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Minimizing Power Consumption of MIMO Network Using A Novel Quantum Genetic Algorithm

B.Sc. Dissertation

by

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Abstract

In this thesis, we delve into the captivating domain of minimizing power consumption in Multiple-Input Multiple-Output (MIMO) networks, harnessing the potential of a novel Unconstrained Quantum Genetic Algorithm (UQGA). The research endeavors to bridge the realms of quantum computing and communications, laying a solid foundation by presenting fundamental knowledge and techniques in these fields. An exhaustive exploration of existing classical and quantum genetic algorithms is undertaken, delineating the state-of-the-art methodologies in this domain.

The thesis presents a meticulously designed downlink MIMO model catering to a large-scale user and base station scenario, providing a robust framework for the subsequent optimization endeavors. Drawing inspiration from the Quantum Extreme Value Searching Algorithm (QEVSA), a groundbreaking Unconstrained Quantum Genetic Algorithm (UQGA) is crafted to address the inherent power consumption challenges of the MIMO system. The UQGA demonstrates its prowess by adeptly optimizing the overall power consumption of the proposed downlink MIMO system, paving the way for enhanced energy efficiency and sustainability.

Moreover, the research entails the computation of parameter setups tailored to the UQGA, meticulously fine-tuning the algorithm for optimal performance. A comparative analysis of the computational complexity of both classical and quantum genetic algorithms is conducted, shedding light on the efficiency gains offered by the UQGA. To validate the efficacy of the proposed approach, a robust simulation environment is meticulously crafted, enabling thorough examination of the UQGA's performance in realistic scenarios.

The thesis showcases the profound impact of the novel unconstrained quantum genetic algorithm in minimizing power consumption within MIMO networks, revolutionizing the field and opening up new avenues for future research. Through a comprehensive analysis of the experimental results and simulations, the potential of the UQGA is unequivocally demonstrated, propelling the advancement of energy-efficient communication systems in the era of quantum computing.

STUDENT DECLARATION

I, **Areeba Tabassum Shoaib**, the undersigned, hereby declare that the present BSc/ thesis work has been prepared by myself and without any unauthorized help or assistance. Only the specified sources (references, tools, etc.) were used. All parts taken from other sources word by word, or after rephrasing but with identical meaning, were unambiguously identified with explicit reference to the sources utilized.

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Budapest, 1 June 2023

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Areeba Tabassum Shoaib

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Thank you for being the shining stars that have illuminated my path and made this journey truly remarkable.

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Acronyms

MIMO: Multiple Input Multiple Output

SISO: Single Input Single Output

SIMO: Single Input Multiple Output

MISO: Multiple Input Single Output

UCGA: Unconstrained Classical Genetic Algorithm

QEVSA: Quantum Extreme Value Searching Algorithm

UQGA: Unconstrained Quantum Genetic Algorithm

QBC: Quantum Blind Computing

QKD: Quantum Key Distribution

ACO: Ant Colony Optimization

PSO: Particle Swarm Optimization

Chapter 1

Motivation

With an increase in connected devices and data traffic, wireless networks have the challenge of offering fast, dependable connections while consuming as little energy as possible. MIMO (Multiple-Input, Multiple-Output) systems provide improved capacity without requiring additional bandwidth. However, the increasing complexity of MIMO systems consumes a large amount of electricity, raising issues about energy efficiency and sustainability. As networks progress to more complex architectures such as 5G, optimizing power utilization in MIMO systems becomes increasingly important. Developing solutions for power optimization in MIMO networks is not only a research challenge, but it is also critical for long-term worldwide connection.[1]–[3]

Quantum computation revolutionizes optimization, cryptography, and machine learning by leveraging qubits and quantum principles. With exponential acceleration and parallel processing, quantum algorithms like Shor's and Grover's offer significant advantages over classical counterparts, enhancing speed and efficiency. These advancements have broad implications, from compromising cryptography to improving optimization and data analysis. They offer exponential acceleration, resulting in quicker computations and more efficient solutions [4], [5].

MIMO technology has revolutionized wireless communication, but it remains difficult to optimize power consumption and energy efficiency [2]. This study explores the capabilities of Unconstrained Quantum Genetic Algorithm (UQGA) in minimizing the overall power usage of MIMO system. The proposed quantum strategy exploits the power of Quantum Blind Computing (QBC) and Quantum Extreme Value Searching Algorithm (QEVSA) in handling the search in a vast and unsorted search space/database.

In this research, I showed that the UQGA can be utilized as an embedded tool in the computational process of MIMO system, Moreover, I demonstrated through rigorous analysis and experimental investigations that the UQGA can minimize the total power usage and dramatically reduce the computational complexity of the MIMO system [1].

The second chapter examines the background of quantum computing and communication. This chapter provides a comprehensive overview of fundamental quantum computing concepts and principles, such as quantum computing postulates, quantum entanglement, no-cloning theorem, quantum teleportation, quantum parallelism, and Grover’s Algorithm. By delving into these topics, the second chapter of the thesis provides the requisite background on quantum computing for subsequent chapters.

Moving forward to the third chapter, an in-depth overview of Multiple-Input Multiple-Output (MIMO) technology is provided. It outlines the basics of MIMO systems, their benefits, and the ways in which they can be used in wireless communication.

As we embark on the next phase, the fourth chapter unveils a groundbreaking innovation: the Unconstrained Quantum Genetic Algorithm (UQGA). Exploiting the power of quantum blind computing and quantum extreme value searching algorithm, the UQGA enhances the search process of the unconstrained classical genetic algorithm (UCGA). This chapter comprehensively scrutinizes state-of-the-art classical optimization algorithm metaheuristics and deterministic approaches, elucidating their underlying principles, inherent strengths, limitations, and diverse applications. Furthermore, it introduces pioneering concepts such as the quantum extreme value searching algorithm and quantum blind computing, which serve as groundbreaking cornerstones for propelling the field of optimization to new heights.

In the fifth chapter, an innovative and pioneering Unconstrained Quantum Genetic Algorithm (UQGA) is judiciously employed within the intricate framework of a downlink Multiple-Input Multiple-Output (MIMO) system. This pragmatic and empirically driven application serve as an incontrovertible testament to the formidable efficacy of the UQGA in effectuating substantial reductions in power consumption and computational complexity. Moreover, the chapter unveils a methodical and painstakingly thorough approach for accurately estimating the stochastic parameters of the UQGA, thereby potentiating its optimization prowess to unprecedented levels. Through an astute exhibition of the UQGA's real-world performance and an incisive analysis of pivotal metrics, this chapter bestows priceless insights into the algorithm's pragmatic implications and tangible benefits, thus safeguarding its scholarly merit and originality.

In the sixth chapter, a meticulous and comprehensive analysis is undertaken to scrutinize the efficacy of the UQGA in mitigating power consumption in Multiple-Input MIMO systems. The researcher executed extensive computational simulations utilizing intricate configurations, sophisticated methodologies, and stringent performance metrics. Through assiduous examination of the simulation outcomes, they derived profound insights into the algorithm's feasibility and its capacity to attain optimal power optimization.

The seventh chapter of this dissertation serves as a succinct and perspicacious synthesis of the notable findings and seminal contributions elicited throughout the meticulous research endeavor. Moreover, it delves into a comprehensive and meticulous scrutiny of potential constraints, meticulously navigating the intricacies and subtleties inherent in the obtained results. By cogently elucidating the multifaceted implications and far-reaching ramifications of the findings, it engenders a nuanced and profound understanding of the research's substantive significance and transformative impact. Furthermore, it propounds a captivating and intellectually stimulating exploration of hitherto unexplored frontiers, beckoning future scholars to embark upon novel and uncharted pathways of erudition and discovery within this field of inquiry.

Chapter 2

Introduction

2.1 Quantum Computing Overview

In classical computing, the smallest unit of information is referred to as a "bit" and can be represented by one of two states, "0" or "1"; these states are also known as classical states. The classical processor carries out a variety of transformations on classical states, i.e., information processing using classical gates. Comparable to classical computing, Quantum computing employs specific quantum elements that do not exist in traditional computation. It is important to note that there are four primary postulates that describe quantum computer, and they are as follows [6]:

2.1.1 Postulates of Quantum Computing

First postulate (State-space)

A qubit is the fundamental quantum systems unit in the quantum universe that can simultaneously contemplate both classical states, referred as superposition. Below is an illustration of a qubit:

$$|\varphi>=a|0>+b|1>, \tag{2.1}$$

Where a and b are complex coefficients, and $|0>$ and $|1>$ are the so-called computational basis states:

$$\left(|0>=\begin{bmatrix}1\\0\end{bmatrix}\right),\left(|1>=\begin{bmatrix}0\\1\end{bmatrix}\right), \tag{2.2}$$

such that,

$$|a|^2+|b|^2=1. \tag{2.3}$$

In the realm of quantum computing, a qubit, which is the fundamental unit of quantum information, can indeed exhibit the coexistence of two classical states. An illustrative example of a qubit can be conceived by considering the outcome of a fair coin flip. Let us assume that the coin is unbiased, such that the probability of obtaining either a head or a tail is equal, i.e., 0.5 for each outcome.

In the context of quantum computing, it is imperative to emphasize that the quantum state $|\varphi>$ associated with the qubit exists as a superposition of two distinct states. The explicit formulation of this superposition, denoted by equation (2.1), can be expressed academically as follows:

$$|\varphi \geq a \begin{bmatrix} 1 \\ 0 \end{bmatrix} + b \begin{bmatrix} 0 \\ 1 \end{bmatrix}. \tag{2.4}$$

Second postulate (Evolution)

In the framework of quantum computing, the second postulate concerns the evolution of a quantum state. In the context of quantum computing, a quantum gate is essentially a unitary operator denoted as U. The fundamental characteristic of a unitary operator is that it adheres to a specific formula, which can be stated as follows:

$$U * U = UU^* = I, \tag{2.5}$$

Where, U^* denotes the conjugate transpose (also known as the adjoint or Hermitian conjugate) of the unitary operator U, and I represent the identity operator.

Quantum gates are fundamental building blocks of quantum circuits. A crucial distinction between quantum gates and classical gates lies in their reversibility. Quantum gates are reversible, whereas classical gates are not. Another significant aspect is that a unitary transformation preserves the unit norm of a quantum state.

Assuming that $|\psi>$ is the input quantum state and $|\psi'>$ is the output quantum state obtained after applying the unitary transform U (as depicted in Figure 2.1), the relationship between $|\psi>$ and $|\psi'>$ can be described as follows:

$$|\psi' \geq U|\psi>, \tag{2.6}$$

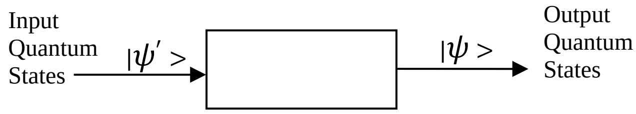

Figure 2.1: The Relationship between the Input Quantum State, the Output Quantum State, and the Unitary Operator U.

