's physical layer, such as channel estimation. It identifies the connections between amplitude encoding in the quantum domain and the recovery of channel information. The authors in [60] and [61], provide an estimate of the quantum channel itself. In various scenarios of quantum information processing, the quantum channel, a fundamental concept in this field, is often not fully known and may contain one or more unknown parameters. The task of quantum channel estimation, therefore, involves the metrological determination of these unknown parameters.

Indoor localization presents another challenge for 6G communications. With the advent of mmW technology, the formation of pencil beams is necessary to reduce multi-user interference and enhance throughput. This requires precise knowledge of the user's position to accurately direct each user with its own beam. Position estimation can be achieved based on user transmissions or received signals. Uplink mmW-based and downlink Visible Light Communications (VLC)-based localization are integrated in [62]. Quantum search algorithms are utilized to reduce the computational complexity necessary for achieving optimal full-search-based performance. For uplink mmW-based localization, a single anchor equipped with multiple antenna elements is employed, exploiting the specular multipath components created by the room's walls.

Multi-objective routing optimization in wireless communications presents several challenges, primarily due to the need to simultaneously address multiple, often conflicting objectives such as maximizing data throughput, minimizing latency, enhancing energy efficiency, and ensuring robust security. Balancing these objectives requires sophisticated algorithms capable of efficiently navigating the trade-offs, which can be highly complex and computationally intensive. Additionally, the dynamic and heterogeneous nature of wireless environments, including varying channel conditions, user mobility, and diverse quality of service requirements, further complicates the optimization process. These challenges necessitate the development of adaptive and scalable optimization techniques that can respond in real-time to changing network conditions while maintaining a balance across multiple performance metrics [63]. Despite the nascent stage of quantum device development, numerous research papers have explored the integration of QC to address routing optimization problems in wireless networks. This represents one of the most challenging and promising use cases for 6G technology [54], [64].

MIMO communication was first introduced in the quantum domain in 2006 by Gabay and Arnon according to [65], who presented a QKD scheme using a free-space Multiple-Input Multiple-Output (MIMO) system [66]. Subsequently, notable contributions have emerged in this area, such as a new QKD

scheme in free space proposed in 2009 [67]. The authors in [65] also introduced a quantum MIMO communication scheme based on quantum teleportation with triplet states, enabling transmission of an n -qubit sequence of quantum signals through the MIMO channel using diversity techniques in the quantum realm. In 2019, a quantum MIMO architecture for antenna wireless communications was developed, aimed at establishing a foundational theory for MIMO communications over quantum channels [68], where classical information is conveyed through quantum states rather than classical electromagnetic fields. Recent research has focused on addressing the inherent complexity of MIMO technology. For instance, in [69], a quantum algorithm was devised to optimize power allocation in MIMO systems, addressing the challenge posed by the significantly larger number of antennas at the transmitter compared to conventional systems with one or a few antennas, where power allocation was relatively straightforward.

NOMA signal detection presents several fundamental performance challenges, including high computational complexity in scenarios with a large number of users, inefficient use of transmission time, and the need for accurate Channel State Information (CSI) estimation for numerous users. Integrating channel estimation, channel equalization, and symbol decoding into a single process may address these challenges. QC and QML hold promise as significant enablers, potentially accelerating multi-user transmission and detection optimization. Furthermore, QML is expected to play a crucial role in re-defining multiple-access strategies for 6G and future communication systems [54]. Hence, there is growing interest in leveraging quantum-based methods for multi-user digital modulation schemes, whether operating under orthogonal or non-orthogonal assumptions. The objective of employing quantum approaches is to perform specific strategic computations required by these schemes at a significantly faster rate compared to classical computing methods.

Resource allocation in wireless communication pertains to the strategic distribution of limited resources, such as bandwidth, power, and time slots, among various users, devices, or services within a wireless network. This process is essential to improve the performance, efficiency and Quality of Service (QoS) in wireless networks. In this regard, [53] offers a comprehensive overview of quantum-inspired real-time optimization and its application to optimal resource allocation in 6G wireless networks, highlighting initial research results and the potential impact on emerging 6G technologies, while also discussing the associated challenges and opportunities.

Security and privacy is one of the major challenges in the evolving technological landscape. In this context, QC plays a pivotal role. Quantum cryptography, with its ability to generate secret keys, is widely regarded as a promising solution for future security and privacy needs [54]. A complete roadmap to 6G

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security and privacy is presented in [70]. The survey examines how security may impact envisioned 6G wireless systems, explores potential challenges with various 6G technologies, and discusses possible solutions. It presents a vision of 6G security and security Key Performance Indicators (KPIs), alongside a tentative threat landscape based on the anticipated 6G network architecture.

Sensing in 6G refers to the integration of advanced sensing capabilities within 6G wireless communication networks. Unlike previous generations, 6G aims to seamlessly merge communication and sensing functions, enabling the network to not only transmit data but also gather environmental information. This dual functionality can be used for a wide range of applications, including enhanced location-based services, environmental monitoring, health monitoring, and smart city infrastructure. This integration is expected to significantly enhance the performance and intelligence of future wireless networks. Incorporating QC in 6G networks could significantly enhance both sensing precision and data processing capabilities. QC can process vast amounts of data at unprecedented speeds, enabling real-time analysis and decision-making for the vast sensor networks integrated into 6G infrastructure [71].

Considering the use cases outlined in this section, this thesis investigates the potential of QC to improve solutions in several critical areas, namely indoor localization, multi-objective routing optimization, Software-Defined Networking (SDN), and MIMO communication systems based on maximum likelihood detection.

Firstly, indoor location applications in massive networks pose significant challenges and were traditionally not based on quantum Euclidean distances before this thesis. As such, indoor localization was selected as the initial use case to address, providing a rationale for integrating QC into future 6G networks. This crucial and challenging contribution involved introducing the calculation of Euclidean distances in its quantum form, utilizing the Qiskit Software Development Kit (SDK) from IBM.

Secondly, optimization problems in network routing have consistently posed significant challenges. Poor routing strategies, irrespective of network type, can detrimentally impact overall network performance. Motivated by the connectivity requirements of 6G, the capabilities offered by quantum computation, and the essential role of routing strategies in wireless communications, this thesis investigates a multi-objective routing optimization based on quantum optimization algorithms use case. Additionally, a quantum-enhanced framework for SDN, aimed at optimizing routing decisions, is proposed.

From a Bit Error Rate (BER) performance perspective, the Maximum Likelihood Detection (MLD) is the most accurate due to its exhaustive search across all possible solutions in a constellation of symbols to identify the transmitted signal. However, in mMIMO scenarios with a large number of antennas, MLD

is classified as an Non-Deterministic Polynomial-Time (NP-hard) problem for classical computers. In contrast, quantum computers can enhance performance by leveraging quantum mechanical properties. This thesis introduces this approach as one of the primary use cases for 6G. Furthermore, the integration of MIMO Non-Orthogonal Multiple Access (NOMA) is proposed, given its complexity and innovative potential.

2.3 Quantum Computing and SDGs

In developing standards for new generations of mobile communications, it is crucial to address not only established requirements like spectrum efficiency, energy consumption, cost, and latency but also to tackle global challenges such as pandemics, climate change, social inequalities, and growing skepticism in democracy. Integrating these broader issues into the design and implementation of mobile communication standards ensures that technology not only advances technically, but also contributes positively to society, enhancing resilience, sustainability, and equity in a rapidly changing world. As noted in [1], the comprehensive and sustainable digitization of the global economy and society is crucial for addressing contemporary economic, social, and political challenges. This transformation is significantly driven by emerging and revolutionary digital technologies, with wireless networks playing a key role in facilitating this extensive change.

One of the topics explored in this Thesis was the cost associated with quantum systems despite their numerous advantages in computational capabilities for future wireless networks. While most research focuses on the benefits of QC in data processing and solving complex problems, fewer studies address the costs of building and maintaining quantum systems and their potential impact on societal sustainability. Inspired by this fact and the 17 SDGs set by the United Nations in 2015 for Agenda 2030 (Fig. 2.4), the paper “In-Network Quantum Computing for Future 6G Networks” was published [5].

A summary of the SDG targets relevant to 6G is categorized as follows [5]:

- **Environmental Sustainability (SDGs 6, 13, 14, and 15):** 6G technologies must be capable of preserving and using natural resources like air, water, life, and land sustainably, as well as protecting all natural life forms. This entails addressing issues such as climate change, deforestation, water pollution, and biodiversity loss.
- **Economic Sustainability (SDGs 8, 9, 10, and 12):** Economic sustainability through 6G involves creating productive employment, fostering innovative industrialization, and developing infrastructure. It also

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Figure 2.4: Sustainable Development Goals. [5]

aims to promote higher resource consumption responsibly. A strong economy would help bring countries closer together, facilitating global cooperation.

- **Social Sustainability (SDGs 1, 2, 3, 4, 5, 7, 11, and 16):** 6G aims to improve human life by ensuring ample food, peace, prosperity, clean energy, quality education, and sustainable communities for all. This includes tackling poverty, hunger, health, gender equality, and creating inclusive and safe communities.

Lastly, **SDG 17** focuses on bringing all these goals together to achieve overall sustainability through 6G. These SDGs are interrelated and significantly impact each other. For example, quality education and good health promote gender equality and help build a peaceful and just society. Similarly, protecting and mindfully consuming natural resources enhances the quality of life, contributing to goals like zero hunger and sustainable cities. In general, investing in innovation and infrastructure is crucial to sustainably accelerate economic growth.

2.3.1 6G KVIs related to QC

The core pillars of 6G's vision encompass sustainability, trustworthiness that includes security, resilience, reliability, and scalability or digital inclusion. This section explores how QC interacts with these pillars, evaluating their alignment, potential synergies, and the challenges at their intersection. Figure 2.5 provides a summary of the relationship between the primary 6G KVIs and the essential characteristics of current quantum computers on the left.

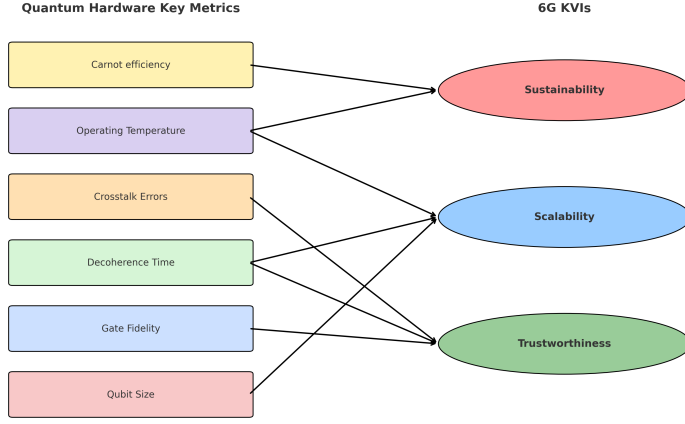


Figure 2.5: 6G KVIs and QC hardware parameters.

To maintain quantum properties such as superposition and entanglement, qubits need to be isolated from their external environment to preserve coherence and must be kept at extremely low temperatures. Cryogenics, the field focusing on the production, behavior, and effects of materials at temperatures below -150 degrees Celsius (-238 degrees Fahrenheit) or even colder, is essential to achieve these conditions. This technology is crucial for most qubits, especially superconducting qubits, which operate at temperatures as low as 15 milliKelvin (mK) [37]. In contrast, photon qubits require less stringent cryogenics, with operating temperatures between 4 and 10K for their photon sources and detectors. To handle quantum systems at such low temperatures, cryostats are used to maintain the cryogenic environment needed for storing and operating trapped ions and superconducting qubits. A cryostat is essentially a container designed to keep devices or liquids at very low temperatures, typically below 120K, much colder than the naturally occurring temperatures on Earth. The performance of a cryostat is measured by its Carnot efficiency, which is the maximum thermal efficiency it can achieve, significantly affecting the sustainability and scalability of 6G technologies. Additionally, when considering qubits and quantum gates, it is important to address crosstalk errors and unwanted interactions between qubits that can cause computational errors and decoherence time, the duration a quantum system maintains coherence before environmental factors induce decoherence. Gate fidelity refers to

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the accuracy and reliability with which a quantum gate performs its intended quantum operation.

Sustainability and Energy Efficiency

Sustainability is critical in modern technology, particularly at the intersection of QC and 6G wireless communication systems. Despite efforts by the Information and Communications Technology (ICT) sector to reduce energy use per computational task, the growing digital economy demands more computational resources, connectivity, and bandwidth, increasing overall energy consumption. The development of 6G will be influenced by sustainability paradigms such as decarbonizing energy, adopting circular economy principles, and using sustainable materials [72]. While 6G aims to conserve energy and optimize resources, research has also explored QC's potential to enhance processing capabilities and accelerate information transfer in mobile networks. QC promises superior computational power, but its energy requirements, especially for large-scale applications like smart cities, pose challenges. Evaluating QC's energy efficiency involves considering qubit type and operating temperatures, with efforts to reduce cooling costs and improve design. A comprehensive approach is needed to address the energy implications of quantum technologies. QC could contribute to sustainable 6G by optimizing resource use and reducing environmental impact, but its practical implementation depends on the development of mature quantum technologies. The potential of QC to enhance communication networks while establishing sustainable infrastructures remains uncertain, requiring more efficient and sustainable device development.

Quantum computers have not yet achieved sustainability, but evaluating certain parameters, as outlined in Fig. 2.5, could enhance their energy efficiency. The type of qubit chosen significantly impacts overall energy consumption. For example, the Carnot efficiency of a system operating at the 4K temperature of trapped-ion qubits is over 400 times higher than that of a system operating at the 10mK temperature required by some superconducting qubits. Increasing the operating temperatures for superconducting qubits can greatly improve energy efficiency. While moving electronics out of the cryostat is challenging due to variations in power consumption and heat dissipation, it is crucial for minimizing energy use. Additionally, reducing the physical size of electronics can decrease cooling power requirements. Traditional data center efforts to lower non-computing energy costs by improving engineering design and integration have shown that reducing Power Usage Effectiveness (PUE) from 1.60 to 1.02 can achieve a thirty-fold reduction in non-computational energy expenditures [73].

Scalability

Scalability is vital for 6G as it is closely related to digital inclusion, a key component of future wireless communication networks. Digital inclusion ensures that all individuals and communities, including those in remote or underserved areas, have access to and can benefit from digital technologies and services. Scalability refers to the system's ability to manage expansion and increased demands from a growing number of users, devices, and applications. Both scalability and digital inclusion are essential for developing a 6G ecosystem that is technologically advanced and capable of serving diverse user needs, making their balance crucial for successful global deployment and adoption of future wireless networks. The concept of key-value inclusion, as mentioned in [1], involves ensuring ease of access to services, incorporating technical aspects like network coverage and user-centric factors such as service availability and accessibility for specific groups, potentially involving innovative Human Machine Interfaces (HMIs) or interaction with robots.

6G's architecture envisions a complex network of intelligent orchestration supported by real-time data and adaptive management protocols, with QC playing a central role due to its ability to process complex computations at unprecedented speeds. Use cases such as telepresence, earth monitoring, and e-health stand to benefit from QC, provided there are sufficient qubits and low-noise systems to ensure precision. However, scaling quantum systems increases energy consumption due to the required operating temperatures. The type of qubit technology is also critical; for instance, trapped ions offer high fidelity but are slow and challenging to scale beyond a hundred ions. While easier to produce, superconducting qubits operate at extremely low temperatures (15 mK) and face scalability challenges with increased wiring and control frequency adjustments. Quantum dots electron spin qubits, produced using CMOS circuits, offer better scalability and operate at higher temperatures (100 mK to 1K), allowing more electronics integration. Photons, used as flying qubits, operate mostly at room temperature, though their sources and detectors require cooling to 4-10K, a less demanding requirement than for superconducting qubits.

Recent advancements in quantum research have highlighted potential solutions to scalability challenges, but achieving scalability depends on various factors, including qubit size, which ranges from 1 to 100 nanometers. Scalable quantum systems must maintain decoherence time and manage noise, which are crucial for accurate measurements. Enhancing qubit connectivity and enabling parallel operations are essential to maintain the performance of QC algorithms in large-scale systems.

Trustworthiness

Trustworthiness in 6G encompasses the reliability, security, and overall integrity of the forthcoming generation of wireless communication technology. Ensuring trustworthiness in 6G entails addressing a range of challenges related to privacy, data security, network resilience, and the prevention of cyber threats. This includes developing and implementing robust encryption techniques, secure authentication protocols, and measures to safeguard against emerging cybersecurity risks. The concept highlights the necessity of establishing a safe and reliable foundation for the advanced communication technologies that will define the 6G era.

This underscores the potential role of quantum communication in 6G networks, particularly in enhancing security through QKD. Integrating QC with future mobile communications requires balancing both technologies' inherent strengths and weaknesses. To fully capitalize on the security and reliability advantages offered by QC, addressing potential conflicts, especially concerning sustainability and scalability, is crucial. If scalability is not adequately achieved to meet the complex demands of 6G, the path forward may become challenging. Discussions on security, reliability, and resilience must account for factors such as errors, operating temperatures, and decoherence times associated with current quantum devices, as illustrated in Fig. 2.5. Establishing an optimal balance among these factors is essential to advance QC in alignment with the evolving requirements of 6G technology.

2.4 Conclusions

This chapter has provided a comprehensive exploration of QC, firmly rooted in the foundational principles of quantum mechanics, which have driven remarkable advancements in both theoretical frameworks and practical hardware development. Quantum hardware technologies, such as superconducting qubits, trapped ions, and photonic qubits, each offer distinctive strengths and challenges. These include issues related to scalability, coherence times, and error correction. Efforts to meet the DiVincenzo criteria remain essential for assessing the viability and future potential of quantum systems. Meanwhile, continuous innovation and the integration of these technologies promise to expand computational power and problem-solving capabilities, further demonstrating the transformative potential of QC. The symbiotic relationship between theoretical advancements and experimental breakthroughs underscores the dynamic growth of this rapidly evolving field.

The potential applications of integrating QC with 6G communication technologies, emphasizing the transformative impact of quantum technologies on

future mobile networks, were also reviewed. QC has the potential to revolutionize 6G by enhancing data processing capabilities to handle massive data volumes, optimizing resource allocation for greater efficiency, and advancing network design and management to achieve superior performance, security, and reliability. By leveraging the unique advantages of QC, 6G networks could unlock unprecedented levels of speed, efficiency, and functionality.

However, while much of the existing literature focuses on the benefits of QC, it often overlooks the sustainability challenges associated with the development and operation of quantum devices. A critical analysis of these challenges is necessary, particularly in the context of the KVIs outlined for 6G development. Key aspects such as the operating temperatures required for qubits and the persistent noise issues in current quantum systems must be addressed to align QC with the sustainability goals of 6G.

To this end, the chapter provides an overview of 6G and the SDGs, examining the potential alignment of QC with 6G's objectives of sustainability, scalability, and trustworthiness. This analysis highlights the interplay between the advancements in 6G and the nuanced considerations required for successfully integrating QC technologies. By addressing these challenges, this chapter aims to provide insights into the strategic integration of QC within 6G, paving the way for a more sustainable and capable future in mobile communication networks.

Chapter 3

Location Techniques Enhanced by Quantum Computing

Localization within communication systems has historically represented a significant technological challenge, drawing sustained attention from the research community. While early efforts predominantly relied on Global Positioning System (GPS) technologies, the contemporary focus has shifted towards the development of high-precision, energy-efficient indoor localization solutions. This transition is largely motivated by the proliferation of Wireless Sensor Networks (WSNs) and the Internet of Things (IoT), where accurate knowledge of node positioning is pivotal for the efficient functioning of spatio-temporal IoT systems. As these paradigms evolve, precise localization emerges as a fundamental enabler for network optimization and the realization of novel, context-aware applications [74].

In parallel, advanced localization techniques will be indispensable for meeting the stringent performance requirements of Sixth Generation (6G) and future wireless communication systems. Ultra-precise positioning is essential to support critical use cases such as autonomous vehicles, smart manufacturing, and industrial automation. These techniques enhance resource allocation by facilitating adaptive and location-aware network management, thereby improving overall system efficiency and Quality of Service (QoS). Moreover, accurate spatial awareness supports seamless operation in high-mobility environments, enables context-driven services, and reinforces security protocols through location-based authentication mechanisms. The integration of

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Artificial Intelligence (AI) and Machine Learning (ML) further empowers these systems by enabling predictive analytics and supporting cutting-edge applications including drone navigation, intelligent transportation systems, and smart urban infrastructure.

Concurrently, the rapid advancement of quantum technologies holds great promise for redefining the landscape of localization in future wireless networks. Quantum Computing (QC), with its inherent ability to solve complex optimization and estimation problems with exceptional precision, is expected to substantially enhance localization accuracy. Its superior processing capabilities offer real-time data handling and dynamic optimization, while its scalability ensures robustness in handling the increasing complexity and data volume of next-generation communication systems. As quantum technologies become more integrated into wireless infrastructure, they are poised to revolutionize localization by making it more accurate, efficient, and responsive to the multifaceted requirements of advanced networked environments.

This chapter explores a novel approach to indoor localization based on a quantum-enhanced Euclidean distance estimator, and is structured as follows:

- Section 3.1 begins with an overview of localization technologies and techniques, with a particular emphasis on indoor localization.
- Section 3.2 introduced the quantum euclidean distance in a step by step manner to emphasize its differences from and advancements over the traditional Euclidean distance.
- Section 3.3 outlines the main conclusions of the chapter

3.1 Indoor Localization

Indoor localization refers to the systematic process of accurately determining the position of a device or user within enclosed environments. This technology plays a critical role across diverse domains, including healthcare, disaster response, building automation, industrial operations, and the broader ecosystem of the IoT, particularly in scenarios characterized by massive Machine Type Communications (mMTC). As the demands of these applications grow, next-generation systems are required to deliver ultra-high precision, enabling functionalities such as pencil beamforming at Millimeter Wave (mmW) frequencies and the autonomous navigation of robots in factory environments. These use cases demand millimeter-level accuracy and the capability to process vast volumes of data, requirements that current localization systems are still struggling to fully meet.

3.1.1 Localization Technologies

A variety of technologies such as Wi-Fi triangulation, Bluetooth beacons, Zonal Intercommunication Global-standard (ZigBee), Radio Frequency Identification (RFID), Ultra-Wideband (UWB), Visible Light Communications (VLC), and smartphone sensors like accelerometers and gyroscopes are employed by indoor localization approaches, [75]. Other low-power options include acoustic and ultrasound signals with high accuracy, as well as Long Range (LoRa), which provides wide coverage. Wi-Fi is among the most widely studied technologies and is integrated into most smartphones and laptops, making it an attractive candidate for localization [76], [77], [78], [79]. However, since Wi-Fi networks are primarily optimized for data rate and coverage, new methods are required to enhance their localization accuracy.

Apple introduced iBeacons at the World Wide Developers Conference (WWDC) 2013 as a protocol for proximity services. A Bluetooth Low Energy (BLE) device (beacon) broadcasts signals periodically, which can also be used for indoor localization. A limitation, however, is that Apple restricts devices to receive only one averaged signal strength per second, despite beacons transmitting every 50 ms [75].

ZigBee is well suited for indoor localization due to its reliability and low energy use. In ZigBee-based systems, mobile devices communicate with fixed anchor nodes, and algorithms estimate locations from signal measurements. Its mesh networking further improves coverage, accuracy, and robustness against interference [80].

In RFID-based systems, tags attached to objects or people communicate with fixed readers, enabling location estimation through multiple signals. A deep learning-based method proposed in [81] enhances three-dimensional localization by analyzing received signal strength and phase, combining absolute and relative positions. This approach is applied in a smart library setting.

UWB is attractive for indoor localization because of its wide spectrum and resistance to interference. Low-frequency UWB signals can even penetrate walls, though they are affected by metals and liquids. In [82], a modified Saleh-Valenzuela (SV) channel model and external UWB signals are used to propose a localization framework. Two approaches are tested: one using deep learning (Multi-layer Perceptron (MLP), Convolutional Neural Networks (CNN)) and another using ML (MLP, Support Vector Machine (SVM)), with the CNN-based method achieving a Mean Absolute Error (MAE) of about 3 cm.