Here, U represents the corresponding output gate or unitary operator that acts on the

input quantum state $|\psi >$ to produce the output state $|\psi' >$.

Quantum gates in quantum circuits manipulate and alter qubits, similar to logic gates in digital circuits. Unlike logic gates, quantum gates are reversible, allowing for easy conversion between input and output quantum states.

Some well-known quantum gates that operate on a single qubit presented in (2.7) are given as follows:

$$|\varphi > = a|0 > +b|1 > \Longrightarrow \begin{bmatrix} a \\ b \end{bmatrix}. \tag{2.7}$$

- **Pauli-X gate:** It is often referred to as the classical "not gate" in traditional computing, It operates on quantum states by flipping the amplitudes of the $|0 >$ and $|1 >$ states.

$$|\psi > = X|\varphi > = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} b \\ a \end{bmatrix} = b|0 > +a|1 >. \tag{2.8}$$

- **Pauli-Y gate:** It exchanges the probability amplitudes of the quantum states and introduces a phase factor of $-j$ (the imaginary unit) when applied to the computational basis state.

$$|\psi > = Y|\varphi > = \begin{bmatrix} 0 & -j \\ -j & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \begin{bmatrix} -Jb \\ Ja \end{bmatrix} = -Jb|0 > +Ja|1 >. \tag{2.9}$$

- **Pauli-Z gate:** It alters the quantum state by multiplying the probability amplitude of the computational basis state $|1\rangle$ by -1.

$$|\psi> = Z|\varphi> = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \begin{bmatrix} a \\ -b \end{bmatrix} = a|0> - b|1>. \tag{2.10}$$

- **Hadamard-gate:** All quantum algorithms rely heavily on this operator during their startup phase. It is well known that when the Hadamard gate is dominated by classical states, uniform probability distributions of all computational basis states are generated.

$$|\psi> = H|\varphi> = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \begin{bmatrix} \frac{a+b}{\sqrt{2}} \\ \frac{a-b}{\sqrt{2}} \end{bmatrix} = \frac{a+b}{\sqrt{2}}|0> + \frac{a-b}{\sqrt{2}}|1>. \tag{2.11}$$

It is worth emphasizing that the application of the Hadamard operation on the states $|0>$ and $|1>$ yields the following results, respectively.

$$H|0> = \frac{|0> + |1>}{\sqrt{2}}, \tag{2.12}$$

And,

$$H|1> = \frac{|0> - |1>}{\sqrt{2}}. \tag{2.13}$$

Third postulate (Measurement)

It is important to note that directly observing a quantum state is impossible. The only way to determine its state is by conducting a measurement. These measurements are represented by measurement operators, denoted as M_m, where m represents a potential measurement outcome. The probability of obtaining the measurement outcome m when the quantum system is in the state $|\varphi>$ can be expressed as follows:

$$P(m||\varphi>) = |\varphi>^{+} M_m^{+} M_m |\varphi>, \tag{2.14}$$

where the adjoint of M_m is denoted by M_m^+ and the adjoint of $|\varphi >$ is denoted by $|\varphi >^+$. The measurement apparatus is viewed as a connection between the classical and quantum worlds; hence, in order to validate the precision of the constructed measurement apparatus, the following completeness relationship needs to be satisfied:

$$\sum_m M_m^+ M_m \equiv I. \tag{2.15}$$

Fourth postulate (Composite systems)

This postulate describes a quantum register. The term "quantum register" refers to the component that is created when numerous quantum states are grouped together using a mathematical technique called the "tensor product." Take, for instance, the case where there are three qubits available. In order to combine these three qubits into a single quantum register, we will make use of the tensor product.

The first qubit can be represented in the following manner:

$$|\varphi_1 >= \frac{1}{\sqrt{2}}(|0 > +|1 >) \tag{2.16}$$

While the second and third qubits are respectively described as,

$$|\varphi_2 >= \frac{1}{\sqrt{2}}(|0 > +|1 >) \tag{2.17}$$

$$|\varphi_3 >= \frac{1}{\sqrt{2}}(|0 > +|1 >) \tag{2.18}$$

It is possible to achieve the composite of these three qubits in the following manner:

$$|\varphi> = \frac{1}{\sqrt{2}}(|0> + |1>) \otimes \frac{1}{\sqrt{2}}(|0> + |1>) \otimes \frac{1}{\sqrt{2}}(|0> + |1>) = \tag{2.19}$$

$$= \frac{1}{\sqrt{2^3}}(|0> + |1> + |2> + |3> + |4> + |5> + |6> + |7>).$$

2.1.2 Quantum Entanglement

The entanglement of qubits represents a unique connection between two or more qubits, where measuring the state of one qubit allows us to determine the state of the other qubit. Quantum entanglement can be achieved using a specialized quantum gate called the Controlled NOT (CNOT) gate, illustrated in Figure 2.2. This gate has two inputs and two outputs. One input is designated for data, while the other serves as a control. If the control input is set to one, the output data is reversed; whereas, if it is set to zero, the output data remains unchanged. Entanglement enables faster-than-light communication between entangled states, a phenomenon exclusive to quantum computing and absent in the classical world. However, it's important to note that quantum entanglement is fragile and can be easily disrupted. Measurement destroys the entanglement behavior of the quantum state. Nevertheless, quantum entanglement is a powerful tool extensively utilized in various applications, including quantum teleportation, superdense coding, and other areas of quantum information theory.

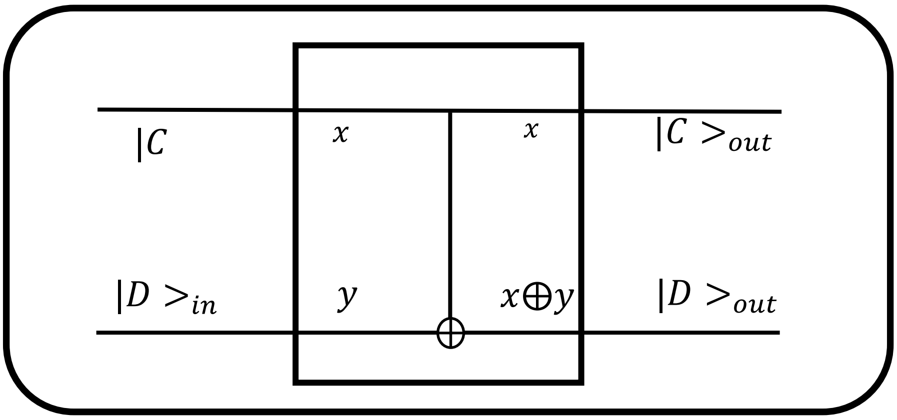

Figure 2.2: Controlled NOT gate.

The explicit formula of the CNOT gate is written as:

$$CNOT: |x> |y> \rightarrow |x> |y \oplus x>. \tag{2.20}$$

The Bell States are widely recognized as the most famous entangled states. They can be generated by utilizing both the Hadamard Gate and the CNOT Gate. Figure 2.3 depicts a circuit that produces a Bell state.

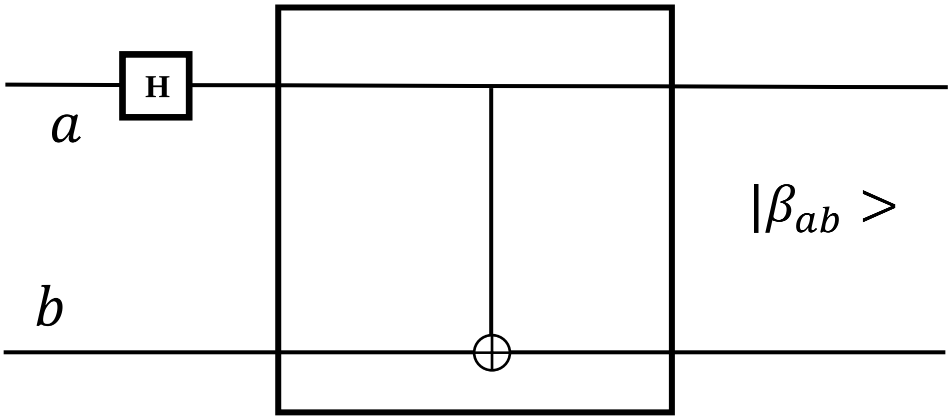

Figure 2.3: Circuit for producing Bell states.

The circuit illustrated in Figure 2.3 is designed to create four unique pairs of entangled "Bell states." Here is a sequential list of these states, arranged by priority.

$$|\beta_{00}> = \frac{|00> + |11>}{\sqrt{2}} \quad (2.21)$$

$$|\beta_{01}> = \frac{|01> + |10>}{\sqrt{2}} \quad (2.22)$$

$$|\beta_{10}> = \frac{|00> - |11>}{\sqrt{2}} \quad (2.23)$$

$$|\beta_{11}> = \frac{|01> - |10>}{\sqrt{2}} \quad (2.24)$$

2.1.3 No-cloning Theorem

According to the no-cloning theorem in quantum computing, it is not possible to create an exact copy of an arbitrary unknown quantum state. This applies to both recognized quantum states and orthogonal quantum states. The theorem states that it is impossible to clone quantum states perfectly, meaning that one cannot create identical backups of quantum states in advance in quantum computing. The no-cloning theorem has significant implications for various applications in quantum information processing. For example, it prohibits the cloning of quantum states in quantum key distribution (QKD), a secure communication method that relies on the principles of quantum mechanics. The inability to clone the generated key ensures its security against eavesdroppers. In summary, the no-cloning theorem establishes the fundamental limitation of cloning unknown quantum states and plays a crucial role in areas such as quantum cryptography. It is essential to understand and respect this theorem when working with quantum systems and exploring the possibilities and limitations of quantum information processing.

2.1.4 Quantum Teleportation

Quantum teleportation comprises a series of steps. First, the object to be transmitted is divided into smaller constituents, such as electrons and photons, which adhere to the laws of quantum mechanics. These particles are then transmitted through a channel, which can be either classical or quantum in nature. Finally, the object is received and recreated at the destination, often situated in a different location or cabin. Throughout this process, the principles of quantum computing enable the transfer of information or properties from one location to another, offering unique possibilities for secure and efficient communication[6].

There are two approaches to teleporting an object: utilizing either a quantum channel or a classical channel.

- **Quantum Channel:** The quantum channel method for teleportation involves transmitting an object through a dedicated quantum channel. However, this approach poses significant challenges in establishing a reliable and error-free transmission channel capable of quantum error correction. Consequently, using a quantum channel for teleportation is considered impractical and unsafe. The inherent difficulties in maintaining the integrity of quantum information during transmission can lead to undesired outcomes, such as receiving unexpected entities on the receiving end [6].
- **Classical Channel:** The classical channel method offers an alternative approach to teleporting objects. It involves segmenting, encoding, and transmitting the object through a classical channel. At the receiving end, the data is reconstructed. However, this method theoretically requires an infinite number of measurements for accurate recreation. Quantum teleportation remains a challenging task that requires ongoing advancements and solutions [6].

Let's consider a scenario where Alice and Bob intend to teleport a single qubit. To achieve this, they need to follow a series of steps. Initially, Alice and Bob must share a Bell pair denoted as $|\beta 00\rangle$. Afterward, Alice applies a sequence of operations, such as CNOT and

Hadamard gates, to her qubits. Subsequently, Alice performs a measurement, obtaining a result that she sends to Bob using a classical communication channel. Finally, Bob can retrieve the original qubit sent by Alice by applying one of the following gates: I gate, ZX gate, X gate, or Z gate [6].

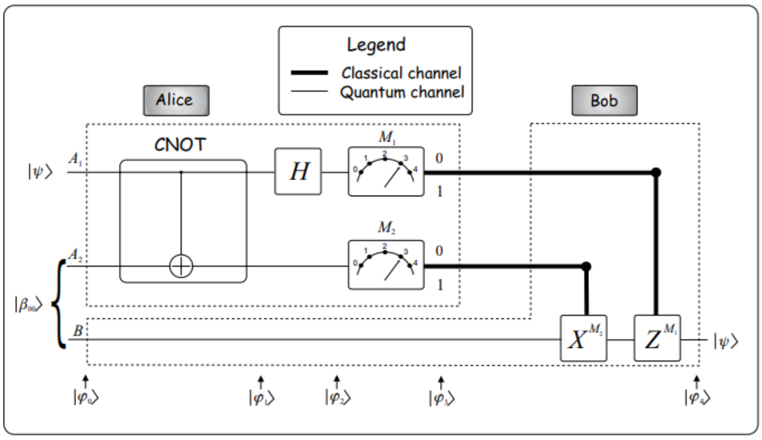

Figure 2.4: The teleportation scenario

2.1.5 Grover’s Algorithm

Grover's algorithm offers a highly efficient approach to locating a desired item within an unsorted database, resulting in a substantial reduction in computational complexity [6]. In contrast to classical searching methods that require N steps to find the target, Grover's algorithm achieves the same outcome in just $\sqrt{N}$ steps, representing a significant speedup. It's worth noting that any quantum algorithm consists of three key components [6]:

- Initialization: Prepare a quantum register by applying an identical number of Hadamard gates to achieve a uniform probability amplitude distribution. Set the register to the $|0>$ state.
- Quantum Parallelism: Process all computational basis states simultaneously, leveraging the inherent parallelism of quantum computing.
- Amplification: Amplify the probability amplitude of the target item, driving it towards convergence to 1. This step enhances the chances of finding the desired solution.

The structure of Grover's algorithm is depicted in Figure 2.5. It illustrates the sequence of steps involved in the algorithm's strategy.

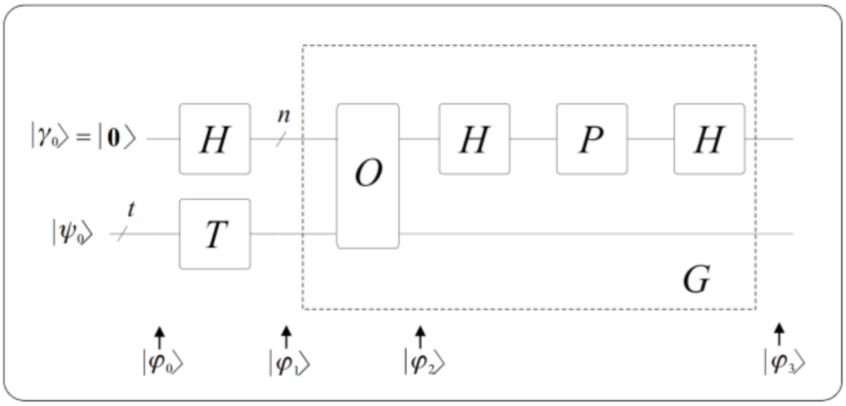

Figure 2.5: Circuit implementing the Grover operator.

The initialization step of Grover's algorithm involves applying a Hadamard gate to the auxiliary qubit. Subsequently, the Grover operator is applied, which comprises several other operators [6]. The first operator is the Oracle, responsible for multiplying the desired states by -1. To amplify the probability amplitude of the target results, the inversion about the average method is employed using HPH gates. The Grover operator needs to be applied multiple times in succession to enhance the amplitude of the desired searched item. The optimal number of times to apply the Grover operator is approximately $\frac{\pi}{4}\sqrt{\frac{N}{M}}$, where N represents the total number of items in the database, and M corresponds to the number of occurrences of the searched item.

2.2 Conclusion

In conclusion, the inaugural chapter of this thesis provided an incisive and comprehensive introduction to the realm of quantum computing, meticulously focusing on its elemental postulates and pivotal algorithms. The chapter was designed with the explicit intention of acquainting the reader with the bedrock principles underlying quantum computing and furnishing a panoramic overview of indispensable quantum algorithms. By delving into the fundamental postulates of quantum computing and delving into critical algorithms, we attained profound insights into the distinctive properties and potential computational advantages conferred by quantum systems. This chapter acts as a crucial steppingstone for the subsequent foray into advanced quantum algorithms, scrutiny of quantum computing architectures, and meticulous analysis of the practical complexities and considerations encompassing quantum technology. As we journey forward in this thesis, we shall embark upon a more profound exploration of sophisticated quantum algorithms, delve into the intricacies of quantum computing architectures, and meticulously evaluate the pragmatic implications and challenges intrinsic to quantum technology. Collectively, this chapter provides a robust and substantial groundwork for comprehending the tenets and algorithms of quantum computing, paving the way for further inquisition and research within this captivating and rapidly advancing domain.

Chapter 3

Overview About MIMO System

Since Marconi's initial experiments in the late 1800s, there has been a remarkable advancement in communication technology, particularly in the realm of wireless communications. What once began as a fascination has now evolved into high-capacity networks that offer fast and consistent data transmission. Today, wireless technology finds applications in various fields, ranging from widespread voice services that can replace fixed line services to the establishment of wireless local area networks in residential, office, and public settings. Additionally, personal area networks, like Bluetooth connections, enable wireless interactions between different consumer electronic devices. However, the pursuit of enhancing wireless communications' capabilities, including improved throughput and reliability, continues unabated [7]–[10].

Furthermore, the landscape of wireless technology is poised to transcend conventional boundaries and flourish in multifarious environments, teeming with unprecedented possibilities. However, amidst the burgeoning proliferation of wireless applications, the perennial conundrum of bandwidth scarcity persists, akin to the era of Marconi's groundbreaking endeavors. This dearth of available bandwidth has impelled an ardent quest for pioneering transmission strategies that defy the status quo. Amidst this fervent quest, the emergence of MIMO systems has catalyzed an upsurge of research zeal in recent years, captivating the scholarly community with its uncharted vistas and tantalizing promise.

3.1 History About MIMO

The history of Multiple-Input Multiple-Output (MIMO) technology traces back to the late 1980s and early 1990s when researchers started exploring the idea of utilizing multiple antennas for wireless communication systems [11]. The concept of MIMO gained significant attention due to its potential to improve the spectral efficiency and reliability of wireless links [7], [11]. In the late 1990s, pioneering research by Gerard J. Foschini and Michael J. Gans demonstrated the potential capacity gains of MIMO systems through spatial multiplexing and diversity techniques. The breakthroughs led to a surge of interest in MIMO, both in academia and industry. The early 2000s witnessed the adoption of MIMO in various wireless standards, including the IEEE 802.11n (Wi-Fi) and 3GPP (LTE) standards. These deployments marked a significant milestone in MIMO technology, enabling higher data rates and improved link performance. In subsequent years, further advancements in MIMO techniques, such as multiuser MIMO and massive MIMO, have continued to revolutionize wireless communications, forming the foundation for modern wireless networks and future 5G and beyond systems [7], [8], [11].

The primary objective of the MIMO systems is to enhance communication quality and expand the capacity of wireless channels. The MIMO systems involve the use of multiple antennas at both ends of the communication link. The rank of a MIMO system is determined by the total number of antennas employed. For instance, a 2x2 MIMO system utilizes two transmit antennas and two receive antennas. The MIMO systems enable the transmitter to transmit multiple data streams simultaneously through the utilization of multiple antennas. At the receiving end, the various antennas receive this combined information, which has been intertwined with other streams prior to transmission. Through signal processing techniques, the receiver separates and recovers the original data into its constituent streams [11].

The MIMO technology confers numerous advantages in the realm of wireless communication, thereby revolutionizing its efficacy. Primarily, it augments the overall capacity of the system by enabling the simultaneous transmission of multiple data streams through distinct antennas, as depicted in Figure 3.1. This breakthrough allows for heightened data rates, superior spectral efficiency, and the capability to accommodate a greater number of users concurrently. Moreover, MIMO technology bestows the advantage of spatial diversity, thereby mitigating the adverse effects of fading and interference. This, in turn, culminates in improved reliability and expanded coverage, ensuring a seamless and uninterrupted communication experience. Furthermore, MIMO systems can attain superior signal quality and diminished error rates, thereby elevating the overall performance of the communication infrastructure. In summation, the MIMO technology assumes a pivotal role in optimizing the efficiency, capacity, and dependability of wireless communication systems [2].

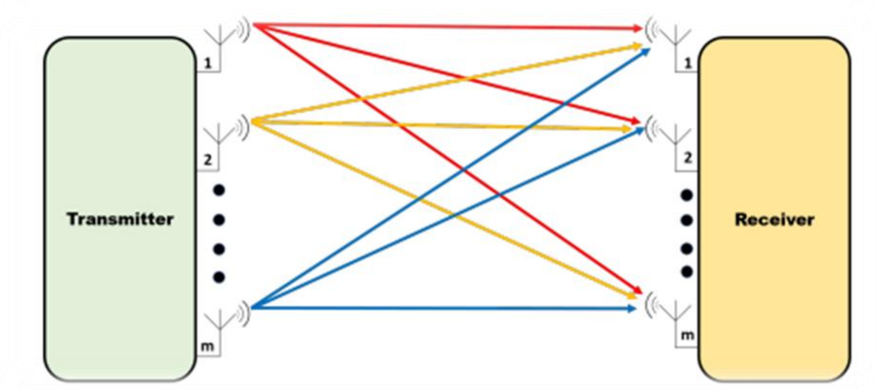

Figure 3.1: Multiple-input multiple-output (MIMO) link, in which the transmitting base station directs three separate spatial beams at the receiver.