VLC-based localization is also promising due to its low deployment cost, as it uses existing LED infrastructure, and its high throughput with minimal wireless interference. Since light cannot penetrate walls, it also provides improved

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security against eavesdropping, making VLC cost-effective, efficient, and secure [83].

Fifth Generation (5G) networks further improve indoor localization thanks to advanced features such as high precision and mmW communication. Accurate positioning is essential for effective pencil-beamforming, which reduces interference and increases throughput.

Finally, deep learning, ML, and AI have been widely integrated to enhance these technologies. Future systems are expected to include adaptive and self-learning capabilities [84]. Extensive work on 5G-based localization already shows improved accuracy and reliability [85], [86], [87]. Moreover, QC is anticipated to play an important role as mobile communications evolve and data volumes increase.

3.1.2 Localization Techniques

In addition to the technologies mentioned above, various signal metrics are used to determine the location of a device. In the following table 3.1, an explanation of the primary techniques is provided.

3.2 Quantum-Enhanced Indoor Localization

QC presents promising capabilities for enhancing the accuracy, efficiency, and scalability of indoor localization systems, positioning it as a transformative technology for the future of wireless communication and positioning infrastructures. One notable application lies in optimizing the selection algorithms for wireless Access Points (APs), such as Wi-Fi routers. Selecting a larger number of APs generally increases computational load, energy consumption, and latency. Therefore, achieving an optimal trade-off becomes essential, especially considering the resource limitations inherent to low-power devices in the IoT ecosystem. Minimizing redundant APs not only reduces overhead but can also improve localization accuracy [91].

In this context, [92] proposes a quantum-based APs selection algorithm tailored for large-scale localization systems. The method formulates the selection task as a Quadratic Unconstrained Binary Optimization (QUBO) problem, making it well-suited for resolution via quantum annealing. This algorithm identifies the minimal set of APs required to preserve the original system's localization accuracy, effectively eliminating both redundancy and noise.

Beyond access point selection, fingerprinting methods for indoor localization face critical challenges, including high calibration costs, in-band interference, and, notably, scalability. The latter becomes increasingly relevant in IoT en-

3.2 Quantum-Enhanced Indoor Localization

Technique	Description
Received Signal Strength (RSS)	A measurement of the power level detected by a receiver from a transmitted signal. Commonly used to estimate the distance between devices and to assess signal quality in wireless communication systems. Measured in units like decibel-milliwatts (dBm) or milliwatts (mW), a higher RSS value generally indicates a shorter distance between the transmitter and receiver [75].
Received Signal Strength Indicator (RSSI)	Often confused with RSS, it is a relative measurement of signal strength in arbitrary units, such as on a scale from 0 to 100 or in dBm, typically defined by each chip manufacturer.
Time of Flight (ToF)	Refers to the measurement of the time it takes for a signal to travel from a transmitter to a receiver. Used in indoor positioning systems to measure the distance between devices, such as in UWB or ultrasound-based systems. By measuring the travel time between a transmitter and multiple receivers, the system can triangulate the device's position [88].
Angle of Arrival (AoA)	Analyzes the angle at which a signal arrives at a sensor or antenna array, used to estimate the signal source's location. Useful in indoor localization, radar systems, and beamforming. With two AoA measurements and known receiver positions, the two-dimensional coordinates of the transmitter can be calculated using triangulation. Accurate AoA measurements require directional antennas or an antenna array, adding complexity and cost [89].
Phase of Arrival (PoA)	Involves measuring the phase difference of a received signal at multiple antennas or sensors. By comparing phase differences, the system can estimate the angle or position of the transmitter relative to the receiver array. Commonly used in radar, sonar, and indoor localization to achieve high positioning accuracy. The effectiveness relies on precise synchronization and accurate phase shift measurements [75].
Channel State Information (CSI)	A detailed representation of the channel characteristics between a transmitter and a receiver. Captures information about the amplitude and phase of the signal as it travels through the channel, providing valuable insights for indoor localization with high accuracy and robustness [90].
Fingerprinting/Scene Analysis	A technique in indoor localization that estimates device position by comparing current signal measurements with a pre-collected database of signal characteristics from known locations. Usually uses RSS or CSI fingerprints. Useful in environments where distance-based methods are less effective due to multipath effects and signal variability. Does not require knowledge of the base station's location or measurement of time and angles, enhancing its practicality for indoor applications. Characterized by straightforward implementation, ease of measurement, and low cost [84].

Table 3.1: Overview of Key Techniques for Indoor Localization

vironments, where the number of Reference Points (RPs) can be substantial. Conventional fingerprinting techniques compare online RSS readings with a pre-established database of measurements from M fingerprint locations and N RPs, leading to a time and space complexity of $O(MN)$. Such requirements pose significant barriers to scalability in both indoor and outdoor deployment scenarios.

To overcome these limitations, [93] introduces a quantum fingerprinting algorithm aimed at large-scale location tracking. The approach leverages quantum encoding techniques to represent RSS measurements and applies quantum similarity computations, specifically cosine similarity, to match online readings with stored fingerprint data. The proposed quantum algorithm demonstrates significant improvements in both memory and runtime efficiency compared to

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classical baselines, thus paving the way for scalable, high-performance localization systems.

In parallel, [94] proposes a hybrid quantum deep neural network model for enhancing indoor positioning accuracy. This model combines the strengths of QC, notably, its capacity for parallelism via superposition and entanglement, with the feature extraction and pattern recognition capabilities of classical Deep Neural Networks (DNNs). The hybrid model proves particularly effective even with smaller datasets, addressing a fundamental constraint in indoor localization where data acquisition is both labor-intensive and resource-demanding.

Motivated by the aforementioned challenges, and noting the absence of studies on quantum-based Euclidean distance computation at the time of researching, this doctoral work proposes a novel indoor localization framework that integrates fingerprinting with quantum Euclidean distance estimation [95]. This methodology is designed with scalability in mind, anticipating scenarios involving high-dimensional vectors derived from extensive antenna arrays in next-generation wireless networks. As quantum technologies mature, such approaches are expected to offer substantial performance advantages over classical counterparts.

The proposed methodology begins with a detailed measurement campaign that discretizes the environment into a structured grid. At each point of the grid, comprehensive signal features, such as RSSI, ToF, AoA, among others, could be recorded across all visible APs. In high-dimensional settings, such as those employing Massive MIMO (mMIMO) systems, the resulting vectors may consist of tens of thousands of elements. These offline measurements populate a database that serves as the reference for online localization. While reducing grid granularity improves positioning accuracy, it also leads to an exponential growth in database size and comparison operations.

To address the resulting scalability bottleneck, the use of QC techniques is proposed. By exploiting quantum parallelism, Euclidean distances between real-time and stored vectors can be calculated simultaneously, dramatically reducing computational time. A quantum algorithm encodes the measured vectors and performs the distance evaluations in superposition, allowing all comparisons to be executed in a single operation.

To further reduce computational complexity, a hierarchical tile-based refinement strategy is implemented. The localization area is initially divided into a small number of coarse-grained tiles (e.g., four quadrants). Based on the closest match, the region is recursively subdivided, with each iteration refining the resolution of the estimated location. This process continues until the tile corresponding to the finest granularity is identified. Through this iterative narrowing, the system minimizes the number of required comparisons, preserving high accuracy while improving computational efficiency.

A defining feature of this quantum-assisted framework is its ability to process both stored and live data concurrently. This enables rapid analysis of complex radio signal parameters and supports high-precision localization in real time. By integrating quantum techniques into the core of the localization engine, the proposed approach represents a significant advancement toward scalable, energy-efficient, and ultra-accurate indoor positioning systems for future wireless networks.

To provide a visual representation of this iterative refinement process, Fig. 3.1 illustrates examples of tile division and successive iterations. The red-colored regions in the figure highlight the steps involved in progressively narrowing the search space, effectively demonstrating the core concepts described above.

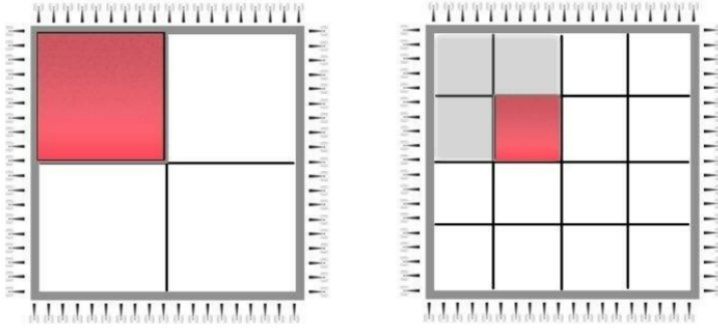


Figure 3.1: First two iterations of the indoor localization proposal.

3.2.1 Quantum Euclidean Distance

The measurement of distance plays a vital role in numerous disciplines, serving as a foundational concept in geometry, physics, and data analysis. Among the various distance metrics, the Euclidean distance is particularly significant, as it quantifies the straight-line length between two points in the Euclidean space [96]. This straightforward concept is extensively used for spatial representation and computational algorithms in classical systems.

However, when transitioning to the domain of quantum mechanics, the notion of distance becomes more intricate and requires a fundamentally different interpretation. In classical systems, the Euclidean distance between two vectors is computed directly on the basis on their coordinates. In contrast, quantum systems operate in Hilbert spaces, where states are represented as vectors,

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but the concept of distance between these states is governed by probabilistic amplitudes and phase relationships. Consequently, the difference between two quantum states cannot be treated in the same manner as the difference between two classical vectors. Instead, quantum measurements often involve metrics such as fidelity, overlap, or norms derived from complex amplitudes, making the computation of distance in quantum mechanics both richer and more challenging.

Given these complexities, the procedure for calculating the Euclidean distance within a quantum framework requires careful formulation and implementation. The following subsection outlines this process step by step, detailing how quantum principles and operations are leveraged to perform distance measurements while preserving the mathematical integrity of quantum mechanics.

Quantum state preparation

The first step in leveraging QC for data processing involves encoding classical data into quantum states, a procedure known as quantum embedding (illustrated in Fig. 3.2). This process transforms a classical data point, denoted as X , into a set of parameters that control the behavior of quantum gates within a quantum circuit. Essentially, quantum embedding acts as a bridge between the classical and quantum domains, enabling classical information to be represented in a format suitable for quantum computation.

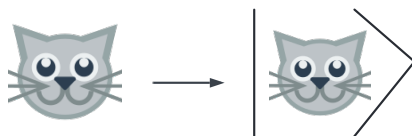


Figure 3.2: Quantum embedding.

Several distinct techniques have been developed to facilitate this embedding process, each offering specific advantages and trade-offs [97]:

- **Basis embedding:** This method maps classical data directly to the computational basis states of a quantum system. For example, each classical data point is represented by a unique binary string, which corresponds to the state of a quantum register. Although conceptually simple, basis embedding often requires a significant number of qubits, making it less scalable for large datasets.

- **Angle embedding:** In this approach, classical data is encoded into the angles of quantum gates, such as rotation gates applied to qubits. Each data point specifies the rotation angle around a given axis (e.g., X, Y, or Z). This technique is particularly useful in variational quantum algorithms, where parameterized gates are optimized to solve specific problems. Angle embedding is computationally efficient and relatively easy to implement in practice.
- **Amplitude embedding:** This technique encodes classical data into the probability amplitudes of a quantum state. The classical data vector is first normalized to ensure it satisfies the constraints of a quantum state (total probability equal to 1). It is then used to define the amplitudes of the quantum state. Amplitude embedding is highly efficient in terms of qubit utilization because it can represent large datasets with relatively few qubits. However, preparing arbitrary quantum states required for this method can be technically challenging, as it involves complex state preparation circuits.
- **Density matrix embedding:** Unlike other methods that encode data into pure states, this approach maps classical data into the density matrix representation of a quantum system, which describes mixed states. This method is particularly advantageous for encoding probabilistic data distributions and noisy datasets, providing greater flexibility and expressiveness compared to pure-state embeddings.

Each of these embedding techniques plays a critical role in the transformation of classical information into quantum representations, enabling the execution of quantum algorithms designed for optimization, classification, ML tasks, among others. The choice of embedding method depends on the specific requirements of the application, including data size, computational constraints, and algorithmic compatibility.

Swap test operator

After encoding classical data into quantum states, the next step involves quantifying the “distance between two quantum states”, which reflects their degree of similarity. This similarity metric is defined by two extreme cases: the states being identical or completely orthogonal. To evaluate this, the SWAP test operator (Fig. 3.3) is employed, which determines the overlap (inner product) between two quantum states, denoted as $|\psi\rangle$ and $|\phi\rangle$, by measuring the probability of an auxiliary qubit. This auxiliary qubit acts as a control for the SWAP operation. A measurement outcome of $P(|0\rangle) = 0.5$ for the auxiliary qubit signifies that the states are orthogonal, while an outcome of $P(|0\rangle) = 1$ implies

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that the states are identical. The SWAP test operator is implemented by applying Hadamard (H) gates before and after the controlled-SWAP (CSWAP) operation on the auxiliary qubit.

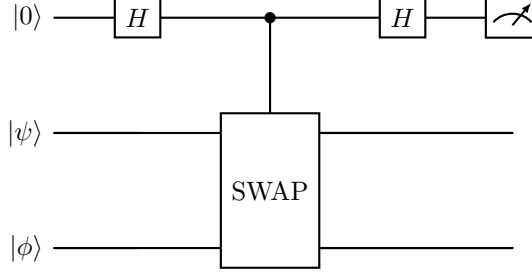


Figure 3.3: Circuit diagram of the SWAP test.

Given two quantum states $|\psi\rangle$ and $|\phi\rangle$ and an ancilla qubit initialized in the $P(|0\rangle)$ state, the SWAP test operates through the following procedure. The protocol begins by applying a Hadamard gate to the ancilla qubit, creating the superposition state $H|0\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$. Next, a controlled-SWAP (CSWAP) operation is performed, where the ancilla serves as the control qubit. The CSWAP gate exchanges the quantum states of the two target qubits if and only if the control qubit is in the $P(|1\rangle)$ state. Here, $\otimes$ will denote the tensor product operation.

The complete SWAP test procedure systematically demonstrates how the final measurement outcomes directly reveal whether the states $|\psi\rangle$ and $|\phi\rangle$ are identical or orthogonal, providing a quantum mechanical method for state comparison.

Initial state:

$$|0\rangle \otimes |\psi\rangle \otimes |\phi\rangle = |0\psi\phi\rangle \quad (3.1)$$

Applying Hadamard on the ancilla qubit:

$$H \rightarrow \frac{1}{\sqrt{2}}(|0\psi\phi\rangle + |1\psi\phi\rangle) \quad (3.2)$$

Applying the controlled-SWAP operator:

$$CSWAP \rightarrow \frac{1}{\sqrt{2}}(|0\psi\phi\rangle + |1\phi\psi\rangle) \quad (3.3)$$

At this stage, the ancilla qubit remains in superposition, while the states $|\psi\rangle$ and $|\phi\rangle$ are swapped whenever the ancilla is in the $|1\rangle$ state.

Applying another Hadamard gate on the ancilla qubit:

$$\begin{aligned} H &\rightarrow \frac{1}{\sqrt{2}}(|0\psi\phi\rangle + |1\psi\phi\rangle + |0\phi\psi\rangle - |1\phi\psi\rangle) \\ &= \frac{1}{2}(|0\rangle[|\psi\phi\rangle + |\phi\psi\rangle] + |1\rangle[|\psi\phi\rangle - |\phi\psi\rangle]) \end{aligned} \quad (3.4)$$

Measuring the ancilla qubit in the $|0\rangle$ state:

$$\begin{aligned} P(|0\rangle) &= \left| \frac{1}{2}(|\psi\phi\rangle + |\phi\psi\rangle) \right|^2 \\ &= \frac{1}{4} (\langle\psi\phi|\psi\phi\rangle + \langle\psi\phi|\phi\psi\rangle + \langle\phi\psi|\psi\phi\rangle + \langle\phi\psi|\phi\psi\rangle) \end{aligned} \quad (3.5)$$

Since:

$$\langle\psi\phi|\phi\psi\rangle = \langle\psi|\phi\rangle \otimes \langle\phi|\psi\rangle = \langle\phi|\psi\rangle \otimes \langle\psi|\phi\rangle \quad (3.6)$$

We obtain:

$$P(|0\rangle) = \frac{1}{2} + \frac{1}{2} \langle\psi|\phi\rangle + \langle\phi|\psi\rangle = \frac{1}{2} + \frac{1}{2} |\langle\psi|\phi\rangle|^2 \quad (3.7)$$

Example: For instance, if $|\psi\rangle = |1\rangle$ and $|\phi\rangle = |0\rangle$, then:

$$P(|0\rangle) = \frac{1}{2} + \frac{1}{2} |\langle 1|0\rangle|^2 = \frac{1}{2} \quad (3.8)$$

This result confirms that orthogonal states yield a probability of $P(|0\rangle) = 0.5$, indicating minimal overlap, while identical states result in $P(|0\rangle) = 1$, signifying complete similarity.

Quantum Euclidean Distance

The Swap Test operator holds significant importance in quantum Euclidean calculations due to its ability to evaluate the similarity between quantum states. This process is particularly valuable in applications requiring the comparison of data patterns or the determination of state overlaps.

The implementation of the quantum Euclidean distance begins by encoding classical data into quantum states, which serves as the foundation for subsequent computations. As outlined in 3.2.1, multiple techniques can be utilized for quantum state preparation. In this specific case, amplitude embedding is selected as the encoding method. This approach is advantageous because it efficiently represents data using only a few qubits, making it a resource-effective solution.

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$$\mathbf{a} \rightarrow |\mathbf{a}\rangle = \frac{1}{|\mathbf{a}|} \sum_i \mathbf{a}_i |i\rangle \quad (3.9)$$

$$\mathbf{r} \rightarrow |\mathbf{r}\rangle = \frac{1}{|\mathbf{r}|} \sum_i \mathbf{r}_i |i\rangle \quad (3.10)$$

Vector $\mathbf{r}$ contains the real-time measured parameters, while vector $\mathbf{a}$ holds the stored values of the same parameters, which could include RSSI, PoA, AoA, among others. Although Euclidean distance is typically calculated using a single parameter, a weighted combination of distance calculations across different variables can be performed to achieve more precise results.

Then, to produce the states $(|\psi\rangle, |\phi\rangle)$, the tensor product is to be used as follows:

$$|\psi\rangle = \frac{1}{\sqrt{2}}[|0\rangle \otimes |\mathbf{r}\rangle + |1\rangle \otimes |\mathbf{a}\rangle], \quad (3.11)$$

$$|\phi\rangle = \frac{1}{\sqrt{z}}[|\mathbf{r}| |0\rangle + |\mathbf{a}| |1\rangle]. \quad (3.12)$$

where z is calculated as follows:

$$z = |\mathbf{r}|^2 + |\mathbf{a}|^2. \quad (3.13)$$

The quantum euclidean distance is obtained solving

$$D^2 = 2z|\langle\phi|\psi\rangle|^2. \quad (3.14)$$

One particularly noteworthy aspect of the quantum states used in the computation of quantum Euclidean distance is their structural asymmetry. Specifically, the state $|\phi\rangle$ is a single-qubit superposition that encodes the relative magnitudes (norms) of the classical input vectors. In contrast, the state $|\psi\rangle$ is a higher-dimensional, entangled state that contains the full amplitude-encoded data of the input vectors. While these states inhabit different Hilbert spaces, $|\psi\rangle$ involving multiple qubits and $|\phi\rangle$ limited to just one, the quantum distance estimation relies not on their direct equivalence in dimensionality, but rather on their engineered overlap. This overlap, measured using a SWAP test, enables the estimation of the squared inner product between the two classical vectors, from which the Euclidean distance is computed.

The preparation of these quantum states requires $\mathcal{O}(\log N)+1$ qubits, where N is the dimension of the original classical vectors. The $\mathcal{O}(\log N)$ term corresponds to the number of qubits necessary to represent the amplitude-encoded

vectors $|R\rangle$ and $|A\rangle$, while the additional qubit is used to control the superposition and distinguish between the two inputs within the composite state $|\psi\rangle$. This design ensures efficient scalability, enabling the processing of high-dimensional data with a relatively modest number of qubits.

To illustrate this concept, Fig. 3.4 presents a simplified quantum circuit that demonstrates the calculation of Euclidean distance using this quantum framework. The circuit highlights the interplay between the control qubit, data-encoding registers, and SWAP test mechanism, offering a practical example of how quantum algorithms can be employed for distance-based comparisons in applications such as localization or classification.

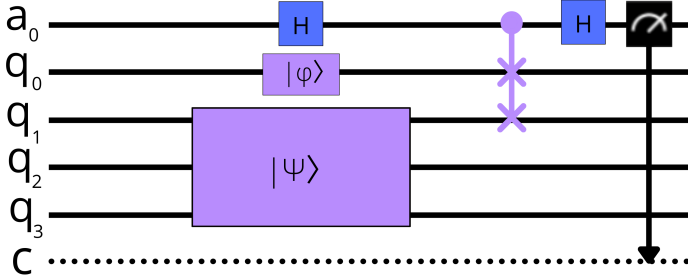


Figure 3.4: Quantum circuit example.

3.2.2 Quantum Indoor Localization

This subsection aims to present a practical example of the proposed approach applied to an indoor localization scenario. Specifically, the implementation leverages one of IBM's Quantum devices, **ibmq_casablanca**, to demonstrate the feasibility of utilizing quantum computation for indoor positioning tasks.

In this example, the performance of the method is evaluated based on the RSSI measured by eight antennas over the course of two iterations (see Fig. 3.5 and 3.6). These measurements serve as input data for the quantum algorithm, enabling the computation of Euclidean distances to estimate the position of the device. It is important to note that while the number of antennas and iterations can be scaled up depending on the computational capacity of the quantum hardware, this example is intentionally kept simple to ensure clarity and to illustrate the fundamental principles of the approach.

Subsequently a detailed explanation of the two iterations conducted in this example is provided, including the computational procedures and the results obtained from the quantum system. This analysis highlights the potential

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of quantum computation for solving localization problems and establishes a foundation for extending the approach to more complex scenarios.

Iteration 1

The vector $\mathbf{r}$ represents the RSSI values recorded by each of the eight antennas deployed in the system. These values correspond to the signal strengths detected at the current position of the device $[R]$. Meanwhile, points $[A]$, $[B]$, $[C]$, and $[D]$ denote the central coordinates of the designated sub-squares within the evaluation area. Each of these points has pre-stored RSSI values in the corresponding $\mathbf{a}$, $\mathbf{b}$, $\mathbf{c}$ and $\mathbf{d}$ vectors, associated with all analyzed antennas, serving as reference data for localization purposes.

Figure 3.5 provides a visual representation of the physical placement of the device and the distribution of the antennas employed to achieve precise localization. The configuration highlights the spatial relationship between the device and the antennas, which is crucial for accurate distance estimation.

Notably, the scalability of this approach allows for the inclusion of additional antennas or radio stripes without introducing a proportional increase in computational complexity. This is because the computational time remains unaffected by the number of antennas, as discussed in Section 3.2.4. Such scalability makes the system adaptable to higher-accuracy requirements by leveraging more measurement points.

To illustrate the methodology, Table 3.2 enumerates the pre-stored RSSI values corresponding to each sub-square center, along with the measured values at the location of the device $[R]$. The Euclidean distance, denoted as $[RX]$, is computed between the RSSI values stored at each center square $[X]$ and the real-time measurements recorded at the device position $[R]$. This distance metric forms the basis for determining the proximity and alignment of the device relative to the predefined reference points, enabling accurate localization.

The Euclidean distance results obtained from both the quantum computer and a classical computer are presented in Table 3.3. Based on these results, point $[A]$ has been identified as the closest location to the position of the device, $[R]$. Consequently, in the subsequent iteration, square $[A]$ will undergo further subdivision into four smaller regions, labeled $[AA]$, $[AB]$, $[AC]$, and $[AD]$. This hierarchical refinement process will be repeated to enhance localization accuracy by narrowing down the search area.