The Multiple-Input Multiple-Output (MIMO) systems have emerged as a captivating and consequential realm of investigation owing to their multifaceted advantages and profound influence on wireless communication systems. Researchers have diligently delved into diverse facets of MIMO technology, fervently striving to augment its performance, optimize system capacity, and devise ingenious algorithms [12]. This chapter offers a comprehensive overview of the MIMO paradigm, meticulously elucidating its manifold benefits and underscoring its indispensable significance within the context of 5G networks.

3.2 Exploring the Diverse World of MIMO Antenna Configurations

The MIMO is a technology that uses multiple antennas at both transmitter and receiver to exploit multipath propagation that increases the data capacity of the radio frequency (RF) link [7]. The MIMO has been widely used in various communication standards, including Wi-Fi, WiMAX, HSPA+, and LTE. The basic structure of a MIMO system is shown in Figure 3.2.

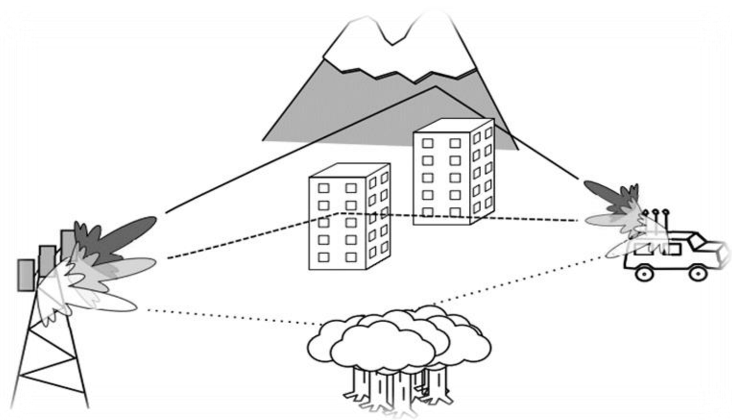

Figure 3.2: Basic MIMO Structure

The first description of the MIMO channels was discovered in 1970 by A.R. Kaye and D.A George, and in 1974, Branderburg and Wyner did a capacity analysis of MIMO [7], [10]. The receiver structure of MIMO was developed in 1975 by W. van Etten. The major breakthrough in MIMO, the concept of spatial multiplexing, was developed in 1993 by A. Paulraj and T. Kailath. Then Bell Labs demonstrated the first prototype of MIMO spatial multiplexing in 1998. The spatial multiplexing here drastically improved the performance of MIMO communication systems. In 2001 Iospan Wireless Inc. developed the first commercial system using MIMO with OFDM. Then various standards were developed in later years: IEEE 802.11n (2006), IEEE 802.11e WiMAX (2006), and 3GPP HSDPA, LTE standards (2008).

There are four basic antenna configurations in MIMO systems. The different antenna technology for MIMO is :

a. SISO

The Single Input Single Output (SISO) is the simplest form of radio link which has a single antenna on the transmitter side and a single antenna on the receiver side. This configuration doesn’t use any diversity, and no additional computations are required. This system is impacted the most by the interference and noise, and bandwidth is also limited by Shannon’s capacity [12]–[14]. A SISO antenna configuration is shown in Figure 3.3.

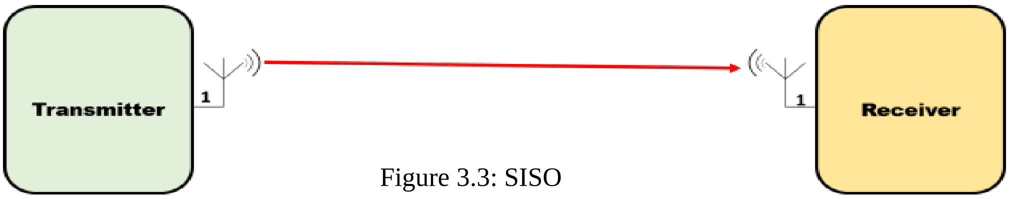

Figure 3.3: SISO

b. SIMO

The Single Input Multiple Output (SIMO) has one antenna on the transmitter side and multiple antennas on the receiver side. The SIMO antenna configuration is also known as the receive diversity [12]–[14]. In SIMO, the transmitted signals are combined at the receiver, which reduces the effect of fading and interference. A SISO antenna configuration is shown in Figure 3.4.

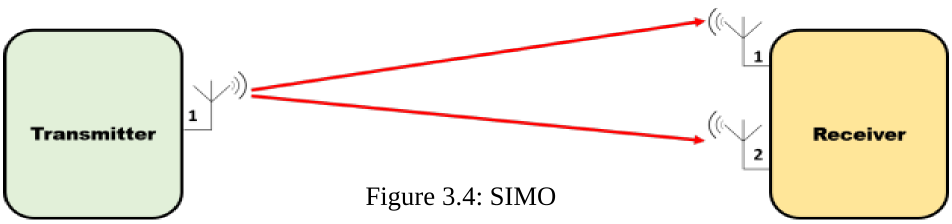

Figure 3.4: SIMO

c. MISO

The Multiple Input Single Output (MISO) configuration has multiple antennas on the transmitter side and a single antenna on the receiver side. In the MISO system, the same data is transmitted redundantly from the different transmitting antenna, which enables the receiver to receive the optimum signal. This antenna configuration is also known as transmit diversity. Unlike SIMO, all the processing in MISO configuration is handled by the transmitter, which makes it useful for communicating with small devices like a cell phone with limited battery life [12]–[14]. A MISO antenna configuration is shown in Figure 3.5.

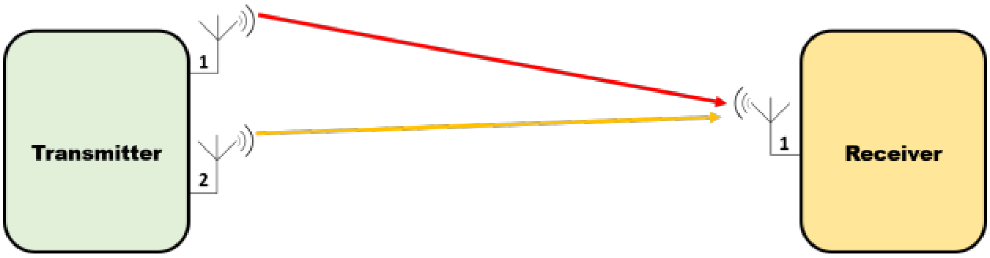

Figure 3.5: MISO

d. MIMO

The MIMO configuration has multiple antennas at both transmitter and the receiver. The MIMO configuration provides improved reliability, efficiency, and channel throughput. Simple to complex processing may be required at both transmitter and receiver depending upon the number of antennas used. A basic 2 x 2 MIMO antenna configuration is shown in Figure. 3.6.

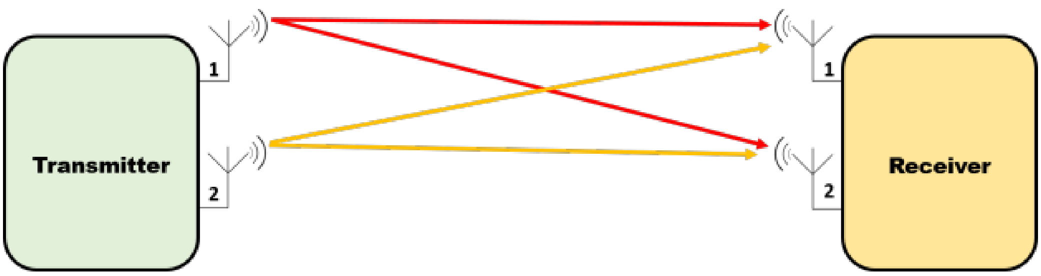

Figure 3.6: MIMO

Chapter 4

Devising A New Unconstrained Quantum Genetic Algorithm

Solving optimization problems is important in many fields because it enables researchers, engineers, and practitioners to find the best possible solutions for various challenges. Optimization plays a critical role in numerous domains. Here are some of the many reasons why optimization is important in many fields:

- **Efficiency:** Optimization lets us use our limited time, money, or energy in the most effective way possible [15]. By finding the best way to do things, we can reach our goals without wasting the least amount of time and being as productive as possible.
- **System design:** Optimization is an important part of engineering and system design because it helps find the best parameters or configurations that give the best performance, safety, and cost-effectiveness [16].

Depending on the problem and domain, optimization problems can be hard in different ways. Some of the main problems that come up when optimizing are:

- **Complexity:** Many optimization problems in the real world are very hard to solve because they have a lot of variables, constraints, and interactions. Because there are so many possible solutions, it can take a long time to find the best one.
- **Nonlinearity:** In many optimization problems, the relationships between the variables are not linear. This can lead to more than one local optimum, which makes it hard to find the global optimum.

To overcome these challenges, researchers and practitioners employ various optimization techniques, including linear and nonlinear programming, evolutionary algorithms, metaheuristic algorithms, and hybrid methods. They also develop problem-specific heuristics and approximations to find near-optimal solutions in a reasonable amount of time.

Deterministic (heuristic) and metaheuristic optimization methods are approaches used to find approximate solutions to complex optimization problems. These methods are especially useful when exact solutions are either impossible or computationally expensive to obtain.

In the context of optimization problems, deterministic algorithms are utilized quite frequently; the linear and nonlinear programming approaches are among the most well-known of these [17]. No matter how many times we re-execute the heuristic algorithm, it always provides an accurate answer for the produced inputs, even going so far as to forecast what the next step will be. It is important to point out that the traditional deterministic algorithms that are used in computer applications consistently fail to perform the search appropriately when some of the input parameters are missing, the size of the database is very large, or there are many local minima. This is because these factors all contribute to a more difficult search (or many local maximum).

Metaheuristic algorithms have gained significant attention because they offer solutions that are highly relevant to real-world applications. Unlike deterministic optimization methods, which struggle to reach the optimal solution, metaheuristic algorithms consistently generate satisfactory outcomes. Additionally, when compared to other heuristic optimization strategies, metaheuristic approaches are capable of delivering high-quality solutions in a shorter timeframe.

There are numerous optimization algorithms designed to tackle different types of optimization problems. Some of the most widely used optimization algorithms include:

Ant Colony Optimization (ACO): This algorithm is classified as a metaheuristic algorithm that belongs to the category of probabilistic techniques used for solving computational problems [18]. It particularly focuses on finding optimal paths within graphs. ACO is inspired by the behavior of real ants and employs artificial ants as agents. The computational complexity of ACO is expressed as $O(n^2)$, indicating its time complexity in relation to the problem size. The limitation of this computational complexity is that it can become computationally expensive for large problem instances. As 'n' increases, the number of iterations and computations required by the algorithm also increases significantly. This can result in longer execution times and may make the algorithm impractical or inefficient for very large problem sizes.

Particle Swarm Algorithm (PSO): This algorithm is a metaheuristic optimization technique inspired by the collective behavior of bird flocks or fish schools. It iteratively improves a population of particles representing potential solutions by adjusting their positions based on their own previous best solution and the global best solution discovered by any particle. PSO starts with random initialization of particles in the search space and continues updating their positions until a stopping criterion is met. The computational complexity of PSO is generally moderate, with a time complexity of $O(N * D)$, where N, is the number of particles and D, is the problem's dimensionality. As the number of particles or the problem's dimensionality increases, the computational cost of PSO also increases proportionally. However, actual performance may vary depending on the implementation and problem characteristics.

Genetic Algorithm (GA): Genetic Algorithm is a classic metaheuristic search method that is used to solve optimization problems such as function optimization, machine learning, and scheduling problems [19]. It is based on Charles Darwin's ideas about how things change over time. This strategy can be used as a simulation on a computer, and the new solution can be used in the next iteration of the algorithm. They operate on a population of candidate solutions and use concepts from biology, such as selection, crossover (recombination), and mutation, to evolve the population towards better solutions.

Computational complexity is closely linked to the specific operations utilized in the optimization process, particularly crossover and mutation. In the worst-case scenario, the computational complexity is $O(gnm)$ steps for a genetic algorithm, where n represents the population size, m indicates the size of the individuals (genomes), and g denotes the number of generations.

Based on the preceding discussion, it can be inferred that traditional optimization algorithms, including heuristic and metaheuristic techniques, exhibit limitations in terms of computational complexity and solution quality. They also face challenges when confronted with new practical tasks. However, it is crucial to acknowledge that these traditional optimization strategies have laid the foundation for the development of numerous advanced approaches that prove invaluable in tackling complex modern applications.

This research aims to enhance the search capability of Genetic Algorithms by integrating quantum computing into the existing framework. The primary focus is on developing a novel approach known as the Unconstrained Quantum Genetic Algorithm (UQGA). In order to gain a comprehensive understanding of the developed UQGA, it is essential to have prior knowledge of related algorithms, including Unconstrained Classical Genetic Algorithm (CGA) and Quantum Extreme Value Searching Algorithm (QEVSA). These algorithms will be thoroughly discussed in subsequent subsections to provide the necessary background for comprehending the advancements introduced by the UQGA.

4.1 Unconstrained Classical Genetic Algorithm

The Unconstrained Classical Genetic Algorithm (UCGA) stands as an evolved variant of the Genetic Algorithm (GA), meticulously tailored to tackle optimization quandaries devoid of any explicit limitations imposed upon the variables or the solution space. Within the framework of UCGA, a meticulously crafted assemblage of prospective outcomes, denoted as individuals or chromosomes, takes shape through a randomized initialization process or by virtue of a meticulously devised algorithmic approach. Each distinctive individual therein serves as an intricate embodiment of a potential solution, intimately entwined with the very essence of the optimization quandary at hand.

The UCGA follows an iterative process inspired by biological evolution to improve the population over multiple generations. It incorporates three main operations: selection, crossover, and mutation. In the selection phase, individuals are chosen from the current population based on their fitness or objective function value. This selection process favors individuals with higher fitness, increasing the probability of preserving their genetic material for the next generation.

During the crossover phase, a pivotal stage in the evolutionary process, meticulously chosen individuals undergo genetic recombination, facilitating the exchange of genetic material segments to engender offspring [15]. This intricate process emulates the fundamental principles of mating and inheritance observed in biological evolution, striving to amalgamate beneficial traits from disparate individuals, thereby fostering the potential for the emergence of enhanced solutions.

The mutation phase introduces small random changes in the genetic material of the offspring [15], [16]. This introduces diversity into the population, allowing exploration of new regions of the search space that may contain better solutions.

The newly generated offspring, resulting from crossover and mutation, replace a portion of the least fit individuals in the current population. This means that the individuals with lower fitness values are removed from the population and replaced by the newly generated offspring, which are expected to potentially possess better or improved fitness values.

By replacing the least fit individuals, the algorithm aims to gradually improve the overall fitness of the population over successive generations. This allows the algorithm to explore and exploit the search space more effectively, as the fitter individuals have a higher chance of producing better offspring in subsequent generations.

The precise proportion of the least proficient individuals subject to substitution may exhibit variability contingent upon the algorithm's instantiation and the selection strategy adopted. This process could encompass the substitution of a predetermined quantity or a distinct proportion of the most substandard individuals. The integration of this substitution mechanism actively propels the population towards superior solutions, augmenting the overarching optimization endeavor aimed at attaining satisfactory or even optimal resolutions.

This process continues for multiple generations until a termination criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory solution.

There are various versions of UCGAs, and the version we will discuss follows a specific process, as shown in the flowchart in Figure 4.1. In this version, the algorithm begins by randomly generating a population of chromosomes, where each chromosome represents a potential solution. Fitness evaluation is then performed to assess the quality of each chromosome based on a defined fitness function. Next, a selection process is applied to choose the fittest individuals, by selecting half of the chromosomes with the highest fitness values. Crossover and mutation operators are then applied to create offspring, promoting genetic diversity, and introducing small variations. The parents (selected individuals) and the offspring generated through crossover and mutation are merged to form the new population for the next generation. This merging ensures that the good solutions from the previous generation are retained while introducing new genetic material. The process of fitness evaluation, selection, crossover, and mutation is repeated iteratively for a certain number of generations or until a termination criterion is met. By mimicking natural evolution, the algorithm explores the search space and converges towards optimal or near-optimal solutions to the problem at hand .

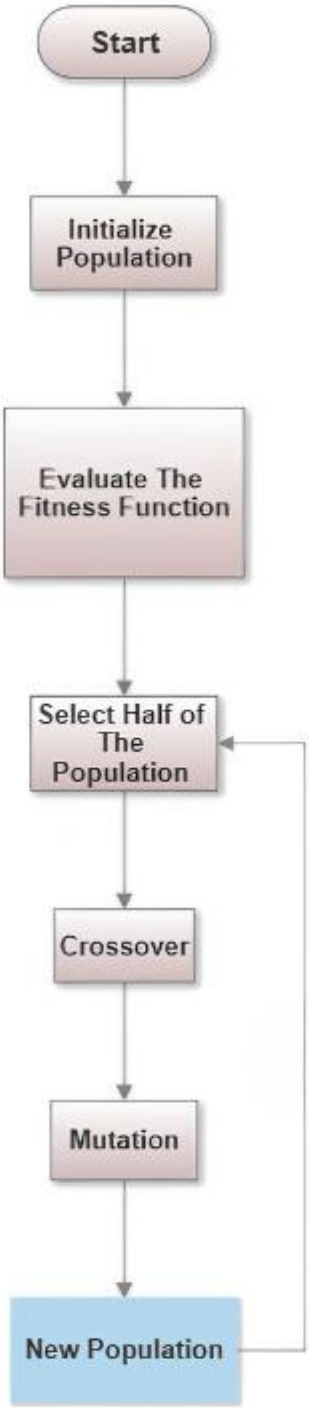

Figure 4.1: The Working Methodology Of UCGA

4.2 Quantum Extreme Value Searching Algorithm

The Quantum Extreme Value Searching Algorithm (QEVSA) is an innovative approach to quantum optimization that excels in locating the maximum or minimum value of an unconstrained objective function [20]. This groundbreaking method seamlessly integrates two key elements: the ingenious binary search algorithm and the extraordinary power of Quantum Existing Testing (QET).

QET is a specialized algorithm that is derived from the quantum counting algorithm [21]. While the quantum counting algorithm is designed to determine the frequency of a specific value in a database, the QET focuses on answering a fundamental question: whether the searched value or item exists within the given database.

What makes the QET particularly fascinating is its ability to handle unsorted databases. Typically, traditional search algorithms rely on a sorted database for efficient searching. However, the QET allows the logarithmic search algorithm within QEVSA to operate optimally even in the absence of a sorted database [21]. The answer provided by the QET is either a definitive "Yes" if the value is present or a conclusive "No" if it is not found. The QET is a critical component of the QEVSA in contributing to its effectiveness in solving optimization problems.

In summary, the QET plays a crucial role within the QEVSA by efficiently determining whether the searched value exists in an unsorted database. Its integration with the logarithmic search algorithm enhances the overall performance and effectiveness of QEVSA in solving optimization problems.

The QEVSA is represented as follows:

---

1. We start with $S = 0$: $G_{min\ 1} = G_{\min 0}$, $G_{max\ 1} = G_{\max 0}$, $and\ \Delta G = G_{\max 0} - G_{\min 1}$
2. $S = S + 1$
3. $G_{med\ s} = G_{\min s} + \left[\frac{G_{\max s} - G_{\min s}}{2}\right]$
4. $flag = QET\ (G_{med\ s})$:
   - If the flag is YES then $G_{\max s+1} = G_{med\ s}$, $G_{\min s+1} = G_{min}$,
   - or else $G_{\max s+1} = G_{\max s}$, $G_{\min s+1} = G_{med}$
5. If $S < \log_2(T)$ then it goes to step 2 else stop, and the result is $G_{med\ s}$

The parameter T indicates the maximum number of steps that must be taken in order to execute the QEVSA's logarithmic searching algorithm, and the value G refers to the unconstrained objective function. The QET $(G_{med\ s})$ function has one variable $G_{med\ s}$ which denotes the value of the point that divides the database horizontally into two subregions

The working methodology of algorithm is described below [21]:

1. Initially, we have a function $y = g(x)$ that takes an integer input x and gives an integer output y.
2. The goal of the algorithm is to determine the smallest possible value that the function $g(x)$ can produce. In other words, the algorithm aims to find the minimum output value, y, of the function $g(x)$ within the given range $[G_{\min 0}, G_{\max 0}]$.
3. The algorithm starts by dividing the search space into two subregions. It calculates $G_{med\ s}$, which is the middle value that separates the two subregions.
4. The quantum existence testing algorithm, represented by the function $QET(z)$, is then used to check if there is a marked state (indicating a value less than z) in the lower subregion or not.
5. If there is a marked state in the lower subregion, it means the minimum value must be in that subregion. So, the algorithm proceeds to the next searching step using the lower subregion as the new search space.
6. If there is no marked state in the lower subregion, it means the minimum value must be in the upper subregion. So, the algorithm proceeds to the next searching step using the upper subregion as the new search space.
7. The algorithm continues this process recursively, halving the search space in each step, until it eventually finds the minimum value.

By combining the classical binary search technique with the quantum existence testing, this algorithm is able to efficiently search for the minimum value in an unsorted database. It reduces the number of queries required compared to classical approaches.