It is important to emphasize that the reported values do not represent the exact physical distances between points. Instead, they serve as relative measures to estimate proximity. This limitation arises due to inherent errors in qubit calibration, which quantum computers currently face. Despite these imperfections, the calculated distances demonstrate sufficient precision to reliably

3.2 Quantum-Enhanced Indoor Localization

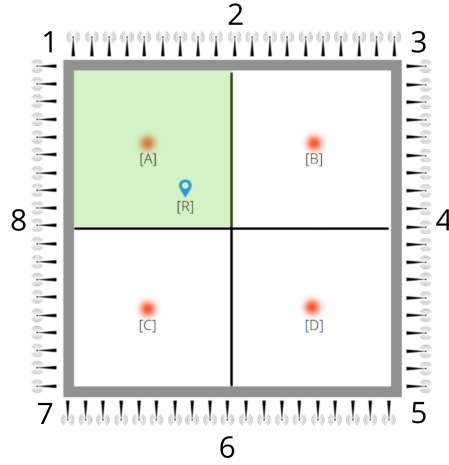


Figure 3.5: First iteration square divisions.

Table 3.2: Values for iteration 1

Antenna measured	RSSI (dBm)				
	R	A	B	C	D
1	-85	-82	-95	-93	-106
2	-82	-77	-90	-90	-104
3	-98	-99	-80	-107	-96
4	-91	-85	-74	-100	-78
5	-93	-95	-109	-82	-94
6	-78	-87	-99	-74	-75
7	-103	-107	-98	-96	-81
8	-74	-78	-81	-78	-88

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identify the specific region or square in which the device is located ($[R]$). This iterative approach, supported by both quantum and classical computations, allows for progressively improving the localization resolution while maintaining computational efficiency.

Table 3.3: Distances in dB obtained from iteration 1

Parameter measured	Vector				
	RA	RB	RC	RD	$Smallest$
Classic. Eucl. Dist.	13.71	39.34	22.18	42.28	RA
Quantum. Eucl. Dist.	13.91	39.42	23.35	42.19	RA

Iteration 2

As mentioned, square $[A]$ is further subdivided into four smaller sub-squares, labeled $[AA]$, $[AB]$, $[AC]$, and $[AD]$. Each of these sub-squares is assigned a central reference point, which is pre-characterized by storing the RSSI values corresponding to all the analyzed antennas. These pre-stored values serve as reference data for refining the localization process within this finer grid structure.

Figure 3.6 illustrates the updated spatial division, showing the actual position of the device in relation to the newly defined sub-squares and their respective central points. This hierarchical approach allows for higher-resolution localization by progressively narrowing down the search area.

To support this refined analysis, Table 3.4 lists the RSSI values recorded at the central points of each sub-square, as well as the measured values corresponding to $[R]$, the device position. These values are utilized to compute distances between the device and the reference points, enabling more precise estimations of its location. This iterative process of subdivision and refinement exemplifies the scalability and adaptability of the proposed localization framework, which can systematically improve accuracy without imposing significant computational overhead.

The Euclidean distance calculations derived from the quantum and the classical computer are presented in Table 3.5. These results indicate that point $[AD]$ exhibits the smallest Euclidean distance relative to $[R]$. This finding suggests that the device is most likely located within the region corresponding to sub-square $[AD]$.

Building upon this observation, the localization process proceeds to a third iteration, where square $[AD]$ is further subdivided into four smaller sub-squares,

3.2 Quantum-Enhanced Indoor Localization

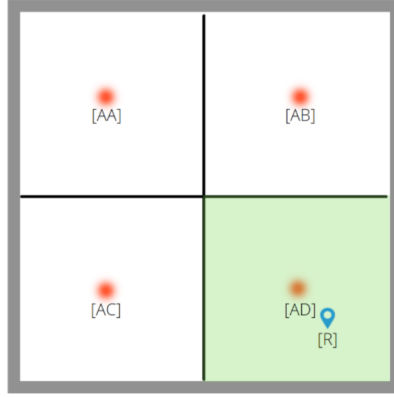


Figure 3.6: Second iteration square divisions.

Table 3.4: Values for iteration 2

Antenna measured	RSSI (dBm)				
	R	A	B	C	D
1	-85	-78	-82	-80	-87
2	-82	-89	-74	-76	-86
3	-98	-101	-90	-102	-95
4	-91	-94	-95	-93	-87
5	-93	-99	-98	-99	-90
6	-78	-85	-87	-84	-77
7	-103	-106	-108	-91	-95
8	-74	-76	-79	-80	-74

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labeled $[ADA]$, $[ADB]$, $[ADC]$, and $[ADD]$. Each of these sub-squares will have its central point marked and pre-stored with RSSI values corresponding to all the analyzed antennas. These values will serve as new reference points for subsequent calculations.

This iterative refinement process is designed to progressively narrow the search area by focusing on the region that exhibits the highest similarity to the measured RSSI values of the device. At each iteration, quantum Euclidean distances are recalculated to determine the closest sub-square, enabling the localization algorithm to achieve increasingly higher levels of precision.

The procedure continues until the desired localization accuracy is attained, ensuring that the system can adapt to varying resolution requirements without imposing substantial computational overhead. This hierarchical approach highlights the flexibility and scalability of the quantum-assisted localization framework, making it suitable for applications requiring fine-grained spatial resolution.

Table 3.5: Distances in dB obtained from iteration 2

Parameter measured	Vector				
	<i>RAA</i>	<i>RAB</i>	<i>RAC</i>	<i>RAD</i>	<i>Smallest</i>
Classic. Eucl. Dist.	14.63	17.56	18.25	10.91	RAD
Quantum. Eucl. Dist.	14.91	17.70	18.29	11.08	RAD

After completing two iterations, the system determines that the device is most likely located near the sub-square labeled $[AD]$. The precision of this localization can be quantitatively assessed using the maximum localization error, denoted in meters, as described by (3.15). This error metric is a function of both the number of iterations, n , and the side length of the original square, L . Specifically, the formula calculates the Euclidean distance from the center of a sub-square to its farthest corner, considering the progressive division of the area with each iteration. The denominator, $2^{(n+1)}$, reflects the exponential refinement of the grid as the number of iterations increases, leading to smaller sub-squares and consequently reduced localization error. Thus, by incrementing the number of iterations, the system can achieve finer spatial resolution, minimizing the maximum localization error and improving the accuracy of the device's position estimation.

$$MaxE = \sqrt{\left(\frac{L}{2^{(n+1)}}\right)^2 + \left(\frac{L}{2^{(n+1)}}\right)^2} \quad (3.15)$$

3.2.3 Quantum-Based Parallel Comparison for Euclidean Distance Estimation

While the two-vector example in this thesis helps illustrate the core mechanics and reflects current hardware limits, a quantum computer can, in principle, compare a single real-time input vector against an arbitrarily large database of reference vectors in one coherent operation. By exploiting quantum parallelism, all swap tests run simultaneously, producing Euclidean distance estimates in a single computational step. As both, dimensionality and database size increase, exactly a scenario that will be faced by 6G systems with massive antenna arrays and high-dimensional signal spaces, this parallelism slashes total runtime compared to any sequential classical approach. In practice, one encodes each vector into a quantum register and applies a bank of swap-test circuits in parallel, enabling the processor to pinpoint the nearest neighbor with far fewer gate operations and memory accesses than a classical algorithm. This combination of scalability and efficiency makes quantum distance estimation a particularly promising technique for next-generation wireless applications, where real-time performance over massive, high-dimensional datasets is paramount.

The following outlines the high-level process:

1. Input Preparation:

The real-time classical vector $\mathbf{R}$ is encoded into a quantum state using amplitude embedding:

$$\mathbf{R} \longrightarrow |R\rangle \quad (3.16)$$

2. Superposition and Parallel Comparison:

The quantum state $|R\rangle$ is put in superposition and compared simultaneously with a set of stored fingerprint quantum states $|A_1\rangle, |A_2\rangle, \dots, |A_n\rangle$ using swap tests:

$$\begin{array}{ccccccc} |R\rangle \leftrightarrow |A_1\rangle & |R\rangle \leftrightarrow |A_2\rangle & \cdots & |R\rangle \leftrightarrow |A_n\rangle \\ \text{Swap Test}_1 & \text{Swap Test}_2 & \cdots & \text{Swap Test}_n \end{array} \quad (3.17)$$

3. Measurement:

Each swap test yields a probability

$$P_i = \Pr(\text{ancilla} = |0\rangle), \quad (3.18)$$

which reflects the similarity between $|R\rangle$ and $|A_i\rangle$.

4. Decision Rule:

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The stored vector corresponding to the highest probability P_i is selected as the best match:

$$\arg \max_i P_i \Rightarrow \text{Estimated Location or Class} \quad (3.19)$$

3.2.4 Challenges and Expectations in Quantum Supremacy

Quantum computers currently, at the time of this Thesis writing, face inherent limitations due to instability and errors caused by the imperfect control of atomic states, which affect the reliability of computations. To mitigate these challenges, multiple experimental iterations were performed on a real quantum computer, systematically varying the number of shots, repeated measurements of the quantum circuit output, to determine the optimal quantity required for accurate results. Figure 3.7 provides a visual representation of the relationship between the quantum computer's relative error in calculating the quantum Euclidean distance and the number of shots executed. A relative error of 100% implies that the computed distance is twice the actual value, highlighting the impact of measurement noise and system imperfections.

Increasing the number of shots generally improves computational accuracy by averaging out noise and errors; however, this comes at the cost of longer execution times. As demonstrated in Fig. 3.7, 4000 shots were sufficient to achieve acceptable accuracy in this study, requiring approximately 7 seconds for execution. This result underscores the trade-off between precision and computation time. Looking forward, advancements in quantum hardware, particularly improvements in qubit coherence and gate fidelity, are expected to significantly reduce the number of required iterations. Such enhancements could decrease computation time by several orders of magnitude, making quantum algorithms more practical for real-world applications.

Figure 3.8, on the other hand, presents a comparative analysis of the time required to compute the Euclidean distance using a classical computer and a quantum computer, specifically the IBM Quantum system, **ibmq_casablanca**. The figure also identifies an estimated threshold at which a quantum computer could be expected to outperform a classical counterpart, marking the emergence of “quantum advantages” for this particular application.

Two critical observations arise from this comparison. First, QC technology is advancing rapidly, leading to substantial reductions in execution times. For instance, quantum systems available just two years ago required approximately twice the time taken by the current **ibmq_casablanca** device to perform the same computations. This trend strongly suggests that practical implementations of quantum-based calculations could become viable within the next

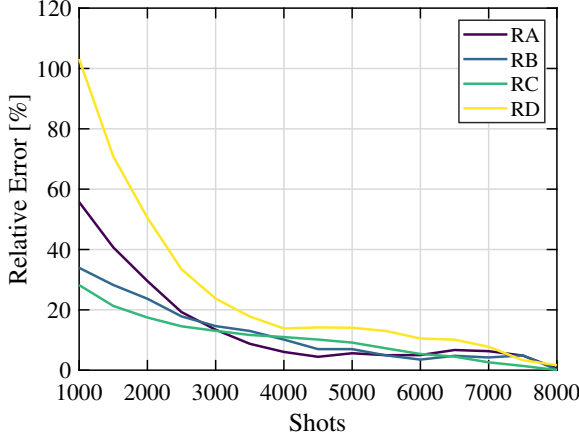


Figure 3.7: Relative error in the first iteration.

years. Projections indicate that with continued improvements, such calculations may eventually be executed in under one second. Moreover, as quantum hardware becomes more stable and better calibrated, the requirement for 4000 shots, currently needed to achieve high accuracy, is expected to decrease. This reduction would further enhance processing efficiency by significantly reducing computation times.

Second, achieving higher accuracy in fingerprint-based localization algorithms often necessitates collecting and processing larger datasets. While classical computers face scalability challenges due to exponential increases in processing time with larger datasets, quantum computers inherently excel at managing such expansions without proportional time penalties. This capability positions quantum systems as particularly well-suited for big-data environments. The onset of quantum supremacy in this context is likely to occur when the size of the information vector surpasses a critical threshold, a scenario that is becoming increasingly realistic with the proliferation of technologies such as massive radio stripes, dense sensor networks, and the data-intensive demands of future 6G wireless systems. These systems require high precision, often at the millimeter level, to support advanced applications, making QC an attractive and scalable solution for next-generation localization and communication technologies.

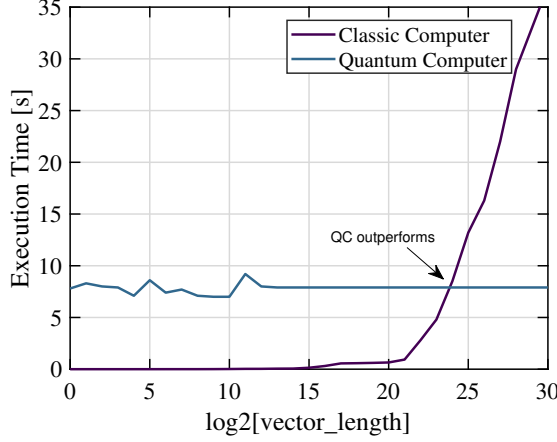


Figure 3.8: Time taken to calculate distances.

3.3 Conclusions

This chapter has explored a groundbreaking application of QC within the framework of future 6G communication networks, focusing on indoor localization through the quantum computation of the Euclidean distance. The chapter begins by examining the current state of indoor localization technologies and methodologies, providing a comprehensive overview of the challenges and limitations associated with traditional classical approaches. These include issues such as limited scalability, computational inefficiency, and inaccuracies in dynamic or complex environments. By contextualizing these challenges, the chapter underscores the potential advantages of incorporating QC, particularly its ability to handle complex computations with superior speed and scalability. This integration has the potential to significantly enhance both accuracy and overall performance in future localization systems.

The chapter provides an in-depth review of the state-of-the-art approaches to indoor localization using QC, establishing the novelty and transformative potential of the proposed methodology. This review serves as a prelude to the primary contribution of the chapter: a detailed, step by step explanation of the quantum computation of the Euclidean distance. The approach leverages quantum mechanics properties to address a critical gap in existing research, presenting a computational process that is, both innovative and uniquely suited to the demands of indoor localization in the 6G context. The discussion emphasizes the foundational importance of this contribution to advancing the field,

demonstrating how QC can overcome the limitations of classical localization techniques.

The absence of prior research specifically addressing this application area motivated the research to pioneer this study. The innovative work culminated in a publication by IBM Quantum [98], highlighting its significance within the field. A detailed account of the proposed use case, including the experimental setup, algorithmic framework, and execution on currently available quantum hardware, is provided. These sections offer a comprehensive guide to the practical implementation of the approach, demonstrating its feasibility even within the constraints of contemporary quantum systems.

The results of the experimental analysis are thoroughly discussed, showcasing the effectiveness of the quantum-enhanced localization method. Despite the inherent limitations of current quantum technologies, such as limited qubit counts and noise, the findings underscore the viability of the proposed approach. The chapter concludes by emphasizing the transformative potential of quantum-enhanced localization and outlines avenues for future research. These include improving algorithmic efficiency, enhancing scalability, and leveraging advancements in quantum hardware to unlock the full potential of QC for indoor localization in next-generation communication networks.

Chapter 4

Quantum Routing Optimization in 6G

Explosive growth in mobile devices, the Internet of Things (IoT), and Wireless Sensor Networks (WSNs) has placed unprecedented demands on data delivery, energy consumption, and reliability. At the heart of this challenge lies routing optimization, the design of algorithms that determine how packets traverse a network to minimize latency, conserve energy, and maintain connectivity.

Classical methods leverage Artificial Intelligence (AI) techniques, reinforcement learning, genetic algorithms, and fuzzy logic, to adaptively tune routing decisions in response to real-time conditions. While these approaches enhance adaptability and resilience, they could struggle with scalability and stringent delay requirements found in multimedia streaming or mission-critical IoT applications. To address security concerns, modern protocols also integrate mechanisms to detect and mitigate attacks such as flooding, preserving both data integrity and network stability.

To push beyond these limits, researchers are now exploring hybrid optimization frameworks, combining swarm intelligence with deep learning, to balance exploration and exploitation in dynamic topologies. More recently, Quantum Computing (QC) has emerged as a transformative paradigm for routing. By exploiting superposition and entanglement, quantum algorithms like Grover's search and Variational Quantum Algorithms (VQAs) could potentially solve combinatorial optimization problems with exponential speedups. Such advances promise ultra-reliable, low-latency communications essential for autonomous systems and real-time industrial automation.

This chapter explores the integration of quantum-enhanced routing protocols into next-generation wireless architectures, assessing both their theoretical performance and practical viability in large-scale deployments. Consequently, this chapter examines quantum computing-based routing optimization for future Sixth Generation (6G) networks and is structured as follows.

- Section 4.2 provides an overview of the current state of quantum routing optimization, highlighting prominent quantum algorithms employed in this domain, particularly variational approaches such as Quantum Approximate Optimization Algorithm (QAOA). This section also discusses the significance of Quadratic Unconstrained Binary Optimization (QUBO) problems, which play a pivotal role in formulating optimization challenges solvable through QC.
- Section 4.3 explores a Single-Objective Optimization (SOO) problem addressed in the course of this Thesis [99].
- Section 4.4 presents a Multi-Objective Optimization (MOO) problem, also examined and resolved during this Thesis [99].
- Section 4.5 illustrates a routing optimization problem in Software-Defined Networking (SDN), showcasing the application of QC in this context.
- Section 4.7 summarizes the key findings and conclusions of this chapter.

4.1 Routing Optimization in Wireless Communication Networks

Traditional routing algorithms, designed to determine optimal paths for data transmission within a network, face substantial challenges when applied to large-scale systems, such as those utilized in telecommunications, logistics, and computing infrastructures. These challenges encompass the need to process and manage extensive volumes of data, dynamically adapt to fluctuating network conditions, and simultaneously optimize multiple conflicting objectives, such as minimizing latency while maximizing throughput. The literature has extensively explored routing methodologies in wireless networks, with foundational contributions spanning several decades [100–103]. While earlier studies established the core principles underpinning wireless network routing, recent advancements in network technologies necessitate a reevaluation and expansion of these frameworks to address the growing complexity and enhanced capabilities of contemporary networks.

4.1 Routing Optimization in Wireless Communication Networks

Dijkstra’s algorithm, a foundational approach to routing, is highly effective in identifying the shortest path within a graph when optimizing a single objective, such as minimizing cost or distance. However, this algorithm demonstrates significant limitations in addressing multi-objective routing problems that require balancing competing factors, including latency, energy consumption, and throughput [104]. Additionally, the computational demands of Dijkstra’s algorithm increase considerably in large-scale networks, rendering it less practical for real-time applications in dynamic and expansive environments. These limitations underscore the necessity for more advanced and flexible routing methodologies capable of meeting the evolving demands of modern network systems.

A notable study conducted by [105], published in 2015, investigated the utilization of “opportunities” in wireless network routing to overcome the limitations of traditional methods and enhance the capacity of modern, dynamic, and heterogeneous wireless networks. The authors provided a comprehensive taxonomy of opportunistic routing approaches, categorizing them based on routing objectives, optimization tools, and design methodologies. They identified and analyzed five distinct classes of opportunistic routing: geographic opportunistic routing, link-state-aware opportunistic routing, probabilistic opportunistic routing, optimization-based opportunistic routing, and cross-layer opportunistic routing. Furthermore, the paper reviewed key protocols within each class and concluded with a discussion on future research directions related to the design, optimization, and implementation of opportunistic routing.

More recently, at the time of this Thesis, research on routing optimization in wireless communication networks has expanded significantly, addressing diverse challenges such as energy efficiency, scalability, and adaptability. Contemporary surveys emphasize the integration of AI and Machine Learning (ML) techniques for dynamic routing, particularly in Unmanned Aerial Vehicle (UAV)-enabled networks [106]. Recent discussions increasingly focus on cluster-based and energy-efficient routing protocols, especially in wireless sensor networks [107], while bio-inspired algorithms, such as swarm intelligence, are being proposed for congestion control in vehicular networks [108]. SDN has emerged as a critical framework for achieving Quality of Service (QoS)-aware and flexible routing solutions [109]. Moreover, domain-specific applications, such as IoT-based agricultural networks [110] and maritime wireless networks [111], highlight tailored optimization approaches to address unique operational challenges. Collectively, these advancements underscore the importance of sophisticated optimization techniques, including hybrid evolutionary algorithms and multi-objective strategies, in enhancing network performance and reliability.

In parallel, considering that sensor nodes are responsible for data transmission while operating with a limited energy supply, energy depletion emerges as an inevitable consequence during transmission. Consequently, energy consumption and network longevity become critical concerns in WSNs. Extensive research has been conducted to determine optimal paths between source and destination nodes to maximize energy conservation within a network. Nevertheless, the persistent challenge lies in developing routing algorithms that effectively address the dual objectives of minimizing energy consumption and maximizing network lifetime. Various optimization techniques have been proposed to determine routing paths. For instance, [112] provides a comprehensive overview of studies conducted between 2010 and 2019, analyzing different optimization techniques applied to WSNs. More recently, noteworthy contributions in this field include studies by [113–115].

Finally, with the emergence of Fifth Generation (5G) and the anticipated development of 6G, novel technologies have been integrated into routing optimization in wireless communications. Among these advancements is QC, which introduces a new paradigm in routing optimization, quantum routing optimization. This emerging field leverages the principles of QC to enhance the efficiency and effectiveness of routing strategies in complex networks.

4.2 Quantum Routing Optimization

The research community has been investigating quantum routing optimization for several years [116], [117]. However, this field has recently attracted increased attention due to the evolving requirements of contemporary 5G and future wireless communication systems, along with the substantial data processing demands associated with these technologies.

Addressing vehicle routing problems represents a critical component of Industry 4.0 and 5.0, as well as other sectors. For instance, the potential utilization of near-term quantum devices to solve the Vehicle Routing Problem (VRP) within 5G networks by minimizing the corresponding Ising Hamiltonian through a hybrid quantum-classical heuristic is discussed in [118]. Furthermore, the work presented in [119] introduces a novel methodology to analyze the security and routing of radio optical networks by integrating blockchain, ML, and QC within 5G frameworks. This approach enhances the security of radio optical networks through cryptanalysis, employing a federated blockchain model, while routing optimization is achieved via sparse Fourier Q-adversarial Boltzmann neural networks. The study addresses multiple challenges faced by optical networks and proposes a quantum-secured blockchain-based strategy to protect these networks from intrusions. Experimental evaluations conducted

on various network security datasets evaluated performance metrics such as QoS, data integrity, throughput, latency, packet delivery ratio, and end-to-end delay. The proposed methodology demonstrated 72% QoS, 68% data integrity, 98% throughput, 56% latency, a 96% packet delivery ratio, and 49% end-to-end delay.

Nevertheless, the most extensive body of literature linking wireless communication networks with routing optimization refers to ongoing research in the future 6G technology. The opportunities and challenges associated with quantum-inspired routing optimization are highlighted in [120]. Discussions include a Multiple-Input Multiple-Output (MIMO) detector, error control decoding based on quantum annealing, autonomous communications, and Quantum Machine Learning (QML) for self-organizing wireless networks, which are developed based on data synthesis and learning objective procedures. In [121], various formulations for addressing routing optimization on quantum computers are proposed. These optimization models are evaluated from a QC perspective, focusing on metrics that measure the complexity of solving the underlying QUBO problems. Solutions derived from simulated quantum devices illustrate the comparative strengths of different algorithms and their robustness in practical applications. In addition, numerous other studies address the challenge of quantum routing optimization in various aspects of future 6G networks, including vehicle routing, SDN, and optical networks [122–124].

The existing literature explores diverse approaches to addressing routing optimization problems through QC. Among these, VQAs have emerged as a widely adopted methodology. The formulation of optimization problems continues to be a compelling area of inquiry, presenting ample opportunities for further investigation. In this regard, QUBO problems have emerged as particularly promising candidates within the field.

4.2.1 Variational quantum algorithms

The rapid evolution and deployment of quantum technologies have made it imperative to develop algorithms that fully exploit the distinctive features of quantum systems. Such algorithms are vital not only for unlocking the capabilities of emerging quantum hardware but also for ensuring that QC can tackle practical problems in a computationally feasible way.

VQAs have emerged as a leading strategy to overcome the limitations of near-term quantum devices by coupling a classical optimizer with a parameterized quantum circuit. They have been proposed for nearly every application envisioned for quantum computers, marking them as the most promising route to achieve a quantum advantage on Noisy Intermediate-Scale Quantum (NISQ) hardware. By integrating quantum resources with classical feedback loops,

VQAs establish a versatile and powerful framework for harnessing QC across a broad spectrum of domains.

These algorithms have been adapted to a wide variety of tasks: computing molecular ground states via Variational Quantum Eigensolver (VQE), simulating the dynamics of quantum systems, solving linear systems of equations, factoring integers and extracting principal components in mathematical contexts, as well as tackling combinatorial optimization problems. In the realm of ML, they underpin both generative models and classifiers (Variational Quantum Classifiers (VQC)), further highlighting their flexibility and potential to deliver quantum-accelerated solutions in diverse fields.

Central to all variational approaches is the Hamiltonian formulation, which in quantum mechanics represents the total energy (kinetic plus potential) of a system. In a variational optimization setting, one encodes the cost function of the problem as a Hamiltonian and then seeks its ground state, the lowest energy configuration, which corresponds to the optimal solution of the original problem. This approach leverages quantum superposition and entanglement to explore complex optimization landscapes more efficiently than classical methods.

A particularly notable example of this paradigm is the QAOA, which has garnered significant attention in combinatorial optimization. QAOA constructs approximate solutions by alternately applying problem-specific and mixer Hamiltonians within a parameterized quantum circuit, with a classical routine tuning the parameters to improve solution quality iteratively. Due to its demonstrated effectiveness on Non-Deterministic Polynomial-Time (NP-hard) challenges, QAOA stands as one of the most extensively studied and practically applied algorithms in the field of quantum optimization.

Quantum Approximate Optimization Algorithm

A significant number of natural optimization problems are categorized as NP-hard. To address these complex problems, two principal approaches are commonly employed: approximation algorithms and randomized algorithms. Approximation algorithms aim to generate solutions that closely approximate the optimal result within polynomial time. Conversely, randomized algorithms tackle these problems by incorporating probabilistic techniques to achieve efficient or probabilistic solutions.

The QAOA is classified as an approximation quantum algorithm, as it is designed to produce near-optimal solutions to intricate optimization problems rather than exact optimal results. In the field of combinatorial optimization, where problems are frequently NP-hard and exact solutions are computationally infeasible, QAOA offers a practical approach by approximating the best

possible solution within a reasonable time frame. As a variational quantum algorithm, QAOA operates by constructing a parameterized quantum circuit that iteratively improves solution quality through a combination of quantum operations and classical optimization techniques. Although the algorithm seeks to minimize or maximize a given objective function, the complexity of these problems and the probabilistic nature of QC generally yield solutions that are close to, but not exactly, optimal. Consequently, QAOA proves particularly advantageous in scenarios where achieving a perfectly optimal solution is less critical than obtaining a sufficiently good result within a practical timeframe [125].

This algorithm was initially proposed by Farhi and Goldstone in 2014 [126] to address the MaxCut problem, which involves identifying a cut in a regular graph whose size is at least as large as that of any other cut. A distinguishing feature of this algorithm is its ability to guarantee a lower bound on the approximation ratio, defined as the ratio between the algorithm's output and the cost of the optimal solution. This approximation ratio depends on an integer parameter p (referred to as the number of layers), where $p \geq 1$. As p increases, the quality of the approximation improves, and the depth of the quantum circuit scales linearly with p , multiplied by the number of constraints in the problem [99].

QAOA utilizes a unitary operator, parameterized by γ and β , to prepare a quantum state. The primary objective of the algorithm is to identify the optimal parameters that produce a quantum state closely approximating or encoding the optimal solution to the optimization problem. This methodology relies on iteratively refining these parameters through a classical optimization process to enhance approximation quality. The effectiveness of QAOA thus fundamentally depends on the accurate tuning of and to efficiently explore the solution space, establishing it as a powerful tool for addressing complex optimization tasks that are otherwise computationally infeasible for classical algorithms.

Figure 4.1 depicts the principle of operation of QAOA:

- **Initialization:** Begin with an initial quantum state, typically the equal superposition state $|\psi\rangle$, which is prepared by applying Hadamard (H) gates to all qubits ($|+\rangle^{\otimes n}$). This step sets the stage for exploring the entire solution space.
- **Application of Problem Unit (Cost Hamiltonian):** The cost Hamiltonian $U_C(\gamma) = e^{-i\gamma H_C}$, where H_C encodes the cost function of the optimization problem, is applied. This step introduces a phase based on the cost associated with each state, parameterized by γ .

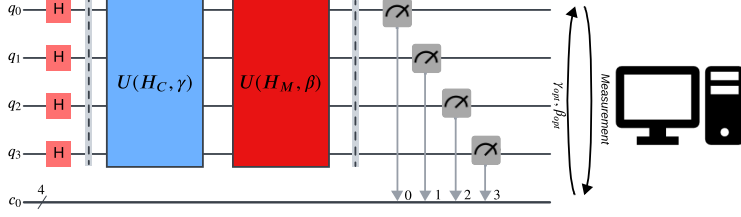


Figure 4.1: QAOA variational quantum circuit.

- **Application of Mixer Unit (Mixer Hamiltonian):** The mixer Hamiltonian $U_B(\beta) = e^{-i\beta H_B}$, typically corresponding to a transverse field (such as applying X gates), is applied. This operation, parameterized by β , helps explore the solution space by altering the amplitudes of the quantum state.
- **Repetition (Layering) of Unitaries:** Steps 2 and 3 are repeated p times (layers), each time using potentially different parameters γ and β . Increasing the value of p allows for a more refined exploration of the solution space, improving the approximation of the optimal solution.
- **Measurement:** After completing the application of p layers of unitaries, the final quantum state is measured in the computational basis. The measurement collapses the quantum state to one of the possible solutions.
- **Classical Optimization:** The outcomes from the quantum measurements are evaluated using a classical optimizer such as Adaptive Moment Estimation (ADAM) [127], Constrained Optimization By Linear Approximations (COBYLA) [128], etc, which adjusts the parameters γ and β to maximize the expectation value of the cost Hamiltonian H_C . This iterative process continues until the parameters converge to the optimal values $(\gamma_{opt}, \beta_{opt})$.
- **Solution Extraction:** Once optimal parameters are found, the corresponding quantum state $|\psi(\gamma_{opt}, \beta_{opt})\rangle$ is measured to extract the solution that closely approximates the optimal solution of the original optimization problem.

4.2.2 Methodology

The approach employed to tackle the routing optimization problem using QC in this Thesis research is depicted in Fig. 4.2. This figure outlines the entire

4.2 Quantum Routing Optimization

process, commencing with the formulation of the problem and concluding with the determination of the optimal solution via the QAOA. A detailed, step by step explanation is provided to ensure clarity and comprehensiveness.

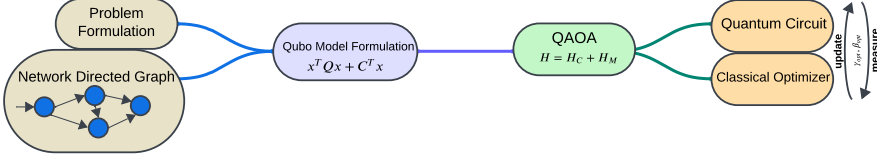


Figure 4.2: Steps followed to map the routing problem onto a gate-based quantum computer or simulator to obtain the optimal solution.

Problem Representation

In the context of a routing optimization network problem, the cost function serves as a metric to evaluate the effectiveness and efficiency of a given routing solution. It incorporates multiple considerations, including overall travel distance or time, utilization of network resources, and adherence to constraints such as bandwidth limitations and node capacities.

To formalize the optimization process, the problem is modeled using a cost function expressed as $C(x) : \{0, 1\}^n \rightarrow \mathbb{R}$. The relevant variables are defined as follows:

- n : Denotes the number of qubits in the quantum model, corresponding to the dimensionality of the solution space. Each qubit represents a binary decision variable in the classical formulation of the problem.
- x : A binary string of length n , where each configuration $x \in \{0, 1\}^n$ represents a candidate solution.
- $C(x)$: Represents the cost function that evaluates the performance or feasibility of a solution x . The optimization process seeks to minimize this value to identify the most optimal configuration, denoted as x^* .

The optimization task can be succinctly described as identifying a solution x^* such that $C(x^*) \leq C(x)$ for all $x \in \{0, 1\}^n$, thereby ensuring the cost function is minimized across the solution space.

Furthermore, in this framework, network routing optimization is modeled as a directed graph problem, denoted by $G(V, E, W)$, where:

- V : Represents the set of vertices, corresponding to network components such as routers, switches, and other devices essential for data transmission and routing operations.
- E : Denotes the set of edges, which symbolize communication pathways enabling data transfer between nodes, source node p , and a destination node, q .
- W : Set of weights (cost, latency, delay, etc) between nodes.

Quadratic Unconstrained Binary Optimization

Once the objective function is established, it must be cast in a form amenable to quantum processing. The preferred vehicle for this transformation is the QUBO model, which has become the defacto standard for encoding combinatorial optimization tasks for quantum hardware.

The QUBO framework excels in its generality, accommodating a vast array of discrete optimization problems. Crucially, any QUBO instance can be mapped directly onto an Ising Hamiltonian, a cornerstone of statistical physics, thereby linking computational optimization with well-studied physical phenomena. This correspondence not only reinforces the theoretical foundations of QUBO formulations but also leverages decades of insights from the physical sciences to inform algorithm design and hardware implementation. As a result, the QUBO model occupies a central role in QC-based optimization, offering a unified and physically grounded approach to solving complex, real-world problems [129].

The QUBO model formulation is expressed by:

$$\min / \max(\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{c}^T \mathbf{x} + c) \quad (4.1)$$

where $\mathbf{x}$ is a vector of binary decision variables, $\mathbf{Q}$ is a square matrix of quadratic coefficients, and $\mathbf{c}$ is a vector of linear coefficients.

QUBO formulations can vary slightly depending on the specific problem at hand, but the core concept remains consistent. The ability to tailor the formulation without altering its fundamental meaning underscores the versatility and robustness of QUBO as a framework, making it a preferred choice for addressing complex problems in QC.

Quantum encoding and QAOA solver

The next phase entails translating the QUBO cost function into a quantum state representation. This procedure involves encoding the cost function into a Hamiltonian, as required by QAOA and explained above. The components of this process are defined as follows:

- H_C : The cost Hamiltonian, where each eigenstate corresponds to a potential solution x . Following the QUBO formulation, H_C is implemented using Pauli-Z operators within the quantum circuit.
- $|\psi(\gamma, \beta)\rangle$: A parameterized quantum state characterized by the parameters γ and β . This state evolves iteratively to approximate the ground state of H_C , which encodes the optimal solution.
- γ and β : Parameter sets optimized using classical algorithms to improve the solution quality.
- H_M : The mixer Hamiltonian, defined as the summation of Pauli-X operators acting on all qubits, facilitating transitions between different quantum states.

Quantum Circuit Construction and Optimization

The construction of the QAOA circuit involves the iterative application of H_C and the H_M to an initially prepared quantum state. The initial state, denoted as $|\psi_0\rangle$, is prepared as an equal superposition of all possible states by applying Hadamard (H) gates to each qubit. This superposition serves as the starting point for subsequent evolution and optimization.

The evolution of the quantum state, represented as $|\psi(\gamma, \beta)\rangle$, is governed by unitary transformations associated with H_C and H_M . These transformations are defined as:

- $U(H_C, \gamma)$: A unitary operator applied based on the cost Hamiltonian, parameterized by γ .
- $U(H_M, \beta)$: A unitary operator applied for the mixing Hamiltonian, parameterized by β .

These transformations are applied iteratively over p layers, where p determines the circuit depth. Increasing the number of layers allows the QAOA to explore more complex solutions and enhances the approximation of the optimal result. However, higher layer counts also increase the circuit's complexity,

requiring additional computational resources and longer quantum coherence times.

The combined effect of these unitary operations constitutes a single layer of the QAOA circuit, as depicted in Figure 4.1. Classical optimization algorithms, such as COBYLA [128] and ADAM [127], are employed to optimize the parameters γ^* and β^* .

The goal of this optimization is to minimize the expectation value of the H_C , thereby encoding the optimal solution within the final quantum state $|\psi(\gamma_{opt}, \beta_{opt})\rangle$. Upon measurement, this state yields a probability distribution, from which the optimal solution can be extracted. This process completes the quantum-enhanced approach to solving the network routing optimization problem.

4.3 Single-objective quantum routing optimization

Communication networks consist of interconnected nodes and links, as previously described. One of the key objectives in such networks is to determine the minimum-cost path for transmitting data from a source node to a destination node, where cost often relates to factors like battery consumption, latency, or bandwidth usage. For instance, as shown in Fig. 4.3, if Node 1 serves as the source and Node 4 is the destination, the primary task is to identify the shortest or most efficient route between these two nodes. This process must account for multiple factors, including network constraints, resource limitations, and performance objectives.

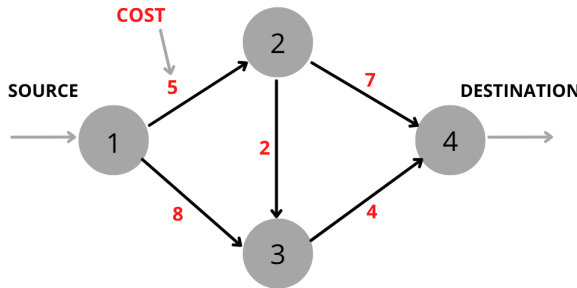


Figure 4.3: Example of a simple network consisting of four interconnected nodes.

4.3 Single-objective quantum routing optimization

Following the methodology proposed in 4.2.2 to address the routing optimization problem derived by the graph, the cost function is defined as:

Objective:

$$\min / \max \left(\sum_{(i,j) \in E} W_{ij} X_{ij} \right) \quad (4.2)$$

Subject to:

$$\sum_{j:(i,j) \in E} X_{ij} - \sum_{j:(i,j) \in E} X_{ji} = 1, \text{ if } i = p, \quad (4.3)$$

$$\sum_{j:(i,j) \in E} X_{ij} - \sum_{j:(i,j) \in E} X_{ji} = 0, \forall i \neq p, q \in V, \quad (4.4)$$

$$X_{ij} \in \{0, 1\}, \quad \forall (i, j) \in E \quad (4.5)$$

where $p \in V$ is the source node and $q \in V$ is the destination node.

The optimization process operates within a defined set of constraints intended to ensure the efficient and reliable functioning of the network. These constraints typically encompass flow conservation principles, capacity limitations, and quality-of-service requirements.

A key principle governing network flow is flow conservation, which mandates that the flow of data through intermediate nodes remains balanced. More precisely, at any intermediate node, excluding the source and destination, the total incoming flow must be equal to the total outgoing flow. Mathematically, this principle is represented as follows:

$$\sum_{\text{incoming edges}} f_{\text{incoming}} = \sum_{\text{outgoing edges}} f_{\text{outgoing}} \quad (4.6)$$

This flow conservation principle, analogous to Kirchhoff's current law in electrical circuits, guarantees that no data is lost or created within the network. Instead, it flows seamlessly between nodes while adhering to constraints imposed by the network's design and operational parameters. Such formulations enable the development of efficient algorithms for routing optimization in diverse communication systems.

In this context, the cost values in the graph, ranging from 1 to 10, are used as proxies for battery consumption. While these values do not accurately reflect real-world conditions, they offer a simplified framework for assessing the performance of QAOA and exploring its potential to address routing optimization problems. The corresponding mathematical formulations are provided in [130].

CHAPTER 4. QUANTUM ROUTING OPTIMIZATION IN 6G

Several factors, such as distance, time, and resource utilization, can influence these cost values. The flow along each edge represents the volume of data or traffic traversing that link and is typically treated as a decision variable in the optimization model. In this formulation, the decision variables, represented by X_{ij} , are binary indicators that determine whether a specific path is selected. A value of 1 indicates that the path is chosen, while a value of 0 implies that the path is excluded as it does not meet the optimization objective.

For this example, the problem formulation is presented below:

$$\min (5X_{12} + 8X_{13} + 2X_{23} + 7X_{24} + 4X_{34}) \quad (4.7)$$

Subject to:

$$X_{12} + X_{13} = 1, \quad (4.8)$$

$$X_{12} - X_{23} - X_{24} = 0, \quad (4.9)$$

$$X_{13} + X_{23} - X_{34} = 0, \quad (4.10)$$

To formulate the cost function within the QUBO framework, it must first be transformed into an unconstrained optimization problem, as outlined in Section 4.2.2. This transformation is achieved by incorporating a penalty term, denoted as P , to enforce constraints, such as maintaining network flow. In the QUBO representation, constraints classified as “hard” which necessitate strict compliance, are enforced by assigning a sufficiently large value to the penalty term P . This approach effectively embeds the constraints within the optimization framework, ensuring adherence while facilitating seamless integration with the QUBO model.

$$\begin{aligned} \min & (5X_{12} + 8X_{13} + 2X_{23} + 7X_{24} + 4X_{34} \\ & + P(X_{12} + X_{13} - 1)^2 \\ & + P(X_{12} - X_{23} - X_{24})^2 \\ & + P(X_{13} + X_{23} - X_{34})^2) \end{aligned} \quad (4.11)$$

Generally, $P = \sum_{i,j} W_{i,j} + 1$ to guarantee the optimality of the chosen path. In this case P is equal to 27, the Q matrix and $\mathbf{c}$ vector are then given by:

$$\mathbf{Q} = \begin{bmatrix} 54 & 27 & -27 & -27 & 0 \\ 27 & 54 & 27 & 0 & -27 \\ -27 & 27 & 54 & 27 & -27 \\ -27 & 0 & 27 & 27 & 0 \\ 0 & -27 & -27 & 0 & 27 \end{bmatrix} \quad (4.12)$$

4.3 Single-objective quantum routing optimization

$$\mathbf{c}^\top = [-49 \quad -46 \quad 2 \quad 7 \quad 4] \quad (4.13)$$

Following the formulation of the problem within the QUBO framework, the next step is to map it onto a Hamiltonian ($H_C + H_M$) to determine its ground state, which corresponds to the optimal solution, using QAOA, as detailed in Section 4.2.2.

$$H_C|x\rangle = (\mathbf{x}^\top \mathbf{Q} \mathbf{x} + \mathbf{c}^\top \mathbf{x} + c)|x\rangle = \left(\sum_{i,j=1}^n x_i \mathbf{Q}_{ij} x_j + \sum_{i=1}^n c_i x_i \right) |x\rangle \quad (4.14)$$

$$H_M = \sum_{i=1}^n X_i \quad (4.15)$$

To define the H_C by Pauli Z -operators, the objective function should be formulated as the Ising spin model: $x_i = \frac{1-Z_i}{2}$

$$\begin{aligned} H_C = & 11(IIII Z_0) - 17.5(IIIZ_1 I) - 28(II Z_2 II) - 17(IZ_3 III) + 11.5(Z_4 IIII) \\ & + 13.5(IIIZ_1 Z_0 - IIZ_2 IZ_0 - IZ_3 IIZ_0 + IIZ_2 Z_1 I - Z_4 IIZ_1 I \\ & + IZ_3 Z_2 II - Z_4 IZ_2 II) \end{aligned} \quad (4.16)$$

With the defined Hamiltonians, H_C and H_M , the corresponding variational quantum circuit for the problem can be constructed. Figure 4.4 illustrates the quantum circuit designed to address the problem.

- The Hadamard (H) gates allow equal superposition on the initial state.
- The R_Z gate represents a linear term ($\mathbf{c}$ vector) and applies a rotation or transformation to the specified qubit (e.g., qubit 0, denoted as $IIII Z_0$) parameterized by γ .
- The R_{ZZ} gate captures the quadratic terms and models interactions between qubits (e.g., qubit 2 and qubit 4, denoted as $Z_4 IZ_2 II$) according to $\mathbf{Q}$ matrix. This operation also depends on γ , with I representing the identity gate.
- The R_X gates consist of a layer of Pauli X -operators, which define the mixer Hamiltonian (H_M) and are parameterized by β .

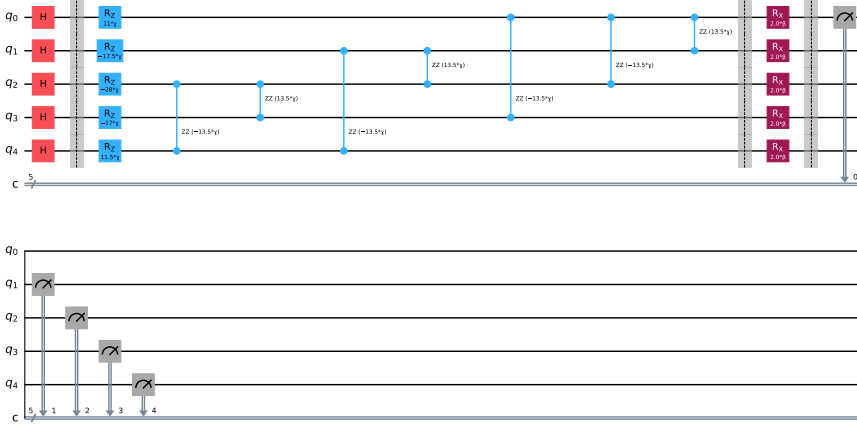


Figure 4.4: Representation of the single-objective, $p = 1$, four-node example QAOA circuit.

The process of achieving optimal results in the QAOA depends on several factors, primarily the number of iterations and the computational time required. These factors are heavily influenced by the characteristics and capabilities of the quantum system being used. In this study, the QAOA circuit was executed on the seven-qubit IBM Quantum System **ibm_perth**.

To accomplish this, the COBYLA algorithm was employed as the classical optimizer. COBYLA is well-suited for problems involving smooth cost functions and a small number of parameters, as it does not require gradient information and operates efficiently in low-dimensional parameter spaces.

In this specific implementation, 59 iterations were necessary for COBYLA to converge on the optimal parameter values. These values were determined to be $\beta_{opt} = 0.28517317$ and $\gamma_{opt} = -5.05969577$. These parameters define the optimal configuration for the QAOA circuit to approximate the solution to the problem at hand.

The convergence of the optimization process reflects the interplay between the quantum system's capabilities (e.g., coherence time, gate fidelity, and qubit connectivity) and the effectiveness of the classical optimizer. While the selected optimizer successfully identified the optimal parameters, the number of iterations required indicates the computational complexity and resource demands of the task. Future improvements in quantum hardware and hybrid quantum-classical optimization strategies could further enhance the efficiency of this process.

4.3 Single-objective quantum routing optimization

The optimal path to minimize costs can be clearly identified as $1 \rightarrow 2 \rightarrow 3 \rightarrow 4$, which results in a total cost of 11 (calculated as $5 + 2 + 4$). Figure 4.5 illustrates the probability distribution of all possible paths, determined by the parameter values of γ and β . Notably, the state $|10101\rangle$ emerges with the highest probability. This state corresponds to the configuration where $X_{12} = 1$, $X_{23} = 1$, and $X_{34} = 1$, accurately representing the optimal path. These variables describe connections in the graph, confirming that the selected path aligns with the desired optimal configuration $X_{12}, X_{13}, X_{23}, X_{24}, X_{34}$.

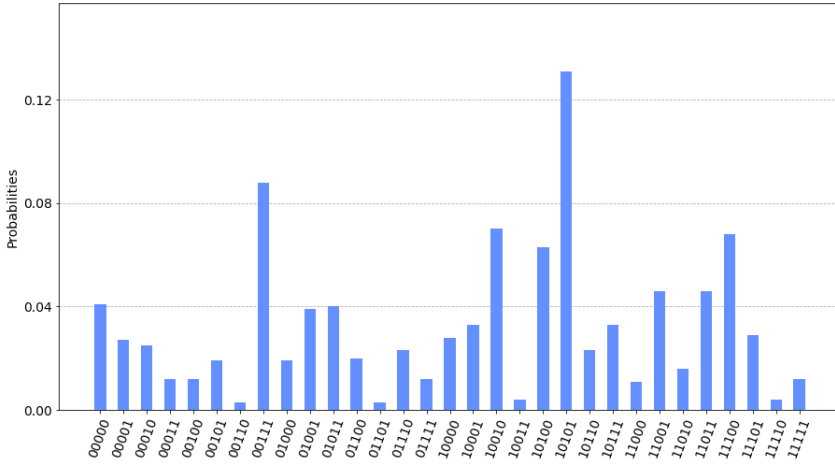


Figure 4.5: Probability results for the example network.