The computational complexity (CC) of the QEVSA depends on two aspects[1], [21]:

- ❖ The computational complexity of the Binary Search Algorithm (BSA) incorporated within the QEVSA is expressed as $O(\log_2(T))$, where T is the maximum number of steps needed to run the logarithmic search..

❖ The computational complexity of the Quantum Existing Testing (QET) algorithm is represented by $O\left(log_2^3(\sqrt{N})\right)$, where N is the entry size of the database. In this case, $N = 2^a$, where a represents the total number of required qubits relative to the size N of the database.

A schematic representation of the QEVSA as minimum searching algorithm example is illustrated in Figure 4.2 [22].

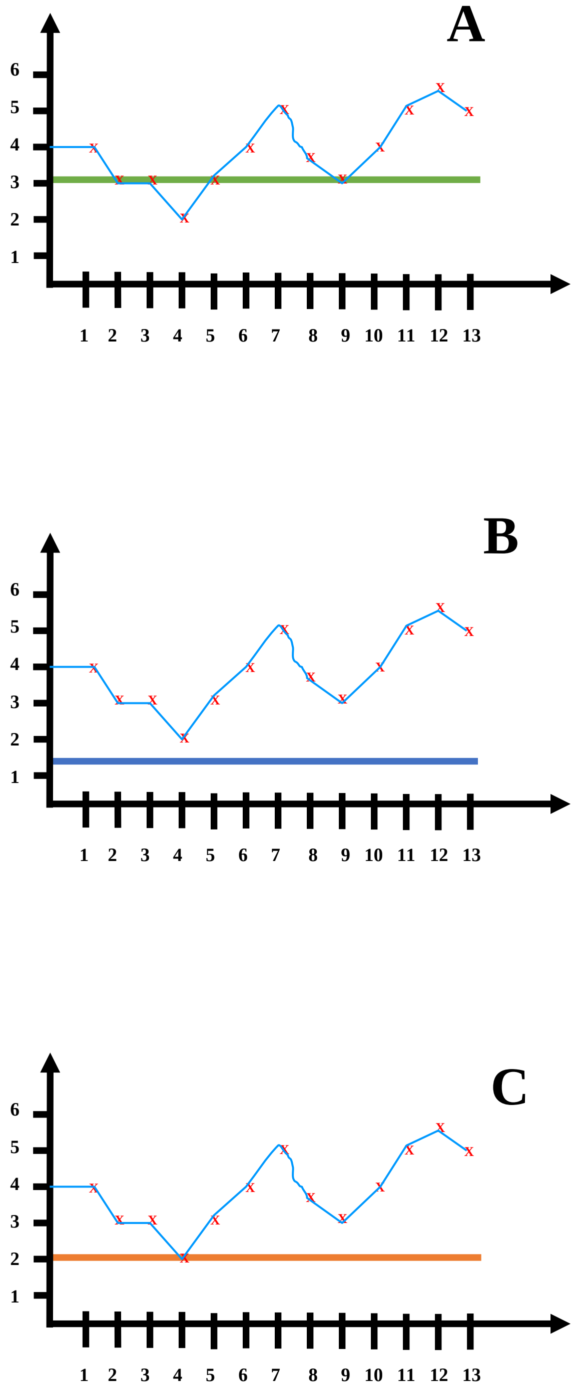

Figure 4.2: The Description Of The QEVSA As A Quantum Minimum Searching Algorithm.

4.3 Quantum Blind Computing

QBC focuses on securing the computation itself rather than solely focusing on securing the communication channel used in quantum computing[1], [23]. The QBC involves a user or client sending multiple computational tasks to other quantum nodes or servers for processing. The key aspect of the QBC is that the quantum nodes or servers that perform the computation are unable to reveal any information about the input or output of the computation to the owner of the quantum computer (referred to as the server or sender). In other words, the client's computational tasks are processed by the quantum nodes, but the nodes do not disclose any details about the specific data or results to the owner of the quantum computer. Preserving privacy in Quantum Blind Computing (QBC) is crucial as it empowers clients to assign computational tasks to external quantum nodes while safeguarding the secrecy of their sensitive data. By preventing the quantum nodes from accessing or divulging any information pertaining to the input or output, the QBC bolsters the security and confidentiality of quantum computations. It is important to acknowledge that the particulars and methodologies involved in implementing QBC can differ, and ongoing research and development continue to explore various approaches and applications in this domain. [23] .

4.4 Unconstrained Quantum Genetic Algorithm

In this dissertation, a novel variant of the Unconstrained Quantum Genetic Algorithm (UQGA) is proposed and introduced. This newly developed algorithm presents an innovative approach to solving optimization and search problems. By integrating innovative techniques, the quantum version of the UCGA strives to overcome challenges such as getting trapped in local minimums and achieving rapid convergence to the optimal solution. Through the utilization of quantum principles and advanced exploration strategies, this enhanced algorithm aims to effectively escape local minimums that hinder traditional optimization algorithms. Additionally, leveraging the inherent parallelism and computational capabilities of quantum systems, the quantum UCGA seeks to converge towards the optimal solution swiftly, enabling efficient and accelerated optimization processes. Through extensive experimentation and analysis, the efficacy and efficiency of the proposed algorithm are evaluated and compared against existing UQGA variants and other state-of-the-art optimization techniques. The introduction of this new UQGA version contributes to the evolving field of evolutionary computation and provides researchers and practitioners with an additional tool to tackle complex optimization problems effectively.

The UQGA aims to enhance the existing UCGA, as introduced in Section 4.1, through a series of substitutions. The following substitutions are performed to transform UCGA into UQGA:

- The conventional heuristic generation in the initialization step of the genetic algorithm is replaced with a quantum-based approach [1]. Instead of relying on heuristics, random regions comprising sets of chromosomes are selected for initialization. These randomly selected regions are then dispatched to quantum computing units by a central quantum server. Within these quantum computing units, the previously defined stochastic method called QEVSA is applied to extract the best chromosomes or individuals from the selected regions. It is important to note that the population size is denoted by S, and the size of each region is uniformly set to R. It is imperative to emphasize the significant impact of the quality of the initialization step in reducing the number of generations required to reach optimal or near-optimal solutions. The quality of the initialization step directly influences the initial population's composition, particularly the inclusion of high-fitness chromosomes. When the initialization step yields a population consisting of chromosomes with low fitness values, it impairs the algorithm's ability to rapidly converge towards satisfactory solutions. Consequently, a suboptimal initialization can result in a larger number of generations being required to achieve desirable solutions. Therefore, ensuring a high-quality initialization step is essential for effectively reducing the number of generations and facilitating more efficient convergence in the unconstrained quantum genetic algorithm.
- In the proposed method, the classical selection procedure is replaced with a quantum-based selection method [1]. Specifically, the QEVSA which is executed $S/2$ times to determine the best half-individuals or parents from the current population. This quantum selection process aims to identify and retain the most promising individuals for the next generation.

The proposed UQGA is presented in detail below [1]:

1. Start by setting the current step to 0 and defining parameters such as the size of the database (N), initial population (S), and the size of the region (R).
2. Generate R regions. Each region represents a subset of the search space.
3. Apply QEVSA in each region. This is a quantum algorithm that helps generate an initial population for each region.

4. The algorithm selects the first half of the population, denoted as the parent set, by applying the QEVSA $S/2$ times.
5. Apply crossover and mutation operations to the parent set. These operations combine and modify the solutions to create a new set of solutions called the offspring set.
6. Combine the parent and offspring sets to create the new population for the next step.
7. Check if the optimum solution has been found. If it has been found, then stop the algorithm. Otherwise, go back to step 4 and continue the process to further improve the solutions.

The algorithm iteratively applies the QEVSA, along with genetic operators like crossover and mutation, to evolve a population of solutions. The goal is to find the optimum solution that provides the best possible result. The algorithm continues this process until it either finds the optimum solution or reaches a predefined stopping condition. The working flowchart of UQGA is depicted in Figure 4.3.

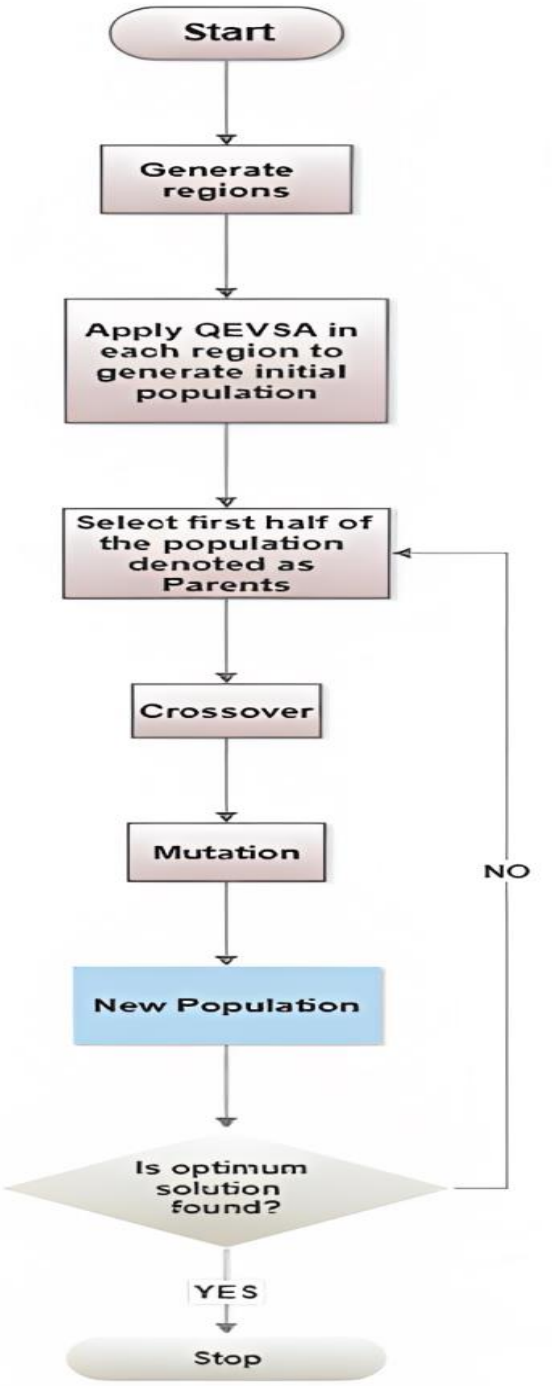

Figure 4.3: The working methodology of UQGA.

Chapter 5

Unleashing The Power of UQGA in MIMO System

5.1 MIMO Channel Model and Capacity

The MIMO system consists of a single base station outfitted with T transmit antennas [2]. In this scenario, there is only one user who possesses R receive antennas, as depicted in Figure 5.1. The channel state information is assumed to be accurately known by both the receiver and the transmitter [24].