While this small example may appear straightforward, involving only five qubits for this specific scenario, the complexity of the problem grows exponentially as the number of nodes increases. This exponential growth quickly renders the problem computationally intractable for classical methods, as traditional algorithms struggle to handle the sheer number of possible configurations. In contrast, quantum methods, such as the QAOA, offer a promising approach to address such challenges by leveraging quantum superposition and entanglement to explore multiple configurations simultaneously.

However, the primary limitation in applying QAOA to larger networks lies in the current hardware constraints, particularly the number of available qubits. This limitation reflects the nascent stage of QC technology rather than a fundamental barrier to solving such problems. While QAOA successfully identified the optimal solution of 11 in this example, it is essential to note that for more complex problems, QAOA's heuristic nature may only yield near-optimal

approximations rather than exact solutions. Despite this, QAOA remains a valuable tool, demonstrating the potential of quantum algorithms to tackle optimization problems that are impractical for classical approaches.

To evaluate the performance of the algorithm relative to the number of QAOA layers, simulations were performed using 500 shots with $p = 1, 2, 3$. In theory, the accuracy of QAOA is expected to improve as the parameter p increases, due to the enhanced ability of the algorithm to approximate the target solution. As shown in Fig. 4.6, the probability of achieving the correct solution increases in fact with higher values of p . Nevertheless, in practical implementations on current quantum hardware, this theoretical improvement is diminished. The increased circuit depth associated with larger values of p amplifies the impact of noise, which adversely affects the performance of the algorithm in real-world applications.

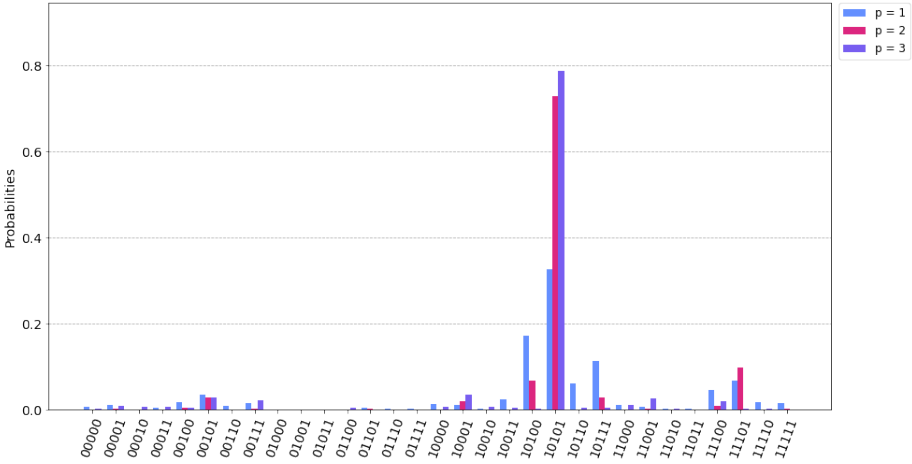


Figure 4.6: QAOA performance comparison according to p values.

4.4 Multi-objective quantum routing optimization

When addressing communication networks, considering multiple performance metrics transforms the optimization task into a multi-objective problem. These metrics may include minimizing costs to enhance quality of service, maximizing

4.4 Multi-objective quantum routing optimization

throughput, or reducing the number of hops to decrease network latency. Optimizing a single parameter often comes at the expense of others, which may no longer meet the required thresholds for a given service. MOO, therefore, seeks to balance these competing criteria and identify solutions that best satisfy the demands of each scenario.

MOO problems are inherently more computationally complex than their single-objective counterparts. Unlike single-objective problems, which have a clear global optimum, multi-objective problems involve trade-offs between objectives, resulting in no single ideal solution. Instead, solutions are assessed based on their ability to reach a state of equilibrium, where improving one objective further would degrade another. Such solutions are known as Pareto optimal points, each representing a compromise that meets the desired performance criteria as effectively as possible.

To identify Pareto-optimal solutions, various algorithms have been developed to address MOO problems [131–134]. These algorithms can be broadly categorized based on two dimensions of optimization methodology: classical methods, which are often deterministic, and metaheuristic or evolutionary methods, which are typically stochastic. These categories describe the approach used to solve the problem, such as utilizing gradients, exact Linear Programming (LP)/Nonlinear Programming (NLP) solvers, or random search operators.

The strategy and framework for handling multiple objectives can further be classified into scalarization-based, population-based evolutionary, gradient-based, interactive, or hybrid approaches. These strategies outline how the multiple objectives are managed within the optimization process.

Different approaches can be combined to tackle MOO problems. For instance, a deterministic scalarization method can be incorporated into a stochastic evolutionary method by solving multiple weighted-sum subproblems within a genetic algorithm. The selection of the most suitable method ultimately depends on various factors, including the problem’s characteristics (e.g., smooth or black-box, convex or non-convex), its size and dimensionality, the availability of gradient information, computational resources, and the decision-maker’s preferences. Table 4.1 provides an overview of methods for addressing MOO.

In this thesis, a practical multi-objective routing optimizer by integrating the QAOA with the lexicographic method is developed. In this scheme, objectives are ordered by priority and addressed in successive stages. At stage n , the n th objective is optimized subject to the constraints derived from the previously attained optima, with slack parameters α_n allowing controlled deviations. For the minimization objectives, $\alpha_n > 1$ allows an acceptable increase above the prior optimum, while for the maximization objectives, $\alpha_n < 1$ allows a controlled decrease. This mechanism ensures that each objective is

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Method	Core Idea	Pros	Cons
Weighted Sum [135]	Combine all objectives into a single objective via weights; vary weights to explore Pareto front.	Simple to implement; easy to understand.	Fails to find non-convex parts of the front; requires multiple runs with different weights.
ϵ-Constraint [136]	Optimize one objective while treating others as constraints with varying bounds (ϵ).	Potentially captures non-convex fronts; flexible if ϵ is chosen well.	Requires careful selection of ϵ ; multiple runs for full Pareto exploration.
Tchebycheff (Chebyshev) [137]	Minimize the maximum weighted distance from a reference point (ℓ_∞ -norm).	Handles non-convex regions better than Weighted Sum; offers good coverage if reference/weights vary.	Choosing the reference point can be tricky; still scalarization-based, so multiple runs may be needed.
NBI (Normal Boundary Intersection) [138]	Projects outward from the utopia point along normals to the boundary formed by extreme solutions.	Good coverage of the Pareto front, especially for non-convex problems.	More complex to implement; must solve a series of sub-problems.
Lexicographic (incl. Parameterized) [139]	Objectives have strict (or near-strict) priority; optimize top-level objective first, then next, etc.	Very clear when objectives have absolute priority; simple hierarchical structure.	Ignores trade-offs once top-priority is “optimized”; can be sensitive to small changes in highest-priority objective.
Goal Programming [140]	Minimize deviations from target goals (soft constraints); can use weighted or preemptive priorities.	Intuitive for decision-makers; natural to specify desired target levels.	Sensitive to chosen goals/weights; does not directly generate a Pareto front (one solution per run).
Evolutionary Algorithms (e.g., NSGA-II, SPEA2, MOEA/D) [141]	Maintain a population of solutions; use genetic or swarm mechanisms to explore Pareto front.	Good for black-box, non-smooth, or discrete problems; can find a set of Pareto solutions in one run.	Potentially slower convergence; requires tuning of parameters (population size, mutation rate, etc.).
Gradient-Based Methods [142]	Extend single-objective gradient optimizers (SQP, interior-point) via scalarization or interactive approaches.	Fast local convergence when gradients are available; can refine solutions found by other methods.	May get stuck in local minima; not suitable for non-smooth or black-box objectives; still often requires multiple runs.
Interactive / Reference-Point Methods [143]	Decision-maker provides preference information or reference points; algorithm iteratively refines in desired regions.	Focuses on most relevant part of the Pareto front; saves computational effort in uninteresting regions.	Requires iterative feedback; relies on accurate expression of preferences.
Hybrid Approaches	Combine elements of multiple methods (e.g., evolutionary + local search, surrogates + MOEA).	Often yields practical benefits; leverages strengths of each component.	More complex to implement and tune; approach depends on problem structure and resources.

Table 4.1: Summary of Common Multi-Objective Optimization Methods

4.4 Multi-objective quantum routing optimization

balanced against earlier priorities, yielding a systematic solution for complex, multi-objective problems in communication networks.

Following the methodology of Section 4.2.2, we illustrate our approach on a six-node network (Fig. 4.7) with three objectives:

- Minimize battery cost
- Maximize available throughput
- Minimize hop count between source and destination

Due to the limited qubit counts available during this study, we first validated feasibility via simulation on IBM Quantum systems. The optimization was then deployed on IBM Cloud using Qiskit Runtime, targeting the 27-qubit `ibm_algiers` backend, which accommodated our problem within the existing hardware constraints.

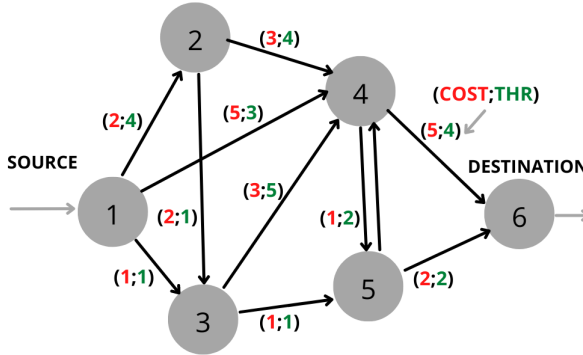


Figure 4.7: Diagram of a sample network with 6 nodes.

The primary goal of the lexicographic approach was to minimize the battery cost, as defined in (4.2). All relevant constraints, specifically (4.3), (4.4), and (4.5) from Section 4.3, were incorporated into the optimization model. By applying this procedure, the solution identified the optimal path as 1–3–5–6, which connected four nodes and required three hops. The total battery cost for this solution was 4, while the resulting throughput was also 4.

After determining the optimal battery cost, this solution was integrated as an inequality constraint into the model using the alpha parameter, α_c , which introduced a controlled degree of flexibility in the battery cost while focusing on optimizing throughput. For this example, the parameter was set to $\alpha_c = 2$. The added constraint in this second stage is represented mathematically in (4.17).

$$C_{ij}X_{ij} \leq (C_{ij}X_{ij}^*)\alpha_c. \quad (4.17)$$

Following this, the secondary objective was to maximize throughput, calculated as the sum of the throughput values across all served nodes. This objective is expressed in (4.18). As with the cost minimization step, the throughput values for each path were evaluated using a simplified approach, which may not precisely reflect real-world scenarios. In this context, higher throughput values are preferred, aligning with the goal of maximizing overall throughput.

$$\max \sum_{(i,j) \in E} Thr_{ij}X_{ij}. \quad (4.18)$$

This multi-step optimization approach allows for prioritization of the battery cost objective while ensuring subsequent optimization of throughput within the defined constraints.

The results revealed an increase in throughput to 10, accompanied by a rise in cost to 7 and an increase in the number of hops to 4. The selected path was 1–3–4–5–6, reflecting a trade-off where higher throughput was achieved at the expense of both cost and the number of hops. This outcome highlights the inherent nature of multi-objective optimization, where no universally “correct” solution exists. Instead, the validity of each result depends on the decision-maker’s preferences, emphasizing their critical role in determining the final outcome.

To further refine the process, a flexibility parameter α_{thr} was introduced for throughput, analogous to the alpha parameter previously used for cost (α_c). This parameter allowed for a degree of leniency in throughput while minimizing the final objective: the number of hops. Given the small scale of the problem, α_{thr} was set to 0.4, a value chosen to provide sufficient clearance to enable transitions between solutions. This adjustment necessitated the inclusion of (4.19) in the model, which ensured throughput met the required thresholds during this phase. Additionally, (4.17) was incorporated into the constraints for the final step, the minimization of hops.

$$Thr_{ij}X_{ij} \geq (Thr_{ij}X_{ij}^*)\alpha_{thr}. \quad (4.19)$$

The final objective, minimizing the number of hops, is expressed as:

$$\min \sum_{(i,j) \in E} H_{ij}X_{ij}. \quad (4.20)$$

All relevant constraints, including (4.3), (4.4), (4.5), (4.17), and (4.19), were integrated into the model. The optimization yielded a solution with three hops,

4.5 Software-Defined Networking with Quantum Enhancement

a cost reduced to 4, and a throughput of 4. This outcome coincided with the solution obtained during the first stage of the optimization process, following the path 1–3–5–6.

In the initial phase of the lexicographic method, the sole focus on minimizing cost led to a solution involving three hops but relatively low throughput. When the throughput was maximized in the subsequent stage, both cost and the number of hops increased slightly. Ultimately, for this particular problem instance, the solution derived from simultaneously considering all three objectives aligned with the result obtained when focusing solely on cost minimization.

The demonstrated optimization process was designed to illustrate the functionality of the lexicographic method. However, altering the alpha parameters or the prioritization of objectives could produce different outcomes. For larger-scale problems, unfortunately beyond the capabilities of the quantum computer or simulators used in this study, small adjustments to alpha parameters are expected to have a more pronounced impact, significantly influencing the final result.

The findings from this study are summarized in Table 4.2, showcasing the interplay between the objectives and the flexibility introduced by alpha parameters.

Objectives	Minimum Cost	Maximum Throughput (Subject to Cost)	Minimum Hops (Subject to Cost and Throughput)
Cost	4	7	4
Throughput	4	10	4
Hops	3	4	3

Table 4.2: Optimization results for the six-node network using the lexicographic approach.

4.5 Software-Defined Networking with Quantum Enhancement

An especially promising extension of the quantum routing optimization framework developed in this Thesis lies in its seamless integration with SDN. Contemporary SDN controllers struggle with scalability and reliability as network topologies grow increasingly complex and traffic volumes [144, 145]. To overcome these limitations, a shift toward distributed control architectures, most notably those built on microservices, has proven transformative. By decomposing the control plane into loosely coupled services, microservice-based SDN

achieves more effective load distribution, heightened fault tolerance, and greater agility, thereby addressing the inherent scalability and resilience shortcomings of monolithic SDN designs and positioning them to meet the exacting demands of next-generation systems such as 6G [146].

SDN is a foundational enabler of the transition from 5G to 6G, supporting fully programmable and adaptive network infrastructures. Its clear separation of control logic from data-forwarding hardware facilitates on-the-fly policy updates and fine-grained resource management, capabilities that are indispensable for delivering high throughput, ultra-low latency, and massive device connectivity required by emerging applications in the IoT, autonomous transportation, and Ultra-Reliable and Low Latency Communications (URLLC) [147, 148].

Marrying QC with SDN heralds a paradigm shift in telecommunications as networks evolve toward 6G. Quantum optimization algorithms, most notably the QAOA, promise to tackle routing and resource allocation problems whose complexity overwhelms classical approaches. Building on the theoretical underpinnings of classical multi-objective heuristics like Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Differential Evolution (MODE), next-generation quantum routines such as the Non-Dominated Quantum-Inspired Optimization (NDQIO) exploit quantum parallelism to deliver superior efficiency and scalability in solving multi-constraint network optimization tasks.

To meet the dual imperatives of growing network complexity and stringent real-time performance, a hybrid quantum-classical SDN architecture (see Fig. 4.8) is proposed. In this design, a central SDN controller aggregates comprehensive link-state data and delegates path-computation tasks to a Quantum Processing Unit (QPU). While a single QPU could, in principle, satisfy the bulk of these workloads, the attendant volume of quantum-classical interactions risks introducing performance bottlenecks or creating single points of failure. Consequently, contemporary deployments frequently adopt a distributed SDN paradigm, wherein multiple local controllers manage subdomains and collaborate with a global orchestrator. Quantum-accelerated routing can be deployed either centrally or across a federation of QPUs, offering a spectrum of trade-offs between optimization speed, fault tolerance, and communication overhead. Although present-day QC hardware remains constrained by noise and limited qubit capacity, ongoing advances suggest that quantum-enhanced SDN will soon play a decisive role in simplifying resource allocation, reducing operational complexity, and forging the robust, high-performance network architectures essential for 6G.

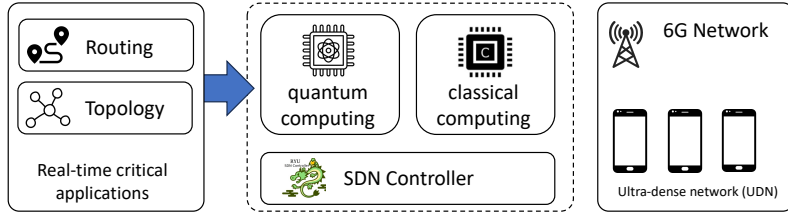


Figure 4.8: Hybrid quantum-classical computing SDN Architecture.

4.5.1 Simulation Environment

The simulation environment is designed to emulate a virtualized network, replicating the characteristics of a real-world SDN infrastructure, as depicted in Fig. 4.8. This setup provides a realistic framework for evaluating the proposed methodologies and technologies. Figure 4.9 illustrates an example network topology represented as a directed graph. In this model, the primary objective is to optimize routing between nodes by minimizing latency, a critical metric for efficient network performance.

The optimization process involves identifying the shortest path between selected hosts, such as H1 and H3, while ensuring minimal latency across the network. To simplify the simulation, the latency values used in this example are intentionally abstract and do not correspond to real-world measurements. Higher numerical values represent increased latency on the links, providing a straightforward mechanism to evaluate the routing algorithms. This abstraction is purposeful, as the focus of the simulation is not on defining an exact cost function but rather on testing the QAOA within a controlled scenario. The goal is to demonstrate how QC could address optimization challenges and improve the performance of future wireless networks.

In this context, the SDN controller is augmented with QC capabilities to perform latency optimization. The controller leverages a quantum computer to identify efficient routing paths, showcasing the potential of QC to enhance decision-making in complex network environments. This approach highlights the promise of integrating quantum technologies to tackle real-time optimization problems, paving the way for advancements in next-generation network architectures.

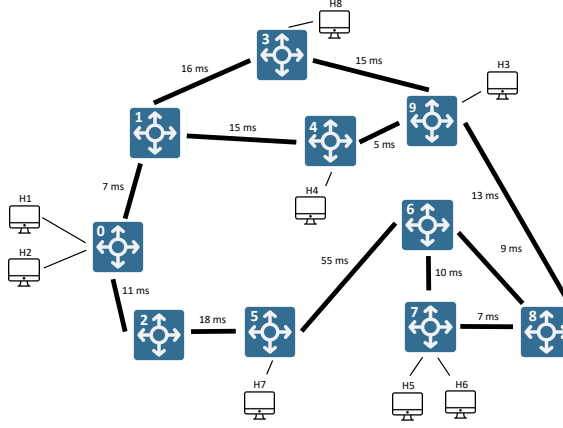


Figure 4.9: Network topology.

This optimization problem is characterized by linear constraints and incorporates 12 binary variables that define routing paths between nodes, including examples such as x_{01} , x_{02} , x_{13} , x_{25} , and x_{89} , as visualized in Fig. 4.9. The binary variables directly determine the quantum resources required, as each variable maps to a qubit on the quantum computer. As the network complexity increases with additional nodes or connections, the corresponding rise in the number of qubits reflects the enhanced computational demands of the problem.

The methodology, elaborated in Section 4.2, begins by formulating the cost function, which sums the latencies of links (measured in milliseconds) into a QUBO model. Constraints ensuring flow conservation, where the inflow equals the outflow at each node, are squared, scaled by a penalty factor P , and incorporated into the objective function. Eight such constraints, representing nodes other than the source and destination, are embedded within the overall objective function. This integration transforms the problem into an unconstrained, quadratic model defined solely by binary variables, making it well-suited for solving within the QUBO framework.

$$\begin{aligned}
& \min \left(\sum_{(i,j) \in E} w_{ij} X_{ij} \right. \\
& + P \left(\sum_{j:(i,j)} X_{ij} - \sum_{j:(i,j)} X_{ji} - 1 \right)^2 \\
& \left. + P \left(\sum_{j:(i,j)} X_{ij} - \sum_{j:(i,j)} X_{ji} \right)^2 \right) \tag{4.21}
\end{aligned}$$

In constructing the quantum circuit, Hadamard (H) gates are first applied to each qubit to establish a superposition across all qubits. The transformation

$$x_i = \frac{1 - Z_i}{2}$$

recasts H_c in terms of Pauli- Z operators, thereby converting the objective function into a Pauli- Z representation. As a result, quadratic and linear coefficients correspond to sequences of quantum gates, rather than classical binary variables. For instance, Fig. 4.10 depicts a segment of the quantum circuit for routing from H1 to H3.

Key components include:

- R_Z gates: These represent the linear terms, applying qubit rotations based on γ . For example, for qubit 0, the operator can be written as $IIIIIIIIIZ_0$.
- R_{ZZ} gates: These capture the quadratic terms, modeling interactions between qubits (e.g., qubits 0 and 1 via $IIIIIIIIIZ_1Z_0$), also parameterized by γ . Identity (I) gates are used on qubits not involved in the interaction.
- R_X gates: These define H_M via Pauli- X operators, with the rotation angles determined by β .

This method effectively encodes the optimization problem within the quantum circuit, allowing for an efficient exploration of possible solutions.

Table 4.3 presents the results from the routing optimization between H1 and H3. Based on the problem constraints, only four paths are feasible. The optimal path (0–1–4–9) incurs a total cost of 27. Employing the COBYLA optimizer for 29 QAOA iterations yields optimal values of $\beta = -0.24027228202065848$ and $\gamma = -5.606865029392289$.

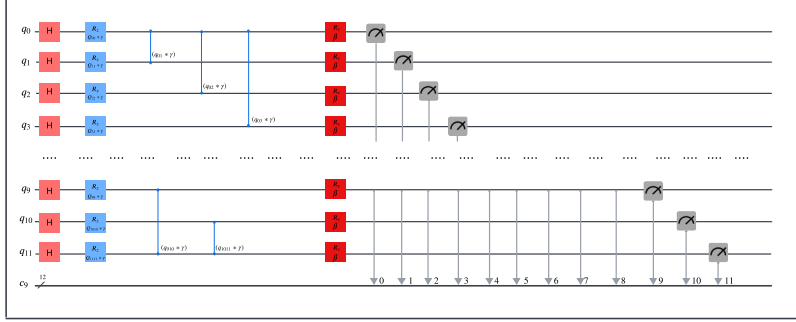


Figure 4.10: Representation of QAOA Quantum Circuit (H1-H3).

Feasible paths from H1 to H3		
Nodes taken	Paths (Binary)	cost
0-1-4-9	100100100000	27
0-1-3-9	101001000000	38
0-2-5-6-8-9	010010010101	106
0-2-5-6-7-8-9	010010011011	114
Feasible paths from H7 to H8		
5-2-0-1-3	111010000000	52
5-2-0-1-4-9-3	110111100000	71
5-6-8-9-3	000001010101	92

Table 4.3: Routing optimization examples

Another routing optimization example addresses data transmission from H7 to H8. Specifically, data must be routed from H7 at node 6 to H8, applying a similar methodology as in the previous scenario. The objective function is first defined by embedding each link's weight into the decision variables. Although the cost function remains the same due to the network's static nature, constraints are slightly modified to maintain flow consistency and capture the graph's directed structure.

Subsequently, a penalty-based reformulation transforms the cost function into a QUBO problem, with $P = 182$. Solving the penalized function then enables constructing the problem Hamiltonian (H_C) using matrix Q . The quantum circuit includes H , R_Z , R_{ZZ} , and R_X gates, which implement the mixer Hamiltonian (H_M).

In this instance, three feasible routes emerge. The optimal path begins at node 6 (H7) and passes through $5 \rightarrow 2 \rightarrow 0 \rightarrow 1 \rightarrow 3$ to reach H8, with a total cost of 52. By employing the COBYLA optimizer, the optimal parameter values for β and γ are found to be $\beta = -1.1491$ and $\gamma = -6.0246$.

4.6 QAOA Advantage: A New Era for Optimization Beyond Classical Limits

Over the past few years, QC has entered a phase in which qubit noise and its mitigation have become paramount. Quantum error correction techniques have gained increasing importance, and Quantum Volume (QV) has emerged as a key figure of merit alongside the raw qubit count. Quantum volume quantifies the practical performance of gate-based quantum computers by considering both the number of qubits and their fidelity [149]. Consequently, the goal of achieving quantum supremacy now hinges on having not only a larger number of qubits but also well-calibrated and reliably functioning qubits.

In addition to QV, IBM introduced another crucial metric for evaluating quantum devices: Circuit Layer Operations per Second (CLOPS). CLOPS measures how many quantum circuits a QPU can execute per second, thus providing insights into the throughput of a quantum computer. Figure 4.11 presents CLOPS as a function of time for several quantum devices, including `ibm_perth`, `ibm_lagos`, and `ibm_jakarta` (each featuring seven qubits), as well as `ibm_manila`, `ibm_bogota`, `ibm_quito`, `ibm_belem`, and `ibm_lima` (each featuring five qubits). This comparison underscores that both the number of qubits and their quality, combined with high throughput, are integral to advancing QC toward practical quantum supremacy.

The observed trend indicates that systems with higher CLOPS generally solve problems faster. However, this is not universally true. The internal architecture of quantum computers and the configuration of qubit connections significantly influence performance. A quantum computer with a lower CLOPS value can perform efficiently for specific problems but may lag in others. Performance variability arises because CLOPS is determined through a general-purpose benchmark developed by IBM. Consequently, for the specific routing problem under study, the Belem and Quito architectures, along with their qubit interconnections, exhibit better performance than the Lima or Manila systems, despite the latter having higher CLOPS values in IBM's standard tests.

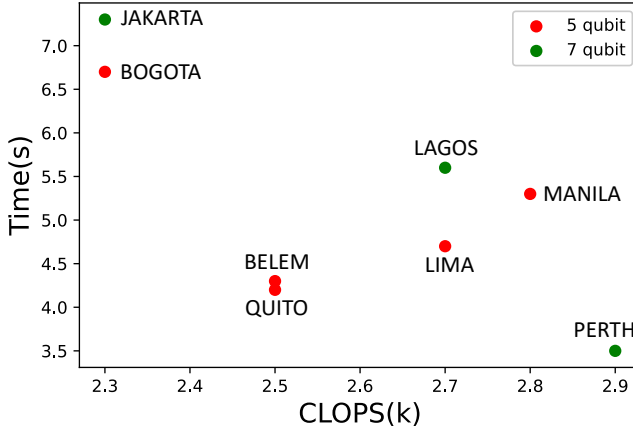


Figure 4.11: Time for solving the four-node problem depending on QC CLOPS.

These results pertain specifically to the single-objective problem. Similar analyses could be extended to other problems, depending on the number and connectivity of qubits available. The findings suggest that CLOPS does influence performance, as systems with higher CLOPS tend to achieve faster solutions on average. However, increasing the number of qubits can introduce additional challenges, such as reduced system coherence. For instance, with 7 qubits and a CLOPS value of 2.9K, the solution time decreases, as illustrated in Fig. 4.11.

Furthermore, simulations presented in [150] predict that the QAOA will demonstrate quantum speedup when applied to problems involving hundreds of qubits, as classical computers begin to struggle with such large problem sizes. Similarly, [151] explores the potential for QAOA to achieve quantum supremacy in optimization problems. Designed for gate-model quantum computers, QAOA becomes challenging to simulate on classical systems as the number of qubits increases. While some classical algorithms may achieve better success probabilities in certain cases, QAOA provides a performance guarantee. Theoretical complexity analyses in [151] conclude that QAOA is a strong candidate for demonstrating quantum supremacy. This conclusion is supported by the algorithm's potential applications in optimization problems and its suitability for near-term quantum devices, which are expected to feature small-to-medium numbers of intermediate-noise qubits.

Since current hardware availability limits testing to IBM quantum systems with a few qubits and relatively low noise levels, theoretical estimations are necessary to explore larger systems. Figure 4.12 presents estimations of pos-

4.6 QAOA Advantage: A New Era for Optimization Beyond Classical Limits

sible quantum advantages for node routing problems based on IBM quantum computers used in this research.

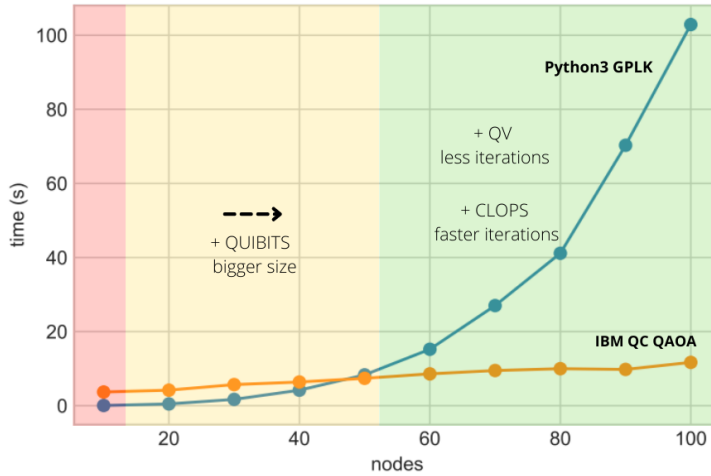


Figure 4.12: QAOA Supremacy estimations for network routing problems.

In Fig. 4.12, the red bar represents the execution results of this study using IBM’s open-for-research quantum systems. Although these solutions required less time than the classical approaches, the execution time remains significantly higher compared to the purely classical methods. The yellow region in the figure denotes IBM’s ongoing advancements, particularly with processors like the Hummingbird (up to 65 qubits), where noise levels are being optimized to enable more accurate computations. The green region represents the expected quantum supremacy zone, where QAOA is projected to outperform classical approaches for routing problems.

The supremacy estimates shown in Fig.4.12 are derived from the complexity analysis in [151]. The underlying mathematical and quantum physics principles of QAOA enable low computational complexities for these problems. However, the primary challenge lies in simulating QAOA efficiently on classical computers. Tests performed on current IBM hardware validate the low complexity of these problems on small scales. To project supremacy thresholds, regression techniques were applied to extrapolate performance trends for larger problems. These projections were compared with a classical implementation using Python’s General-Purpose Linear Programming Kit (GLPK) to estimate the computational costs of classical versus quantum solutions. Supremacy expectations were aligned with IBM’s hardware roadmap.

The research concludes that a few hundred well-calibrated qubits are sufficient to achieve quantum supremacy for this class of problems, where classical algorithms encounter significant difficulty in finding optimal solutions. This milestone is anticipated within the next years, coinciding with the stabilization of IBM's Eagle processor, featuring 127 qubits. Factors that could influence the exact point of quantum supremacy include improvements in CLOPS and QV. Higher CLOPS values reduce computation time, while increased QV enhances algorithmic performance by enabling better solutions with fewer iterations.

4.7 Conclusions

This chapter has introduced a comprehensive quantum routing optimization framework, developed as part of this thesis research [99]. The chapter combines theoretical insights and practical methodologies to address routing optimization challenges using QC techniques. A review of the state-of-the-art in routing optimization was presented, encompassing both single-objective and multi-objective approaches. This review provides a detailed overview of key methods and algorithms from the literature, establishing a strong foundation for the research contributions discussed.

The framework leverages the principles of quantum optimization, with a particular focus on VQAs. Among these, the QAOA was identified as a leading candidate for solving routing optimization problems due to its robust theoretical guarantees and adaptability to near-term quantum hardware. The chapter thoroughly explains the framework methodology, detailing each step of the process, from the formulation of a routing problem as a graph representation to its resolution through QC techniques.

Central to the proposed methodology is the use of QUBO as a formulation strategy. QUBO provides a powerful tool for translating combinatorial optimization problems into a format compatible with quantum computation. This approach is especially relevant given the current limitations of quantum hardware, as it ensures that the problem structure aligns with the capabilities of quantum devices. The chapter discusses the significance of this formulation, emphasizing its role in bridging the gap between classical optimization theory and quantum computation.

By combining a state-of-the-art review, detailed explanations of quantum optimization concepts, and a step by step framework methodology, this chapter lays a solid foundation for addressing complex routing optimization problems using QC. The proposed framework not only highlights the potential of QAOA but also provides a practical roadmap for implementing quantum solutions to combinatorial problems in future wireless communication networks. This work

underscores the transformative potential of QC in optimization and establishes a clear direction for future research in the field.

Finally, the advantages of the QAOA are analyzed in detail with respect to key quantum hardware parameters, such as QV and CLOPS. This analysis includes comparisons between different quantum devices, evaluating their performance in solving optimization problems and their associated time complexity.

By assessing the performance of QAOA on different quantum devices, the interplay between hardware metrics and algorithmic efficiency is explored. For example, devices with higher QV and CLOPS values generally exhibit faster convergence to optimal solutions due to improved coherence and execution speed. However, the analysis also highlights that hardware limitations, such as noise levels and qubit connectivity, can significantly impact QAOA's effectiveness, regardless of these metrics.

The discussion emphasizes the importance of aligning quantum algorithms with the capabilities of the underlying hardware. This alignment not only maximizes the potential of QAOA in solving combinatorial optimization problems but also provides insights into the scalability of quantum solutions as hardware technology advances. By comparing time complexity across devices, the chapter underscores the transformative potential of QAOA and its dependence on ongoing improvements in quantum hardware, paving the way for more efficient and practical applications in the future.

Chapter 5

Quantum Computing for MIMO-NOMA in 6G

The evolution towards Sixth Generation (6G) networks necessitates the deployment of advanced technologies, such as Massive MIMO (mMIMO), to address the stringent requirements of ultra-high data rates, ultra-low latency, and massive connectivity. While Non-Orthogonal Multiple Access (NOMA) has not been adopted in the early Fifth Generation (5G) standard (Rel. 15), it remains under active investigation in subsequent releases (Rel. 16 and Rel. 17) and is being considered as a potential enabler in future 6G systems. Despite the challenges associated with its implementation, such as the reliance on accurate channel estimation and the complexity of Successive Interference Cancellation (SIC), NOMA presents a promising approach for supporting massive Machine Type Communications (mMTC) scenarios by allowing concurrent multi-user transmissions within the same time-frequency resources [152].

Recent research explores hybrid Multiple-Input Multiple-Output (MIMO)–NOMA schemes as a means to enhance both spectral and energy efficiency, particularly in the Terahertz (THz) band, where dense user deployments and severe propagation losses necessitate advanced multiple access strategies [153, 154]. Furthermore, the integration of semi-blind beamforming in MIMO–NOMA architectures offers an effective solution to reduce signaling overhead and latency, while maintaining robustness in heterogeneous environments [155]. These developments underscore the relevance of including NOMA in the broader discussion of enabling technologies for 6G, particularly when considered in conjunction with mMIMO systems.

The concept of leveraging multi-antenna base stations to serve multiple users can be traced back to the late 1980s. MIMO technology has emerged

as a highly promising approach for enhancing data rates by exploiting spatial diversity. This approach substantially improves signal quality, capacity, and reliability of wireless communication links compared to conventional Single Input Single Output (SISO) systems [156]. Additionally, it maintains acceptable Bit Error Rate (BER) levels and has been incorporated into major standards over the past decades, including IEEE 802.11n (WiFi) and Long Term Evolution (LTE) [157]. Furthermore, MIMO techniques play a pivotal role in 5G and future wireless technologies (e.g., 6G), supporting an increased number of antennas at the Base Station (BS) end [158].

In contrast, earlier generations of wireless networks adopted Orthogonal Multiple Access (OMA) schemes, such as Frequency Division Multiple Access (FDMA) in First Generation (1G), Time Division Multiple Access (TDMA) in Second Generation (2G), Code Division Multiple Access (CDMA) in Third Generation (3G), and Orthogonal Frequency Division Multiple Access (OFDMA) in Fourth Generation (4G). These OMA systems assign orthogonal communication resources, time slots, frequency bands, or codes, to users to mitigate multiple access interference [159]. Conversely, NOMA has emerged as a cutting-edge technology that significantly improves spectral efficiency by enabling simultaneous data transmission for multiple users over the same frequency and time resources [160].

The integration of MIMO-NOMA techniques presents a transformative opportunity to improve Quality of Service (QoS), Energy Efficiency (EE), and Spectral Efficiency (SE) in future 6G networks. This combination also enhances fairness, boosts throughput, and fortifies robustness against channel fluctuations. Several detection techniques have been proposed for MIMO-NOMA [161, 162], many of which refine classical approaches like Zero Forcing (ZF) [163], Minimum Mean-Square Error (MMSE) [164], and SIC [165] to achieve near-optimal performance while maintaining low computational complexity.

On the other hand, the Maximum Likelihood Detection (MLD) approach, under an uncoded system assumption, is considered optimal in terms of BER performance. Examines all possible symbol constellations through exhaustive search to determine the transmitted symbol. However, due to the discrete nature of signal constellations, MLD is generally classified as a Non-Deterministic Polynomial-Time (NP-hard) problem [166] for conventional computing systems [167]. Although, exhaustive search remains viable for small-scale scenarios, it becomes computationally infeasible for high-order spatial diversity schemes such as massive MIMO. In practice, numerous suboptimal detection methods approximate MLD. These approaches include computationally accelerated techniques like Sphere Decoding (SD) [168], which still exhibit exponential complexity, and detectors that sacrifice some BER performance

to achieve polynomial complexity, such as Linear Minimum Mean Square Error (LMMSE) [169] and Matched Filter (MF) [170].

Driven by the need to address the challenges of uplink communication in modern wireless systems, this chapter examines an uplink MIMO-NOMA configuration. In this scenario, each mobile User Equipment (UE) independently transmits its signal to the BS using Superposition Coding (SC) techniques [171]. At the BS, the receiver faces the complex task of correctly identifying the individual symbols of each user from a superimposed signal that comprises multiple overlapping transmissions.

To tackle this challenge, a novel MLD framework that employs Quantum Computing (QC) principles, leveraging the inherent advantages of quantum mechanics, such as superposition and entanglement is proposed. The detector design incorporates the Quantum Approximate Optimization Algorithm (QAOA) algorithm and utilizes IBM Quantum computers to solve the combinatorial optimization problem central to the MLD in MIMO-NOMA systems.

Furthermore, recognizing the current technological constraints of QC, specifically its positioning within the Noisy Intermediate-Scale Quantum (NISQ) era, this chapter evaluates the feasibility and implications of achieving a “quantum advantage” in this context. A detailed discussion of the applicability of QAOA for this problem is provided, and it is explored how the proposed approach can be generalized to address challenges in massive MIMO systems, highlighting its potential impact on future wireless communication networks.

- Section 5.1 reviews the state-of-the-art research on integrating quantum technologies with MIMO and NOMA, as presented in the existing literature.
- Section 5.2 introduces a detailed MLD framework that leverages QC using Qiskit, and specifically employing the QAOA algorithm. A step-by-step explanation is provided to enhance the understanding of the MIMO-NOMA detection process described in [172].
- Section 5.3 discusses the primary results, focusing on the “quantum advantages” offered by the proposed methodology.
- Section 5.4 encapsulates the main insights and conclusions drawn from this chapter.

5.1 Quantum Technologies for MIMO and NOMA: State-of-the-Art

5.1.1 Quantum Technologies for NOMA

There has been a recent surge of interest in applying quantum techniques to address some of the complexity-related limitations inherent in future 6G communication systems. This interest is particularly evident in tackling the challenges of operating multi-user mMIMO systems, which employ both orthogonal and non-orthogonal digital modulation schemes. Quantum methods aim to execute the computationally intensive operations required for these systems at significantly faster speeds than classical computation can achieve.

During exploring the current state of research, it is important to differentiate between approaches inspired by quantum mechanics principles and those that directly use QC. For example, some studies utilize concepts like quantum superposition in a metaphorical sense to develop innovative algorithms.

A notable instance is [173], which proposes a Quantum Evolutionary Algorithm (QEA) to optimize user pairing in NOMA systems. Although the QEA draws on quantum-inspired ideas, such as using superposition-like mechanisms, it is implemented entirely within the realm of classical computation. The algorithm represents possible solutions using genetic techniques, evaluates the fitness of each user pairing combination, and selects the pairing that maximizes the sum rate. The results demonstrate an improvement over random user pairing, but all computational simulations rely on classical Monte Carlo methods rather than quantum hardware.

In contrast, recent studies have explored the direct use of real-world quantum computing platforms for addressing challenges in NOMA systems. For instance, [174] implemented a signal detection method for NOMA using Quantum Annealing (QA) on D-WAVE's quantum computing platform. QA is employed to locate the global minimum of a cost function, enabling maximum likelihood estimation for each received signal in NOMA systems. This approach reduces the computational load traditionally required for such tasks on classical systems. By using QA to identify the best-transmitted symbol candidates, the method enhances the performance of traditional NOMA receivers while addressing the complications associated with SIC.

Similarly, in [175], it is used QA to optimize MLD for NOMA systems as an alternative to SIC. Their findings indicate that while the QA-assisted decoder achieves the same BER performance as brute-force constellation searches, it takes longer to execute on current quantum platforms. To overcome this limitation, the authors propose parallelizing the computation to leverage all available qubits effectively. Interestingly, they observed that QA execution time does not

5.1 Quantum Technologies for MIMO and NOMA: State-of-the-Art

scale with the number of qubits in use, highlighting the potential for optimizing performance through parallelization and more efficient qubit allocation.

5.1.2 Quantum Technologies for MIMO

In 2006, Gabay and Arnon were the first to introduce MIMO concepts into the quantum domain [65] by devising a Quantum Key Distribution (QKD) protocol leveraging a free-space MIMO setup [66]. Their groundbreaking work spurred a wave of studies exploring novel approaches for QKD in free-space [67], culminating in, for instance, a quantum MIMO communication scheme based on quantum teleportation with triplet states [65]. In this teleportation-based framework, a sequence of n -qubits carrying quantum signals is relayed through a MIMO channel using diversity techniques in the quantum regime. Recently, a quantum MIMO structure dedicated to antenna-based wireless links was introduced in [68], with the primary aim of establishing a universal theoretical foundation for MIMO transmission via quantum states rather than classical electromagnetic fields.

Modern research has increasingly concentrated on the inherent complexity of MIMO systems, especially where the number of antennas at the transmitter outstrips that of conventional systems, thereby rendering power allocation a challenging optimization problem. A recent contribution [69] demonstrated that quantum optimization could be harnessed to balance and distribute transmit power optimally in MIMO networks by exploiting entanglement and superposition. Along these lines, [176] describes a strategy based on Constrained Quantum Optimization Algorithm (CQOA) aimed at minimizing the total transmit power in varied MIMO scenarios subject to specific user bit rate demands.

In parallel, both QA and QAOA have emerged as potential candidates for addressing optimization tasks through the manipulation of two Hamiltonians. While QA involves a continuous interpolation between these Hamiltonians, QAOA implements them in an alternating sequence. The gradient descent technique used in QA, though challenging to deploy in setups akin to those of the QAOA (for instance, IBM Quantum Experience), has seen considerable progress on D-Wave architectures, which, despite not being universal quantum processors, enable gradient-based approaches for optimization. Several studies, such as [177, 178], have investigated QA-based Machine Learning (ML) detection for MIMO communication. In [177], the authors propose QuAMax, a MIMO centralized radio access network deployed on a 2031-qubit D-Wave 2000Q system, successfully demonstrating that 10 μs of computing on the 2000Q can handle Binary Phase-Shift Keying (BPSK) transmission for 48 users and 48 AP antennas at an Signal to Noise Ratio (SNR) of 20 dB with a BER of

10^{-6} and a 1500-byte frame error rate of 10^{-4} . Meanwhile, [178] provides a performance comparison between the D-Wave 2000Q and its D-Wave Advantage successor for solving large-scale Quadratic Unconstrained Binary Optimization (QUBO) tasks tied to ML channel decoders in MIMO Centralized-Radio Access Network (RAN) systems, which are particularly challenging because of their exponentially expanding search space.

Complementarily, QAOA on gate-model quantum platforms offers a route to tackle combinatorial optimization problems similar to those addressed by QA. A key advantage of QAOA on universal machines is the ability to boost precision, whereas QA achieves probability-1 solutions only as t tends to infinity, which becomes impractical if t grows too large. It has also been demonstrated, for instance in [179], that small-scale QA experiments on a 5-qubit device were unable to find all possible ground states. Nonetheless, which of these two methods, QA or QAOA, is more effective remains an open question. Some works [180] emphasize that simulating the evolution of large quantum spin systems on classical machines is computationally prohibitive, whereas QAOA can be physically implemented on an actual quantum platform. Following this direction, [181] applied QAOA to the problem of ML detection in MIMO configurations. By embedding the task into a level- p QAOA circuit with $2p$ variational parameters, the authors described classical optimization routines to fine-tune these parameters, alongside analytical and numerical explorations of eigenvalue dynamics, computational overhead, and storage scaling. The QAOA-based ML detector demonstrated near-ML performance and exceeded the MMSE baseline in terms of BER.

Despite these advances, there remains a gap in the literature regarding the real-world implementation of QAOA-based detection in mMIMO systems on current-generation NISQ hardware, an objective that this work aims to address.

5.2 Quantum-Enhanced Maximum-Likelihood Detector for MIMO-NOMA

In MIMO-NOMA systems, achieving optimal error performance requires the joint detection of all users' signals using MLD. However, this method faces an exponential rise in computational complexity as the number of users and modulation order increase. With the emergence of 5G and future wireless communication standards prioritizing massive connectivity and higher data rates, the practical implementation of traditional MLD poses considerable computational challenges. Recent advancements in QC offer a transformative approach by leveraging quantum mechanics to address the combinatorial complexity inherent in MLD. This section explores the integration of QC into the MLD

framework, highlights the fundamental principles of quantum-based search and optimization techniques, and evaluates their potential to improve the efficiency and scalability of MIMO-NOMA detection compared to conventional methods.

5.2.1 Non-Orthogonal Multiple Access

NOMA is a communication strategy that allows multiple users to share the same frequency/time resources by overlapping their signals, unlike traditional orthogonal techniques where each user is assigned a distinct time or frequency channel. This overlap can be achieved in two main ways: by assigning different power levels to each user (Power-Domain NOMA) or by mapping each user signal to unique codewords (Code-Domain NOMA) [182].

In Power-Domain NOMA, users located closer to the BS, who typically have stronger signal conditions, transmit at lower power levels, while those farther away operate at higher power. This setup enables a receiver to decode and remove the stronger signals first before detecting the weaker ones. In contrast, Code-Domain methods such as Sparse Code Multiple Access (SCMA) and Multiuser Shared Access (MUSA) use specialized codebooks to differentiate between multiple user signals within the same bandwidth. Both of these approaches allow for a higher number of simultaneous users, optimizing spectrum utilization and making them particularly valuable for modern cellular networks (5G and beyond).

NOMA can be applied to both Downlink (DL) (from BS to users) and Uplink (UL) (from users to BS) transmissions, see Fig. 5.1. In the DL, the BS superimposes all user signals at different power levels, receivers then rely on SIC to decode signals in descending order of power. In UL scenarios, multiple users adjust their transmission power so that the BS can distinguish each signal via SIC. Because NOMA efficiently supports many concurrent connections, it is well suited to handle the diverse and massive traffic demands expected in future mobile networks, enhancing both throughput and latency performance.

In the NOMA UL, the signal received at BS can be expressed as:

$$\mathbf{y} = \sum_{k=1}^K h_k \sqrt{a_k P} \mathbf{s}_k + \mathbf{n}, \quad (5.1)$$

where s_k denotes the transmitted symbol of user k , h_k represents the channel gain of the link between user k and the BS, $0 < a_k < 1$ indicates the power allocation coefficient, P is the maximum transmission power, $\mathbf{n}$ refers to the Additive White Gaussian Noise (AWGN) with zero mean, and σ_n^2 denotes its power density.