Let L represent the total number of the MIMO channels, with $L = R \times T$.

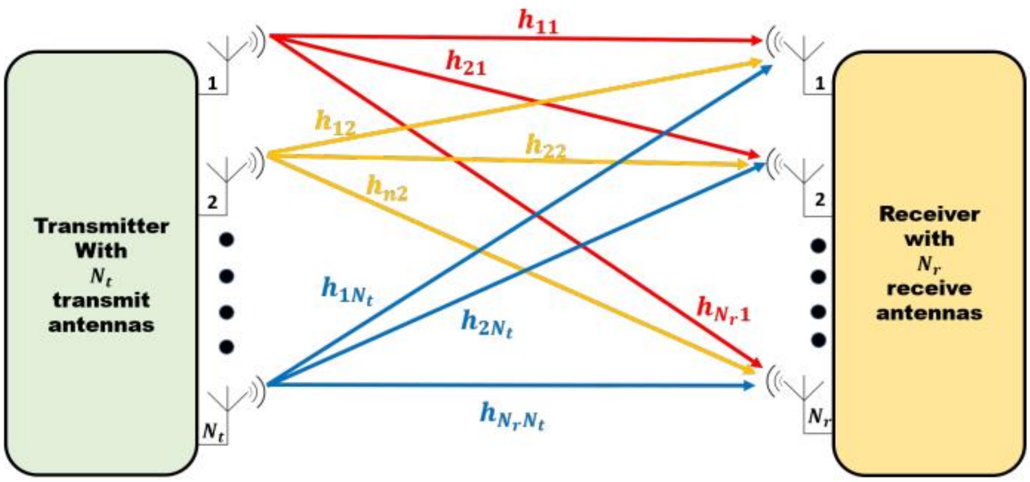

Figure 5.1: MIMO Channel Model

The transmitted signal is denoted as $x = [x_{1,}x_2, x_3, \ldots\ldots, x_T]$. The aim is to minimize power consumption while considering the user's bit rate. In any communication system, when transmitting signals, it is necessary to allocate an appropriate amount of power to each symbol being transmitted. The transmit power for a specific symbol x_t, denoted as p_j^t, is determined based on the assignment scenario j. Importantly, the value of the transmit power, p_j^t, is not fixed and can vary depending on the chosen transmit power set or range. The transmit power set or range refers to the available options for assigning power levels to the symbols during transmission. The choice of the transmit power set or range is determined by the requirements of the application or the communication system. . Applications can have diverse needs related to power usage, signal quality, and interference concerns. As a result, the transmit power values for each symbol may vary depending on the chosen transmit power range or set, which is customized to fulfill the application or system requirements. In summary, x_t signifies the t^{th} symbol in the transmission, and the transmit power p_j^t is linked to a particular assignment scenario j for that symbol. The specific transmit power value can differ based on the chosen transmit power range or set, which is established by the specific demands and limitations of the application or system.

The desired data rate, represented by B_{user}, reflects the speed at which the user intends to send or receive information. In communication systems, the data rate denotes the number of bits transmitted per unit of time, typically measured in bits per second (bps). $B_{user}$is determined based on the user or application requirements. It indicates the preferred transmission speed to meet user needs or fulfill the intended purpose. Various factors, such as the application nature, data type, and desired quality or speed of transmission, influence B_{user}. For instance, real-time streaming or high-definition video applications may have higher target bit rates compared to simple text-based communication. By considering B_{user} during optimization, the system can allocate sufficient resources like transmit power or bandwidth to achieve the desired data transmission rate. This ensures user satisfaction in terms of data speed and capacity, leading to a positive communication experience.

The transmission power of the signal x, based on assignment scenario j, is expressed as $P^j = \left[p_1^j, p_2^j, p_3^j, \dots \dots., p_T^j\right]$. This sequence consists of individual power values p_j^t, where each value corresponds to the transmission power assigned to the corresponding symbol x^t in the sequence.

The power transmission set or range, denoted as M, is suggested by the service provider. It is defined under a certain standard and consists of power values represented by $M = [p_1^s, p_2^s, p_3^s, \dots \dots., p_E^S]$. These values in the set M are ordered in increasing magnitude, $p_1^s < p_2^s < \cdots , p_E^S$. The symbol E represents the total count of elements in set M, indicating the number of power values available within the power transmission set or range.

Regarding power transmission, the set M is predetermined and encompasses a range of power values for the symbol x^t. From this set, a single value is chosen to represent the transmission power. Factors like system requirements, performance objectives, or regulatory aspects may influence the selection of this power value from set M.

To sum up, the service provider proposes a predetermined power transmission set M, which includes a series of power values arranged in a particular order. One of these values from the set M is selected to determine the power level of the symbol x^t during transmission. This pre-established range simplifies power allocation choices and guarantees adherence to the specified communication system standard.

The distribution scenario j represents a specific assignment of transmit power to the vector x. In this case, for a given scenario j, all the transmitted symbols are assigned the same power value; $p^j = [p_1^s, p_1^s, p_1^s, \dots \dots., p_1^S]$. This power assignment is represented as p^j, which consists of a sequence of power values with p_1^s repeated for all symbols.

It's important to note that the total number of distribution scenarios is denoted by Q, which is determined by the total count of elements in the set M (denoted by E) raised to the power of the symbol count (denoted by t). In other words, $\mathrm{Q} = E^t$.

Essentially, each distribution scenario j represents a specific configuration of power assignment to the symbols in the vector x. In a particular scenario j, all symbols are assigned the same power value p_1^s. The total number of possible distribution scenarios is determined by the number of elements in the power transmission set M (E) raised to the power of the symbol count (t).

Let's dive into a detailed example with numeric values to help illustrate the concept of distribution scenarios and power assignments.

Assume we have a power transmission set or range, M, consisting of four power values: $p_1^s = 1$, $p_2^s = 2$, $p_3^s = 3$, and $p_4^s = 4$. Hence, the set M can be represented as $M = [1,2,3,4]$.

Now, consider a vector x with three symbols: $x = [x_{1,} x_2, x_3]$. In this scenario, the total count of elements in set M, denoted by E, is 4. Each distribution scenario j represents a specific assignment of transmit power to the symbols in vector x. Let's explore two different distribution scenarios: scenario $j = 1$ and scenario $j = 2$:

- **Scenario $\boldsymbol{j = 1}$**: For this scenario, all symbols in vector x are assigned the same power value, $p_2^s = 2$. Hence, the power assignment for scenario $j = 1$ can be represented as $p^j = [2,2,2]$. All symbols $x_{1,} x_2$, and x_3 are assigned the power value 2.
- **Scenario $\boldsymbol{j = 2}$**: In this scenario, each symbol in vector x is assigned a different power value from set M. Let's assign the powers as follows:

  $x_{1,}$ is assigned p_3^s= 3

$x_{2,}$ is assigned p_1^s= 1

$x_{3,}$ is assigned p_4^s = 4

Therefore, the power assignment for scenario $j = 1$ can be represented as $p^j = [3,1,4]$.. Each symbol in vector x is assigned a specific power value based on this scenario.

The total number of distribution scenarios, denoted by Q, is determined by the total count of elements in set M (E) raised to the power of the symbol count (t). In our example, if $E = 4$ (four power values in set M) and $t = 3$ (three symbols in vector x), then the total number of distribution scenarios Q is equal to $4^3 = 64$.

In recapitulation, we scrutinized two distinctive scenarios concerning the dissemination of power to symbols within vector x. In scenario $j = 1$, a uniform power value was ascribed to all symbols, whereas in scenario $j = 2$, each symbol received an exclusive power allocation. The total number of plausible distribution scenarios (Q) can be derived by multiplying the aggregate count of power values (E) by the cardinality of symbols (t) encompassed within vector x.

During the transmission of a signal, the signal experiences attenuations. This means that some of the power of the transmitted signal is lost due to factors like reflections, diffraction, or absorptions. In other words, the received signal is weaker compared to the originally transmitted signal due to this loss of power.

Additionally, it is assumed that the transmitted signal does not encounter delay spread, meaning there is no delay between different parts of the signal. This implies that the signal reaches the receiver without any significant delay or distortion in its timing.

Furthermore, it is also assumed that there is no inter-symbol interference. This means that the symbols within the signal do not overlap or interfere with each other, and there is no distortion or mixing of symbols during transmission.

The signal that the user receives from the base station is represented by the following equation

$$y = Hx + n, \tag{5.1}$$

Here is what each component means:

- y: This is the received vector, which represents the signal received by the user from the base station. It has dimensions of $(R \times 1)$, where R represents the number of receive antennas. In other words, it's a column vector with R elements .

- H: This is the channel matrix, which represents the characteristics of the wireless channel between the base station and the user. It has dimensions of $(R \times T)$, where R is the number of receive antennas and T is the number of transmit antennas. Each element of the matrix H, denoted as $h_{r,t}$, represents a coefficient that models the channel gain from the transmit antenna t to the receive antenna r. These coefficients are independently and identically distributed (i.i.d.) random variables drawn from a zero mean and unit variance circularly symmetric complex Gaussian distribution $\mathcal{N}(0, 1)$. This models the Rayleigh fading phenomenon, which is a common assumption in wireless communications.
- x: This represents the signal transmitted by the base station. It has dimensions of $(T \times 1)$, where T represents the number of transmit antennas. Similar to y, it is a column vector with T elements.
- n: This is the complex baseband additive white Gaussian noise vector, which represents the noise introduced in the wireless channel. It has dimensions of $(R \times 1)$, matching the dimensions of y. Each element of n represents the noise value at the corresponding receive antenna.

The Equation 5.1 essentially states that the received signal y is the result of multiplying the transmitted signal x with the channel matrix H and adding the noise vector n.

This model is commonly used to analyze and design wireless communication systems. By understanding the characteristics of the channel matrix H, including the effects of Rayleigh fading, and accounting for the additive noise n, engineers can develop efficient signal processing algorithms to extract the transmitted signal from the received signal in the presence of noise and channel variations.

Equation 5.2 describes the capacity of a communication channel and is used as an upper bound on the achievable bit rate. At this level of modeling, the capacity is considered as the bit rate that can be achieved by utilizing channel coding techniques.

The channel (r, t) related to the distribution assignment j is described by a particular formula:

$$B_{r,t}^{j} = D.\log_2(1 + \frac{1}{N_0} g_{r,t} p_t^{j}). \tag{5.2}$$

In this context, $g_{r,t}$ signifies the channel gain, where $g_{r,t} = |h_{r,t}|^2$. The symbol D represents the bandwidth in use.

It's also worth noting that the component $\frac{1}{N_o} g_{r,t} p_t^j$ in the formula stands for the signal-to-noise ratio (SINR).