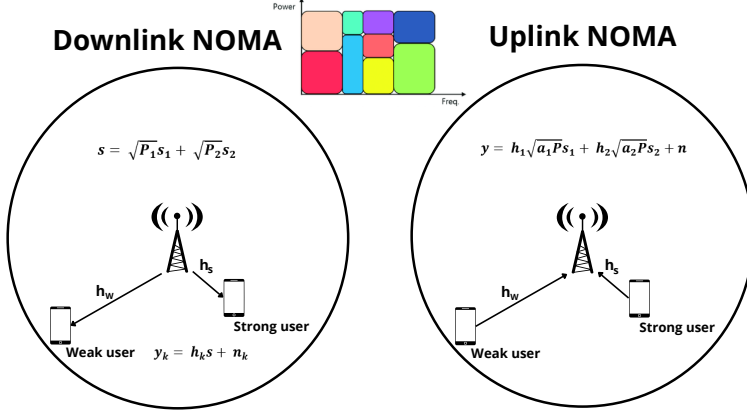


Figure 5.1: Downlink and Uplink NOMA schemes.

One of the key requirements for power domain NOMA involves assigning different levels of transmit power to each user signal information. In the UL scenario, where multiple users, located at various distances from the BS, simultaneously send their data, this aspect becomes especially pertinent. Because signals from all users arrive at the BS as a combined waveform $\mathbf{y}$, the BS receiver must be able to separate the symbol of each individual user from this merged signal.

A common technique used to achieve this separation is SIC. In essence, SIC works by first decoding the data of the user whose signal is strongest, while treating all the signals of the other users as interference. Once the strongest user data are successfully decoded, that decoded user contribution is subtracted from the received signal. This subtraction step helps simplify the subsequent decoding of the next strongest user. This iterative approach continues until all user data have been decoded. However, it is important to recognize that an “error floor” phenomenon may arise during the process, particularly for signals assigned lower power levels. In such situations, residual interference from these weaker signals can lead to degradation of the overall decoding performance.

Even though SIC stands out as the primary candidate for implementing NOMA in upcoming wireless communication generations, it has certain shortcomings that motivate the investigation of alternative NOMA decoding methods. The main disadvantages of SIC are summarized below [174]:

- **Error Propagation:** If an error occurs when decoding the signal of a user in a given iteration, it carries over and affects subsequent decoding stages.
- **Receiver Channel Knowledge:** The receiver must be equipped with complete channel information for all users to correctly perform equalization, which can be challenging in practical systems.
- **Iterative Complexity and Latency:** Because decoding proceeds in multiple rounds, complexity grows with the number of users, potentially leading to latency issues in high-user-density scenarios.
- **Significant Power-Level Differences Required:** The power levels of signals of different users must be sufficiently distinct to enable effective signal separation and detection.

These limitations become increasingly critical as more users share the same resources. Consequently, MLD is often introduced in the literature as an alternative approach that can address some of SIC's shortcomings. By jointly detecting all signals, MLD aims to reduce error propagation and reliance on large power-level disparities, although it may introduce higher computational demands compared to SIC.

5.2.2 Multiple-Input Multiple-Output

Figure 5.2 illustrates an excerpt of a MIMO communication system. In this setup, both the transmitter and the receiver are equipped with multiple antennas. This configuration enables the transmission and reception of multiple signals simultaneously, significantly improving the capacity and reliability of the system.

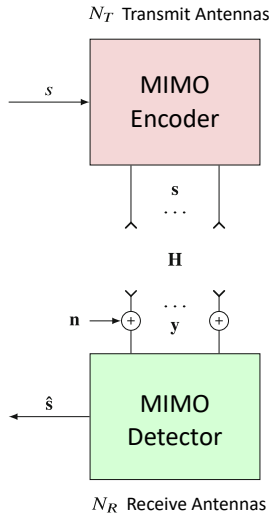


Figure 5.2: Excerpt of a MIMO communication system.

In a MIMO system, the received signal can be mathematically represented by the following equation:

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}, \quad (5.2)$$

Here, the variables are defined as follows.

- $\mathbf{y} \in \mathbb{C}^{N_R \times 1}$: The vector represents the signal received on the receiver side, where N denotes the number of receive antennas.
- $\mathbf{H} \in \mathbb{C}^{N_T \times N_R}$: The channel matrix, which characterizes the communication link between the N_T transmit antennas and the N_R receive antennas. This matrix captures the effects of the propagation environment, such as path loss, fading, and interference.
- $\mathbf{s} \in \mathbb{C}^{N_T \times 1}$: The vector of transmitted symbols, which represents the data sent from the N_T transmit antennas.
- $\mathbf{n} \in \mathbb{C}^{N_R \times 1}$: The additive white Gaussian noise (AWGN) vector, which models the noise introduced during signal transmission.

This equation succinctly describes how the transmitted signal $\mathbf{s}$ is affected by the wireless channel $\mathbf{H}$ and distorted by noise $\mathbf{n}$, resulting in the received signal $\mathbf{y}$. The MIMO framework leverages the spatial diversity provided by

multiple antennas to improve data throughput and resilience against channel impairments.

Since all the variables are complex-valued, to simplify their handling and avoid directly working with complex numbers, (5.2) is transformed into its equivalent real-valued representation using the following convention:

$$\bar{\mathbf{y}} = \bar{\mathbf{H}}\bar{\mathbf{s}} + \bar{\mathbf{n}}, \quad (5.3)$$

where

$$\bar{\mathbf{y}} = \begin{bmatrix} \Re(\mathbf{y}) \\ \Im(\mathbf{y}) \end{bmatrix}, \bar{\mathbf{s}} = \begin{bmatrix} \Re(\mathbf{s}) \\ \Im(\mathbf{s}) \end{bmatrix}, \bar{\mathbf{n}} = \begin{bmatrix} \Re(\mathbf{n}) \\ \Im(\mathbf{n}) \end{bmatrix}, \quad (5.4)$$

$$\bar{\mathbf{H}} = \begin{bmatrix} \Re(\mathbf{H}) & -\Im(\mathbf{H}) \\ \Im(\mathbf{H}) & \Re(\mathbf{H}) \end{bmatrix} \quad (5.5)$$

and $\Re(\cdot)$ and $\Im(\cdot)$ are defined as the real and imaginary parts of a complex matrix or vector, respectively.

MIMO systems have the remarkable capability to leverage multipath propagation and multipath delay spreads, transforming these typically challenging phenomena into advantages for the receiver. The primary benefit of MIMO systems lies in their ability to significantly enhance the SNR by several orders of magnitude without requiring additional bandwidth [156]. However, this improvement comes with a trade-off: the implementation of MIMO introduces considerable processing complexity in both the transmitter and the receiver, requiring advanced software and hardware solutions.

- **Multipath Propagation and Delay Spreads as a Benefit:** In wireless communication, signals often take multiple paths to reach the receiver due to reflections, diffractions, and scattering. This can lead to signal interference and degradation in traditional systems. However, MIMO systems utilize these multiple paths to transmit independent data streams simultaneously, effectively increasing the capacity and reliability of the communication channel.
- **SNR Improvement:** SNR is a critical metric in communication systems, representing the strength of the desired signal relative to background noise. MIMO systems enhance SNR dramatically by exploiting spatial diversity and combining the signals received from multiple antennas. This improvement allows for higher data rates and better quality transmission without consuming extra spectral resources.
- **Complexity Trade-Off:** While MIMO delivers significant performance enhancements, the use of multiple antennas and the need to process complex spatial information demand sophisticated algorithms and hardware.

This includes tasks such as signal encoding, decoding, channel estimation, and interference cancellation, which increase the computational load and power consumption on both the transmitting and receiving ends.

This balance between the substantial benefits of MIMO and its implementation challenges makes it a pivotal technology in modern wireless systems.

5.2.3 Maximum Likelihood Detector

MLD plays a vital role in communication systems, especially in digital communications over noisy channels. The goal of MLD is to recover the transmitted signal that is most likely to have produced the received signal, taking into account noise and channel effects. The process involves evaluating all possible transmitted signals and selecting the one that maximizes the likelihood of the observed received signal [183].

Having the MIMO communication system, for example, the transmitted signal vector $\mathbf{s}$ is drawn from a discrete set of symbols $\mathcal{S}$, such as $\{-1, +1\}$ for BPSK. The detection problem aims to estimate $\mathbf{s}$ by minimizing the Euclidean distance between $\mathbf{y}$ and the predicted signal $\mathbf{H}\mathbf{s}$, resulting in the optimization problem.

$$\hat{\mathbf{s}} = \arg \min_{\mathbf{s} \in \mathcal{S}^n} \|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2 \quad (5.6)$$

The MLD problem is inherently combinatorial because the transmitted signal $\mathbf{s}$ belongs to a discrete and finite search space $\mathcal{S}^n$. For a system with n transmitted symbols and $|\mathcal{S}|$ possible values per symbol, the search space contains $|\mathcal{S}|^n$ combinations. As n grows, the problem becomes computationally challenging due to the exponential increase in possible combinations.

The optimization involves minimizing the quadratic objective function:

$$f(\mathbf{s}) = \|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2 \quad (5.7)$$

where $\mathbf{s}$ is constrained to the discrete set $\mathcal{S}^n$. This makes MLD a constrained combinatorial optimization problem. The search for the optimal $\mathbf{s}$ is computationally demanding, especially for large n or in systems with complex noise and interference.

The exponential growth of the search space means that evaluating all possible combinations of $\mathbf{s}$ via exhaustive search is computationally prohibitive for large systems [184]. Moreover, the problem is classified as NP-hard, particularly in scenarios where the channel matrix $\mathbf{H}$ is ill-conditioned or when the number of transmitted symbols is high.

5.2 Quantum-Enhanced Maximum-Likelihood Detector for MIMO-NOMA

To make the problem tractable, various optimization techniques are employed. Exhaustive search, while guaranteeing the optimal solution, is only practical for small-scale problems. More efficient methods, such as SD, reduce the search space by focusing on vectors within a sphere of a specified radius around the received signal [183]. Approximation algorithms, including greedy methods, can provide suboptimal solutions with reduced complexity. Relaxation techniques, such as linear or semidefinite programming, transform the discrete optimization problem into a continuous one, enabling faster computation at the expense of exactness.

MIMO-NOMA Detector

Considering the scenario in Fig. 5.2, which can also be interpreted as describing an UL single-cell MIMO-NOMA system. In this setting, the BS functions as the receiver equipped with N_R antennas, while K users, each with N_T transmitting antennas, operate under the constraint $N_R = N_T K$. Consequently, each user's distance from the BS and respective transmit power are embedded in (5.8).

Before the symbols are transmitted (a step not shown in Fig. 5.2), $\log_2(M)$ bits are assigned to each symbol in the constellation, where M is the total number of symbols. As an example, BPSK maps one bit per symbol. Once these symbols are formed, a MIMO encoder demultiplexes them into separate streams for the N_T transmit antennas. The receiver, which has N_R antennas, captures the transmitted signals. Each signal encounters a channel gain $h_{i,j}$, representing the propagation from the i -th transmit antenna to the j -th receive antenna. The received signal is then given by [185]:

$$\mathbf{y}_k = \mathbf{H} \sqrt{a_k P} \mathbf{s}_k + \mathbf{n}, \quad (5.8)$$

where all variables are complex. In this expression, $\mathbf{y}_k$ ($N_R \times 1$) is the received signal vector, $\mathbf{H}$ ($N_R \times N_T$) is the channel matrix whose entries are channel gains, $0 < a_k < 1$ denotes the power allocation factor, P is the maximum power budget, and $\mathbf{s}_k$ ($N_T \times 1$) is the transmitted symbol vector. Meanwhile, $\mathbf{n}$ ($N_R \times 1$) represents the AWGN. Its individual elements can be expressed as

$$n_i = \sqrt{\frac{w}{2}}(u + jv), \quad (5.9)$$

where u and v follow standard normal distributions. The term w corresponds to the noise power on the linear scale, often approximated as:

$$w = -174 + 10 \log_{10}(B)(dBm) \quad (5.10)$$

where B is the system bandwidth.

To capture realistic wireless conditions, it is generally assumed that the entries of $\mathbf{H}$ are independent and identically distributed (i.i.d.), which requires sufficient antenna spacing, commonly at least half a wavelength. Once the received vector $\mathbf{y}_k$ is obtained, the MIMO-NOMA detector produces an estimate $\hat{\mathbf{s}}$. To decode each symbol into its bit stream in a way that minimizes the BER, the detector searches over all possible transmitted vectors $\mathbf{x}$ and selects the one that reduces the Euclidean distance between $\mathbf{y}$ and $\mathbf{H}\sqrt{a_k P} \mathbf{s}_k$. Following (5.6), the detector solves :

$$\hat{\mathbf{s}} = \arg \min_{\mathbf{s} \in \mathcal{S}^{N_T}} \|\mathbf{y} - \mathbf{H}\sqrt{a_k P} \mathbf{s}_k\|^2, \quad (5.11)$$

where $\mathcal{S}^{N_T}$ is the set of all N_T -dimensional symbols in the selected modulation scheme. In an uncoded system, this exhaustive search achieves the optimal BER but becomes intractable when N_T or the modulation order is large, owing to the exponential size of $|\mathcal{S}^{N_T}|$.

Lastly, the Rayleigh fading model is commonly employed to simulate environments where there is no direct Line of Sight (LoS) path. Consequently, each entry $h_{i,j}$ of $\mathbf{H}$ adheres to:

$$h_{i,j} = (a + jb) \sqrt{\frac{d_{i,j}^\eta}{2}}, \quad (5.12)$$

where a and b are independent standard normal random variables, $d_{i,j}$ is the distance separating the i -th transmit antenna from the j -th receive antenna, and $\eta = 4$ is the typical path loss exponent. This procedure, dictated by the configuration of MIMO system, helps ensure a realistic depiction of wireless channel conditions.

Quantum MIMO-NOMA Detection

Since MLD is regarded a combinatorial optimization problem, which inherently places it among the class of NP-hard problems. Due to the computational complexity involved, classical methods frequently struggle to handle larger instances efficiently. QC offers a promising avenue to tackle these kinds of problem because it leverages principles such as superposition and entanglement to explore solution spaces more effectively than many conventional algorithms. By harnessing quantum resources, QC can significantly reduce the time required to arrive at high-quality solutions or approximations for MLD tasks.

In Chapter 4, one of the key quantum algorithms highlighted for solving combinatorial optimization problems is the QAOA. QAOA blends classical and quantum computation: It uses a parameterized quantum circuit to explore

5.2 Quantum-Enhanced Maximum-Likelihood Detector for MIMO-NOMA

the solution space, followed by a classical optimization step to refine those parameters. This iterative process continues until the algorithm converges to a promising solution. Taking advantage of quantum parallelism, QAOA can often find near-optimal solutions faster than pure classical algorithms, making it a significant tool for addressing the inherent complexities of NP-hard problems like MLD. For further details on QAOA, refer to Section 4.2 in Chapter 4. In this regard, the procedure employed to solve the MLD problem is closely aligned with the approach previously proposed for quantum routing optimization.

To simplify the problem, assuming BPSK modulation implies that the symbols (i.e., bits) transmitted by each antenna, denoted as s_k for $k \in [1, \dots, N_T]$, are restricted to values within the set $\{-1, +1\}$. Consequently, to adapt to the QUBO model, which operates with binary variables, a straightforward transformation is required: $s_k = 2q_k - 1$. This substitution allows the problem formulation in (5.11) to align with the binary variable constraints of the QUBO framework.

While this approach focuses on the simplicity afforded by BPSK, higher-order modulation schemes, such as Quadrature Phase-Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (QAM), and 64-QAM, can also be employed to enhance system performance. However, incorporating these schemes significantly increases the complexity of the problem and the number of qubits needed to represent the variables. This added demand poses challenges, particularly given the current limitations in quantum hardware, potentially affecting the feasibility and accuracy of the results.

A detailed illustration of the procedure is provided using a MIMO-NOMA 2×2 system with BPSK modulation. This example highlights two critical considerations.

First, in the case of a MIMO system, the communication channel is represented as a matrix, as described by (5.5) in this work. This matrix characterizes the transmission environment and the interactions between transmitting and receiving antennas.

Second, the NOMA framework requires different power allocation levels for each user, denoted as a_1 and a_2 , to account for disparities in user distances from the BS. Specifically, user 1, being farther from the BS, is assumed to be the weaker user, while user 2, being closer, is regarded as the stronger user. This differentiation ensures proper signal decoding for both users.

Building upon these aspects and following the formulations provided in (5.1) and (5.11), MLD problem for a MIMO-NOMA system with $M = 2$ users is expressed as:

$$\hat{s} = \min ||\mathbf{y} - \mathbf{H}(\sqrt{a_k P}(2q_k - 1))||^2 \quad (5.13)$$

where $\mathbf{y}$ is the received signal, $\mathbf{H}$ is the channel matrix, a_k represents the power levels for users, P is the transmitted power, and q_k denotes binary variables corresponding to the BPSK symbols. This equation quantifies the optimization problem for jointly detecting the transmitted symbols while minimizing the error introduced by channel and noise effects.

To facilitate solving the optimization problem using the QAOA framework, the equation above undergoes a series of transformations. By reorganizing and grouping terms, the quadratic and linear components are distinctly separated. This structured representation enables the construction of the QUBO model (see 4.1), which is essential for encoding the problem into a form compatible with quantum optimization techniques. The complete derivation process is detailed in (5.14) through (5.24).

The separation of terms is particularly crucial for forming the QUBO matrix $\mathbf{Q}$, which encodes the optimization problem's cost function. Quadratic terms are categorized into three groups based on their indices: diagonal terms ($Q_{i,i}$), off-diagonal terms with shared indices ($Q_{j,j}$), and mixed-index terms ($Q_{i,j}$). This systematic classification ensures a clear mapping of interactions and self-contributions to the optimization process.

By explicitly isolating these terms, the problem representation is compressed into a format that reduces computational overhead while preserving the essential relationships between variables. This compression is not merely a mathematical convenience but a necessity for leveraging the computational power of quantum systems, as current hardware limitations require optimization models to be as compact and efficient as possible.

Thus, the formulation of $\mathbf{Q}$ through this separation process not only enables the problem to be expressed within the QUBO framework but also ensures scalability and compatibility with the quantum algorithms designed to address such combinatorial challenges. This method underscores the critical role of algebraic restructuring in bridging classical optimization problems with quantum computational approaches.

$$Q_{1,1} = 4\sqrt{a_1 P}(\Re(h_{1,1})^2 + \Im(h_{1,1})^2 + \Re(h_{1,2})^2 + \Im(h_{1,2})^2) \quad (5.14)$$

$$\begin{aligned} Q_{1,2} = & 8\sqrt{a_1 a_2 P}(\Re(h_{1,1})\Re(h_{1,2}) + \Im(h_{1,1})\Im(h_{1,2}) \\ & + \Re(h_{2,1})\Re(h_{2,2}) + \Im(h_{2,1})\Im(h_{2,2})) \end{aligned} \quad (5.15)$$

$$Q_{2,2} = 4\sqrt{a_2 P}(\Re(h_{2,1})^2 + \Im(h_{2,1})^2 + \Re(h_{2,2})^2 + \Im(h_{2,2})^2) \quad (5.16)$$

$$\mathbf{Q} = \begin{bmatrix} Q_{1,1} & Q_{1,2} \\ 0 & Q_{2,2} \end{bmatrix} \quad (5.17)$$

5.2 Quantum-Enhanced Maximum-Likelihood Detector for MIMO-NOMA

For the linear terms, a detailed derivation isolates three distinct contributions, for each user ($M = 2$) by solving, reordering, and grouping terms from the initial formulation in (5.13). These contributions are essential for accurately modeling the interactions and effects of the system's variables. The results are expressed as follows:

1. Self-contribution of each user's channel coefficients: This term represents the direct impact of the channel gains on the optimization problem.

For user 1:

$$L_{1,1} = -4\sqrt{a_1 P}(\Re(h_{1,1})^2 + \Im(h_{1,1})^2 + \Re(h_{1,2})^2 + \Im(h_{1,2})^2) \quad (5.18)$$

where $h_{1,1}$ and $h_{1,2}$ denote the channel coefficients, and a_1 represents the power allocation for user 1.

Similarly, for user 2:

$$L_{1,2} = -4\sqrt{a_2 P}(\Re(h_{2,2})^2 + \Im(h_{2,2})^2 + \Re(h_{2,1})^2 + \Im(h_{2,1})^2) \quad (5.19)$$

2. Interaction between channel coefficients and received signals: This term accounts for the correlation between the received signal and the channel coefficients, capturing their influence on the optimization cost.

For user 1:

$$L_{2,1} = -4\sqrt{a_1 P}(\Re(h_{1,1})\Re(y_1) + \Im(h_{1,1})\Im(y_1) + \Re(h_{1,2})\Re(y_2) + \Im(h_{1,2})\Im(y_2)) \quad (5.20)$$

Similarly, for user 2:

$$L_{2,2} = -4\sqrt{a_2 P}(\Re(h_{2,2})\Re(y_2) + \Im(h_{2,2})\Im(y_2) + \Re(h_{2,1})\Re(y_1) + \Im(h_{2,1})\Im(y_1)) \quad (5.21)$$

3. Cross-user interference terms: This term reflects the interaction between the two users' signals and their channel coefficients.

For user 1:

$$L_{3,1} = -4\sqrt{a_1 a_2 P}(\Re(h_{1,1})\Re(h_{1,2}) + \Im(h_{1,1})\Im(h_{1,2}) + \Re(h_{2,1})\Re(h_{2,2}) + \Im(h_{2,1})\Im(h_{2,2})) \quad (5.22)$$

For user 2:

$$L_{3,2} = -4\sqrt{a_1 a_2 P}(\Re(h_{2,2})\Re(h_{2,1}) + \Im(h_{2,2})\Im(h_{2,1}) + \Re(h_{2,1})\Re(h_{1,1}) + \Im(h_{2,1})\Im(h_{1,1})) \quad (5.23)$$

Finally, the linear contributions for the two users are combined into a single vector:

$$\mathbf{l} = [L_{1,1} + L_{2,1} + L_{3,1}, \quad L_{1,2} + L_{2,2} + L_{3,2}] \quad (5.24)$$

This step of isolating linear terms is critical in simplifying the optimization problem. By breaking the contributions into manageable components, the system's behavior can be better understood and efficiently encoded into the QUBO framework. Each term highlights a distinct aspect of the interaction: the self-contribution emphasizes individual user channel effects, the interaction term captures signal-channel correlations, and the cross-user term accounts for interference. Together, these terms comprehensively model the system dynamics, ensuring that the optimization reflects all key interactions and trade-offs inherent to the MIMO-NOMA setup.

The number of qubits required for quantum computation in this context is directly proportional to the total number of bits transmitted across all antennas. For example, in a MIMO 2×2 system with BPSK modulation, where each antenna transmits a single bit, only two qubits are needed to represent the transmitted symbols. This efficient utilization of qubits is particularly advantageous given the resource limitations of current quantum computers, making the approach scalable for systems with modest configurations.

Once the QUBO model is established, the focus shifts to constructing the cost Hamiltonian, as defined in Section 4.2. This Hamiltonian, central to the QAOA framework, is composed of two key components. The cost Hamiltonian (H_C), outlined in (5.26), represents the cost function to be minimized, mapping the optimization objective into the quantum framework. Complementing this, the mixer Hamiltonian (H_M), described in (5.27), employs Pauli-X operators across all qubits to enable state transitions, ensuring comprehensive exploration of the solution space. Together, these Hamiltonians drive the quantum system toward optimal solutions by leveraging quantum superposition and entanglement, while balancing the exploration of possibilities with the minimization of the cost function.

$$H_C|x\rangle = H_C|x\rangle + H_M, \quad (5.25)$$

$$H_C|x\rangle = \left(\sum_{i,j=1}^n x_i \mathbf{Q}_{ij} x_j + \sum_{i=1}^n l_i x_i \right) |x\rangle \quad (5.26)$$

$$H_M = \sum_{i=1}^n X_i \quad (5.27)$$

Given that the variables are binary, the condition $x_j = x_j^2$ naturally holds. Under this assumption, both the linear and quadratic contributions can be expressed in a unified matrix notation, as detailed in [129]. For simplicity, let us define $l_1 = L_{1,1} + L_{2,1} + L_{3,1}$ for user 1 and $l_2 = L_{1,2} + L_{2,2} + L_{3,2}$ for user 2. Using these notations, the updated matrix $\mathbf{Q}$ is presented as follows:

5.2 Quantum-Enhanced Maximum-Likelihood Detector for MIMO-NOMA

$$\mathbf{Q}_{2 \times 2} = \begin{bmatrix} Q_{1,1} - l_1 & Q_{1,2} \\ 0 & Q_{2,2} - l_2 \end{bmatrix} \quad (5.28)$$

With these fundamental transformations in place, H_C can be defined using Pauli-Z gates, enabling the construction of the QAOA circuit for this specific example:

$$H_C = (Q_{1,1} - l_1)IZ_0 + (Q_{2,2} - l_2)Z_1I + (Q_{1,2})Z_1Z_0 \quad (5.29)$$

As described in (5.25), the QAOA circuit implemented using Qiskit is illustrated in Fig. 5.3. The circuit begins with a layer of Hadamard (H) gates applied to all qubits, creating a superposition state that allows the system to explore the entire solution space simultaneously. Following this, R_z gates are applied to introduce rotations based on the linear terms in the H_C , with each rotation parameterized by γ . Quadratic terms are incorporated through R_{zz} gates, which introduce pairwise interactions between qubits, also parameterized by γ . Finally, prior to measurement, the H_M is implemented using R_x gates, parameterized by β , to enable transitions between states and ensure thorough exploration of the solution space. For further details, refer to Chapter 4.

After measuring the qubits, a classical optimizer, such as COBYLA [128], ADAM [127], or similar algorithms, is employed to iteratively adjust γ and β , refining the parameters to minimize the cost function. This example is designed to provide a conceptual overview of the procedure and the construction of the circuit, focusing on the structure and workflow of the algorithm. Specific numerical values and implementation details are intentionally omitted, as the emphasis is on illustrating the general methodology rather than producing a precise computational result.

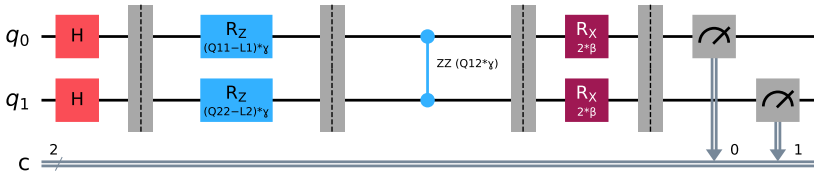


Figure 5.3: QAOA Circuit MIMO 2×2 .

It is important to recognize that MLD inherently involves an exhaustive search for all possible solutions. For example, in the case of BPSK with two

users, there are four potential symbol combinations to evaluate. When additional variables are introduced, such as adjusting transmission power to examine variations in BER results or modifying the number of transmitted bits, the complexity increases significantly. Each variation requires multiple iterations and the construction of distinct QAOA circuits. Furthermore, altering the power allocation coefficients directly impacts system performance, as these coefficients affect the relative signal strength of each user. Specifically, the BER varies as a function of transmission power, the allocated power, and the users' distances from the base station, highlighting the interplay between these parameters.

While the provided 2×2 MIMO-NOMA example is relatively simple, requiring only a small number of qubits and minimal computation, the complexity escalates rapidly with larger MIMO system configurations or more advanced modulation schemes. Scaling to massive MIMO systems introduces an enormous computational burden, rendering the direct application of QAOA impractical without significant optimization or pre-processing. To address these challenges, QAOA is implemented within specialized QC libraries, such as Qiskit by IBM Quantum or PennyLane by Xanadu. These platforms provide robust tools and optimized routines for handling the increased computational demands of larger, more complex quantum optimization problems, enabling practical applications even in resource-intensive scenarios.

5.3 Quantum MLD Results for MIMO-NOMA

This section examines the results obtained from implementing quantum MLD for MIMO-NOMA. For the 2×2 case, two users, A ($a_A = 0.8$, the weaker user) and B ($a_B = 0.2$, the stronger user), are positioned 500 and 200 meters away from the BS, respectively. Assuming BPSK modulation, a preliminary experiment transmitting 1000 bits is summarized in Fig. 5.4. This plot shows the BER as a function of transmitted power, comparing the classical MLD computed using MATLAB with the quantum MLD implemented via QAOA in Qiskit. Transmitted power is expressed relative to a reference power of 1 mW, with negative dBm values indicating lower power levels and positive values representing stronger signals.

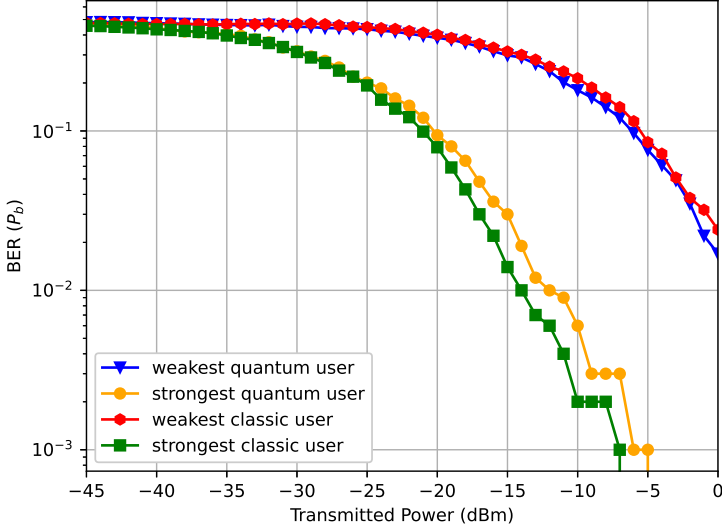


Figure 5.4: BER results for a 2×2 MIMO-NOMA system (2 users, 1000 bits).

The quantum computations were executed on IBM Quantum hardware using 1024 shots, taking approximately 12 hours due to various processing stages, including circuit transpilation, validation, queuing, and execution. Transpilation reformats the circuit to match the quantum device’s constraints by converting gates into standard basis gates and optimizing for the hardware topology. Validation ensures the circuit is compatible with the backend, while queuing and execution times depend on system load and circuit complexity. The execution phase for this experiment took 4.3 seconds, with longer times expected for more complex circuits or increased shot counts. The results indicate that both the classical and quantum MLD approaches achieve similar BER trends, where higher transmitted power leads to lower BER. The difference in BER between users A and B reflects their varying distances from the BS, as anticipated.

Increasing the number of transmitted bits to 10,000 provides smoother BER curves, as shown in Fig. 5.5. The quantum method increasingly matches classical results, demonstrating its capability to achieve similar performance in this setting. In all cases, the BER consistently decreases with higher power levels, reaffirming the effectiveness of both approaches under these conditions.

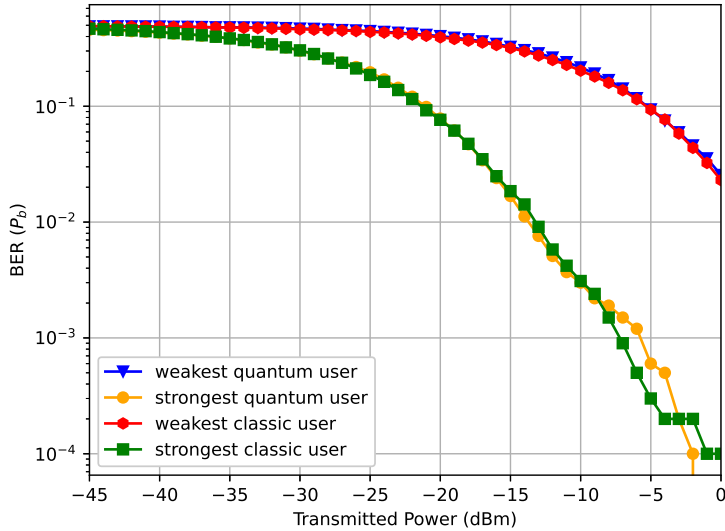


Figure 5.5: BER results for a 2×2 MIMO-NOMA system (2 users, 10,000 bits).

While the 2×2 example is computationally straightforward, scaling to larger MIMO systems or more complex modulation schemes significantly increases the computational demands. For instance, a 4×4 MIMO-NOMA system with users at distances $d = [100, 120, 150, 200]$ meters and power coefficients $a_k = [0.1, 0.15, 0.25, 0.5]$ presents a more challenging scenario. Figure 5.6 shows that the resemblance between classical and quantum results diminishes due to the increased influence of quantum circuit noise and hardware limitations. Despite this, quantum methods show promising precision as the optimization problem grows in complexity.

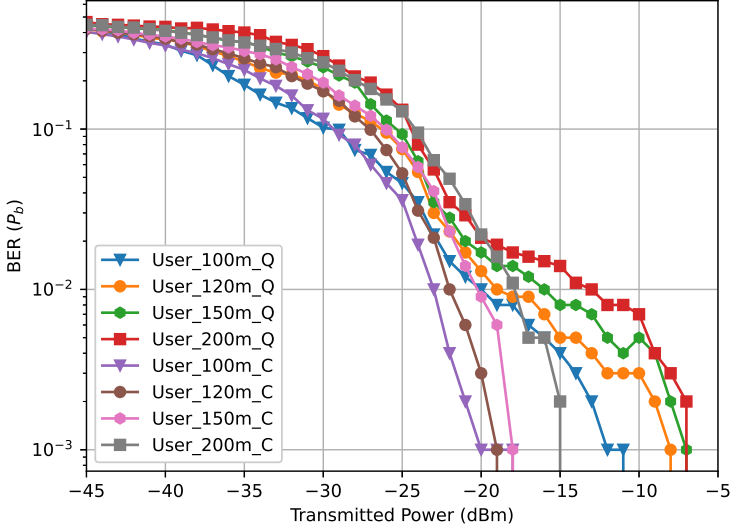


Figure 5.6: BER results for a 4×4 MIMO-NOMA system (4 users, 1000 bits).

The quantum circuit for the 4×4 case is depicted in Fig. 5.7. Constructed based on vector $\mathbf{l}$ (5.30) and matrix $\mathbf{Q}_{4 \times 4}$ (5.31), the circuit starts with Hadamard gates for superposition, followed by R_z and $R_z z$ gates for linear and quadratic terms parameterized by γ . Finally, R_x gates implement the H_M , parameterized by β .

$$\mathbf{l} = [L_1, L_2, L_3, L_4] \quad (5.30)$$

$$\mathbf{Q}_{4 \times 4} = \begin{bmatrix} Q_{1,1} - l_1 & Q_{1,2} & Q_{1,3} & Q_{1,4} \\ 0 & Q_{2,2} - l_2 & Q_{2,3} & Q_{2,4} \\ 0 & 0 & Q_{3,3} - l_3 & Q_{3,4} \\ 0 & 0 & 0 & Q_{4,4} - l_4 \end{bmatrix} \quad (5.31)$$

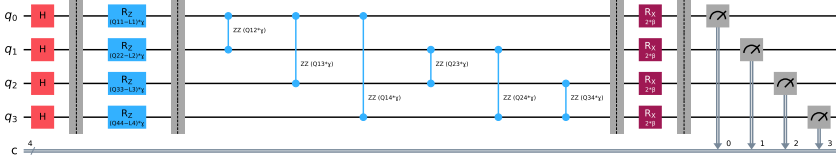


Figure 5.7: QAOA circuit for a 4×4 MIMO-NOMA system.

Exploring Larger Quantum Systems and Limitations

Expanding to a 7×7 system, where users are positioned at $d = [100, 110, 120, 150, 200, 220, 250]$ meters, highlights the growing utility of IBM Quantum simulators (Fig. 5.8). These simulators provide insights into the scaling behavior of quantum circuits, allowing researchers to test error correction strategies and study the impact of noise. While simulator results are not exact replicas of real quantum hardware behavior, they offer valuable guidance for algorithm design and system evaluation.

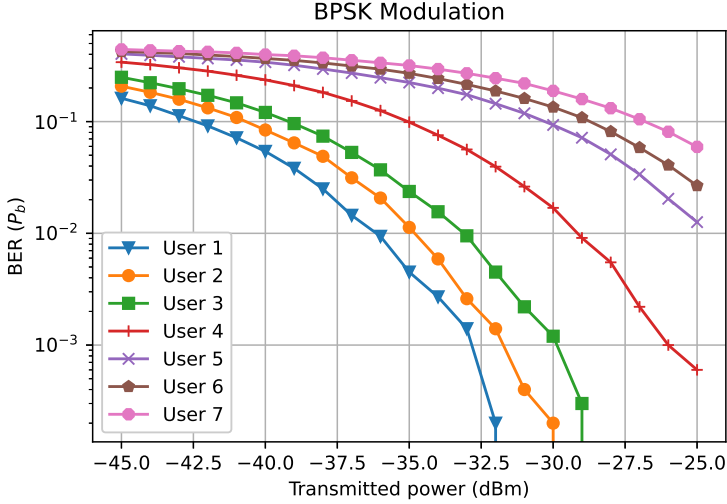


Figure 5.8: BER results for a 7×7 MIMO system (7 users, 10,000 bits).

Figure 5.9 further illustrates the relationship between readout error probabilities and the number of shots required to achieve a 95% confidence level

for BER computation. Reducing measurement errors significantly lowers the required shot count, directly impacting computation time. For instance, decreasing the error rate from 45% to 30–40% reduces the shots from 1024 to 64, improving computational efficiency by a factor of 16.

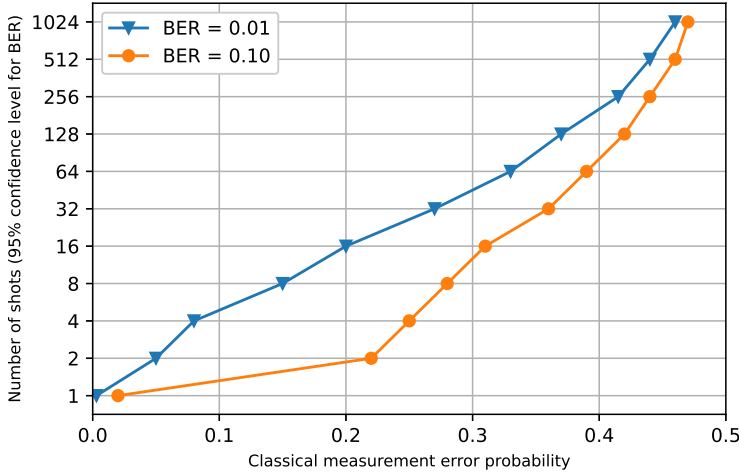


Figure 5.9: Number of shots required for computing BER at a 95% confidence level under varying readout error probabilities.

In summary, while current quantum hardware has limitations in terms of qubit numbers and noise levels, the integration of QAOA into frameworks such as IBM Quantum and PennyLane enables scalable prototyping of quantum circuits for complex communication systems. These advances pave the way for future applications of quantum MLD in wireless technologies, especially as quantum devices improve in capability and reliability.

5.4 Conclusions

This chapter has introduced a novel MLD framework based on QC, addressing one of the core research objectives of this Thesis [172]. By exploring the inherent capabilities of MIMO and NOMA technologies, the proposed approach demonstrates the transformative potential of integrating QC into next-generation wireless communication systems. The synergy between these

advanced paradigms promises unprecedented scalability and computational efficiency, redefining how future networks tackle complex signal processing tasks.

To contextualize the proposed solution, a comprehensive review of the state-of-the-art was conducted, focusing on the intersection of quantum computing with MIMO and NOMA architectures. This critical assessment laid the groundwork for the developed methodology, highlighting both the promising opportunities and the technical challenges that define this emerging research area.

A complete MLD scheme leveraging the QAOA algorithm was presented to address the computational complexity inherent in joint MIMO-NOMA detection. The chapter provides a step-by-step explanation of the proposed quantum detector, offering insight into its design rationale and operational mechanisms. The results obtained through this approach underscore the significant performance improvements achievable through quantum technologies. These findings not only validate the effectiveness of the quantum-enhanced MLD design but also reveal the potential of quantum systems to outperform their classical counterparts.

By providing compelling evidence of the potential quantum advantage within wireless communication contexts, this chapter lays a solid foundation for future investigations into the integration of MIMO, NOMA, and QC. The insights gained herein offer a promising outlook for both theoretical advancements and practical implementations in this rapidly evolving field.

Chapter 6

Conclusions and Future Work

6.1 Concluding Remarks

The main goal of this doctoral Thesis was to investigate the fundamental principles of quantum mechanics and Quantum Computing (QC) in order to propose quantum-based solutions for potential challenges in future wireless communication networks, taking the Sixth Generation (6G) as a reference. Specifically, the work examined how quantum technologies might enhance the performance, security, and efficiency of next-generation wireless systems. To this end, several QC-based applications were developed and tailored to the specific requirements of 6G communication.

First stage in this work was a careful review of current developments in quantum computation and communication pertinent to 6G. Together with the developing ideas of the “quantum network” and “quantum internet,” this review included a thorough analysis of several quantum communication systems including Quantum Key Distribution (QKD), Quantum Teleportation, and Superdense Coding. By offering ultra-secure data transmission systems and launching whole new networking paradigms, these innovative technologies could transform wireless communication. Notwithstanding their general relevance, the thesis focused especially on QC methods and how they may be included into important 6G future applications.

The main programming environment chosen for design, implementation, and testing the quantum-based solutions suggested throughout the research was Qiskit Software Development Kit (SDK). Developed by IBM, Qiskit is

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

an open-source framework providing interface with genuine quantum hardware as well as tools for building and simulating quantum circuits. Experiments using IBM Quantum systems were carried out to confirm the viability and performance of the suggested uses. Using both simulated and physical quantum processors, the work was able to offer useful understanding of the possibilities and constraints of QC in the framework of next-generation wireless networks.

Within this scope, the study looked at how QC might be used to improve several facets of 6G networks, including indoor localization, routing optimization, multi-user detection, Multiple-Input Multiple-Output (MIMO) communication, and Non-Orthogonal Multiple Access (NOMA) signal detection. For example, a first study investigated the idea of quantum Euclidean distance to improve positioning precision and underlined its possibilities for exact indoor localization in next communication systems. Using a classical optimizer to fine-tune a parameterized quantum circuit, Variational Quantum Algorithms (VQAs) were presented in the field of multi-objective routing optimization to solve some of QC's present constraints. One interesting instance is the Quantum Approximate Optimization Algorithm (QAOA), a particular class of VQAs, used to address routing problems in gate-based QC systems.

Moreover, by means of quantum computers, QAOA was applied to solve the Maximum Likelihood Detection (MLD) problem in MIMO-NOMA. Given that MLD is a Non-Deterministic Polynomial-Time (NP-hard) problem, traditional computers find great computing difficulty especially in cases with huge constellation sizes. The exponential growth in viable signal combinations makes traditional methods unable to effectively identify ideal solutions. Conversely, QC uses quantum parallelism to analyze several solutions concurrently, hence enabling quicker and more accurate detection in challenging MIMO-NOMA settings.

Through these investigations, this Thesis underscores the promising role of quantum-based solutions in guiding the development of future wireless networks. In light of these findings, it is important to revisit each hypothesis originally proposed in this work and demonstrate how the research outcomes address and validate them:

- Hypothesis 1: Although QC remains in its early stages, it has already demonstrated potential in supporting emerging 6G technologies through proof-of-concept applications that leverage quantum mechanical principles such as superposition and entanglement. The literature review conducted in this Thesis, along with the presented use case applications, serves to evaluate this premise. These initial demonstrations indicate that the distinctive advantages of QC, including exponentially enhanced computational capabilities and more secure communication, could serve

as key enablers for next-generation wireless networks. Consequently, continued research in this field is expected to accelerate the advancement of sophisticated 6G solutions, highlighting the critical role that quantum-based approaches may play in shaping the future of wireless communication.

- Hypothesis 2: The Euclidean distance, a well-established metric in classical computing, can indeed be computed on quantum hardware by leveraging intrinsic quantum-mechanical properties. Such an approach may ultimately yield performance advantages over classical methods, particularly for computationally demanding tasks. During the development of this thesis, quantum-based Euclidean distance calculation remained an unexplored area. In contrast to measuring dissimilarities between two classical vectors, comparing quantum states requires a distinct set of strategies. Accordingly, Chapter 3 introduces the swap test operator as the core mechanism for implementing a quantum version of the Euclidean distance, alongside the necessary methods for encoding classical vectors into quantum states via amplitude embedding. To showcase the feasibility of this technique, the quantum Euclidean distance is applied to an indoor localization scenario that is relevant for future communication networks. In this example, the proposed method assesses the Received Signal Strength Indicator (RSSI) from eight antennas over the course of two iterations. Although both the number of antennas and iterations can be extended based on the computational capabilities of the quantum hardware, the setup is intentionally kept simple to highlight the essential principles. The results demonstrate that quantum computers can effectively compute Euclidean distance for this use case, thereby supporting the hypothesis and indicating that such calculations hold promise for next-generation tasks in indoor positioning and beyond.
- Hypothesis 3: Although QC currently resides in the Noisy Intermediate-Scale Quantum (NISQ) era, it is still feasible to conduct meaningful demonstrations of quantum routing optimization on existing quantum hardware. By leveraging QAOA, both single-objective and multi-objective optimization problems were formulated and solved, revealing the potential benefits of quantum techniques in enhancing future network performance, especially once quantum technology matures. A practical use case, based on Software-Defined Networking (SDN), further exemplifies this approach. The results imply that, even at this early stage, quantum-based methods can pave the way for more sophisticated and robust networking solutions, potentially improving key metrics such as Quality of Service (QoS) and throughput.

- Hypothesis 4: MLD is widely regarded as an optimal strategy for minimizing error probability; however, its computational demands are quite substantial. As detailed in Chapter 5, a quantum-based solution was introduced for MLD in MIMO-NOMA systems, employing QAOA to address the NP-hard nature of the detection problem. Thanks to the principles of superposition and entanglement in quantum mechanics, QC can offer tangible benefits that may overcome the complexity barriers associated with classical methods. Although the examples presented are necessarily limited by the current capabilities of quantum hardware, these constraints are likely to diminish as the technology matures, paving the way for more efficient and robust communication systems.

6.2 Future Research Lines

This Ph.D. Thesis establishes a solid foundation for multiple future research directions at the intersection of QC and 6G wireless communications. As both QC and next-generation wireless technologies continue to evolve at a rapid pace, sustained investigation and adaptability will be crucial. It is important to contextualize the findings, methodologies and conclusions presented herein within the technological landscape at the time of this research. The quantum algorithms, devices, and frameworks discussed are subject to continuous refinement, and thus, the relevance and applicability of the proposed contributions should be assessed in light of ongoing advancements in the field.

The following key areas merit further investigation:

- The fields of QC and its applications in wireless communications are evolving at an unprecedented pace. Therefore, frequent updates and comprehensive reviews of the state-of-the-art are necessary to ensure that research remains aligned with the latest technological advancements and breakthroughs. This will enable the identification of novel opportunities and the adaptation of quantum techniques to emerging challenges in 6G networks.
- The computation of the Euclidean distance on a quantum computer is fundamentally different from classical approaches. Investigating alternative quantum algorithms and methodologies for solving the quantum Euclidean distance problem is crucial, as it may lead to more efficient and scalable solutions, particularly in the context of high-dimensional quantum data processing.
- Beyond wireless communications, the quantum Euclidean distance can be leveraged in various Machine Learning (ML) applications. For in-

stance, clustering algorithms such as K-means, which are widely used in communication networks for tasks like user clustering and resource allocation, could benefit from quantum speedups. Exploring the integration of quantum-based distance computation with ML techniques could open new avenues for optimizing network operations.

- Routing optimization in communication networks is an ongoing challenge, particularly as networks scale and become increasingly complex in 6G and beyond. Given the anticipated growth in network size and the need for multi-objective optimization, further research should explore quantum algorithms for routing optimization. Investigating larger-scale network scenarios and incorporating additional performance metrics will be essential in preparing for the quantum-enhanced future of wireless networking.
- Quantum-based MLD holds promise in improving the performance of high-order modulation schemes, large-scale MIMO systems, and NOMA architectures. Future research should focus on extending quantum MLD to higher-order constellations and larger MIMO/NOMA configurations. Additionally, exploring alternative quantum algorithms beyond the QAOA for performance benchmarking could provide further insight into the most suitable approaches for quantum-assisted signal detection in next-generation wireless networks.

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