It can be readily confirmed that the aggregate bit rate of the j^{th} distribution scenario can be represented by the following Equation:

$$B^j = \sum_{t=1}^{T} \sum_{r=1}^{R} B_{r,t}^j \quad (5.3)$$

Our objective is to mathematically formulate an optimization problem to determine the optimal transmit power, denoted as P^{opt}, while ensuring that the desired user achieves a specific bit rate target, denoted as B_{user},. The term 'opt' refers to the optimum scenario in this context:

$$P^{opt} = min_{j \epsilon Q} \sum_{t=1}^{T} p_t^j \quad (5.4)$$

5.2 Implementation And Computational Complexity

Our primary objective is to minimize the power consumption of MIMO systems, a crucial aspect in enhancing the energy efficiency of real-world wireless networks. To achieve this, we employed an algorithm developed in chapter 4 called UQGA, specifically using QEVSA. By using UQGA, we can effectively search for the best configuration that minimizes power usage in MIMO systems. This chapter focuses on implementing, configuring, and dealing with the complexity of integrating UQGA in MIMO systems. Through our analysis, we aim to uncover UQGA's potential in reducing power consumption and explore its practical implications for improving the energy efficiency of real-world wireless networks.

Before we explore the detailed complexities of computation in our specific use of UQGA, it's important to understand the general complexity of UQGA. Multiple factors impact complexity, including population size, chromosome size, and the number of generations needed for convergence. This section will introduce the overall complexity of UQGA, providing a foundation for understanding its application to our specific problem.

The computational complexity of the UQGA can be expressed as:

$$O(p, m, g), \tag{5.5}$$

where,

- p represents the size of the population, indicating the number of candidate solutions considered in each generation. A larger population size generally requires more computational resources and time for evaluating, manipulating, and selecting individuals.
- m represents the size of the chromosome. The complexity of the UQGA increases as the size of the chromosome grows larger. The chromosome length depends on the specific problem and the range and precision required for representing the variables within that problem. The chromosome length should be chosen to accommodate the largest value within the search space, ensuring that it can accurately represent all practical solutions
- g denotes the number of generations needed for the algorithm to converge to an optimal solution. The computational complexity of the UQGA grows with the number of generations, as each generation involves evaluating fitness, applying quantum operations, and performing genetic operations such as crossover and mutation.

Now that we have explored the general computational complexity of the UQGA, let us shift our focus to the computational complexity specifically relevant to our MIMO application. In our variant of the UQGA, we prioritize the minimization of the number of generations g required for convergence. This key parameter, g, is influenced by two fundamental components of our approach: quantum initialization and quantum selection.

Let us initiate an academic exploration, delving into the intricate nuances of the initialization process. In traditional genetic algorithms, the initial candidate solutions play a crucial role in determining the convergence speed and effectiveness of the optimization process. These initial solutions are typically generated using classical heuristic methods, which may not always provide the best starting point for the algorithm.

To overcome this limitation and enhance the quality of the initial candidate solutions, our approach replaces the classical heuristic initialization step with a quantum one. This quantum initialization allows to generate initial solutions that have the potential to be more diverse and potentially closer to optimal solutions.

The initialization stage is crucial for optimization and search dynamics in MIMO systems. The complexity of initialization is impacted by the creation of different regions within the search space. Before using QEVSA, it is important to divide the search space into S regions. Each region represents a specific range of values for the variables in the MIMO system. This division enables more efficient exploration and improves optimization. By dividing the search space wisely, we can focus our resources on the most promising parts of the problem and narrow down the search effectively.

Our next step involves applying the QEVSA within each of these regions, to construct the initial population. The QEVSA encompasses the integration of two key elements: the ingenious binary search algorithm and the extraordinary power of the quantum existing testing. The binary search algorithm, a fundamental component of the initialization process, leverages a stochastic parameter G that represents the maximum number of steps required to run the algorithm and is equal to:

$$G = \frac{P_{max} - P_{min}}{\alpha}, \tag{5.6}$$

Where,

- ❖ $P_{max} - P_{min}$: The difference between the system's maximum and minimum power consumption
- ❖ α: The minimum distance between two possible power consumption scenarios. One writes α as,

$$\alpha = \min_{\forall\, i,j} |p_i^T - p_j^T| \tag{5.7}$$

This approach enhances the effectiveness and efficiency of the optimization process, as it focuses on exploring and capturing the extreme values within each region. Ultimately, QEVSA aids in constructing an initial population that has the potential to yield optimal or near-optimal solutions for the problem being addressed, optimization. Its main objective is to search for the minimum value within each region. The utilization of the QEVSA as the quantum minimum searching algorithm enables us to identify the minimum value within each region and construct an initial population that encompasses promising candidate solutions for the optimization problem at hand.

After completing the initialization stage, our focus now shifts to the selection stage within the UQGA framework, specifically tailored for our MIMO application. Building upon the initial population generated through the quantum initialization process, the next step is to select the first half of the population, known as the parent set. To accomplish this, we apply the QEVSA a total of $S/2$ times. This selection process plays a crucial role in determining the individuals that will contribute to the next generation and influence the overall convergence of the optimization process. By seamlessly transitioning from the initialization stage to the selection stage, we ensure a smooth progression in our understanding of the computational complexities and intricacies involved in optimizing the MIMO system using the UQGA framework.

Our analysis will focus on estimating the number of steps required for two crucial stages: the quantum initialization step and the quantum selection stage:

- During the quantum initialization step, the algorithm randomly selects sets of chromosomes, which can have similar or varied sizes. These selected sub-databases are then assigned to quantum computing units by the quantum server. This process, which requires S steps, prepares the sub-databases for quantum evaluation via QEVSA. The QEVSA is performed by the quantum computing units to identify the best individual within each sub-database. The computational complexity of this operation is estimated to require $O\left(\log_2(G) log_2^3\left(\sqrt{R}\right)\right)$ steps. To summarize, creating the initial quantum population in the UQGA involves a computational complexity of $O\left(S.\log_2(G) log_2^3\left(\sqrt{R}\right)\right)$ steps. When contrasting our version of UQGA with UCGA, a notable differentiation arises in terms of computational complexity during the initialization stage. While UCGA exhibits a computational complexity of $O(constant)$, implying a fixed number of operations, its ability to produce high-quality solutions is limited. This highlights a significant advantage of UQGA over UCGA in terms of both computational complexity and the quality of solutions achieved.
- In the quantum selection step, conventional genetic algorithms typically employ classical sorting algorithms to extract the best parent set. The computational complexity of the best classical sorting strategy is $O(S.\log_2(S))$ steps. However, instead of repeatedly using a traditional sorting method, we opt to perform the QEVSA $S/2$ times. This approach reduces the computational complexity of the process to $O\left(\frac{S}{2}.\log_2(G) log_2^3\left(\sqrt{S}\right)\right)$ steps. By utilizing the QEVSA multiple times, we aim to enhance the efficiency and effectiveness of the quantum selection process of the UQGA. This adjusted approach allows us to achieve a more optimized solution while managing the computational complexity associated with the selection stage.

The UQGA shares similarities with the traditional UCGA. The main difference lies in the replacement of the heuristic initialization step in the UCGA's chromosome population with a stochastic quantum initialization step. Similarly, the conventional selection procedure, which involves a traditional sorting strategy, is replaced with a quantum selection procedure. This quantum selection process utilizes the QEVSA $S/2$ times to retrieve the parent set.

From a quantum point of view, the entire region can be represented by a single quantum register. This utilization of quantum superposition allows for a more compact and efficient representation of the problem space. The size of this quantum register is denoted by $\log_2(R)$, where R is the region. This logarithmic size reflects the exponential advantage offered by quantum computing in terms of representing and processing enormous amounts of data.

In terms of processing time, the quantum register, representing the region, can be processed using quantum computing techniques. The processing time of this quantum register can be expressed as $log_2^3(R)$. This indicates that as the number of regions increases, the processing time required by the quantum register grows at a logarithmic rate, emphasizing the importance of efficient algorithms and quantum computing resources in tackling complex optimization problems.

In summary, from a classical perspective, we evaluate each chromosome individually, while from a quantum perspective, the entire region or population can be represented by a quantum register, benefiting from the superposition property and exponential processing advantages of quantum computing.

Our variant of the UQGA offers significant advantages over existing UQGAs found on the internet. While it is true that there are multiple UQGAs available for optimization problems, many of them are designed to be executed on existing quantum computers, which have limited size and computational capabilities. However, in our case, we encounter a unique challenge where the search space is incredibly vast, surpassing the capacity of currently available quantum computers.

To the best of our knowledge, there are no existing UQGAs that specifically address such an expansive and voluminous search space. This distinction sets our UQGA apart, as it is specifically tailored to handle optimization problems with a significantly larger search space, exceeding the limits of conventional quantum computers. By acknowledging and addressing this crucial aspect, our UQGA opens up new possibilities for tackling complex optimization problems that were previously beyond the scope of existing UQGAs.

Chapter 6

Simulations

Within this pivotal section, we embark on a thorough exploration of the experimental framework and the consequential outcomes, meticulously crafted through the utilization of Python on Jupyter Notebook as our esteemed computational milieu. This chapter unveils an expanse of intellectual endeavor, where computational models and algorithms harmoniously converge to simulate and dissect diverse facets of the intricate research conundrum at hand. By embracing the boundless potentiality and unwavering versatility of Python, synergistically fused with the interactive and visually captivating realm of Jupyter Notebook, a compendium of simulations was meticulously orchestrated. These simulations were meticulously designed to unearth profound insights into the behavioral dynamics, performance prowess, and efficacy of the proposed methodologies.

Navigating through the ensuing sections, a panoramic vista of the simulation setup unfurls, disclosing the meticulous selection of datasets, the fine-tuning of parameter configurations, and the judicious choice of discerning evaluation metrics. Armed with this comprehensive blueprint, we meticulously unveil the outcomes of our empirical quest, fortified by an immersive and comprehensive analysis that peers into the essence of performance and the far-reaching implications of the proposed paradigms

6.1 Description Of Simulation

To establish the superiority of the devised Unconstrained Quantum Genetic Algorithm (UQGA), an elaborate and comprehensive simulation was conducted to meticulously assess and compare the efficacy of both UQGA and the conventional Unconstrained Classical Genetic Algorithm (UCGA). The simulation was geared towards evaluating these algorithms based on a myriad of intricate metrics, including the aggregate transmit power and the total number of generations requisite for convergence. By rigorously scrutinizing these intricate metrics, we glean valuable insights into the effectiveness and efficiency of the UQGA in relation to its UCGA counterpart. This meticulous comparative analysis endeavors to illuminate the inherent advantages and potential advancements offered by the UQGA approach in optimizing the targeted problem domain. The culmination of simulation results and their exhaustive analysis furnishes a sturdy framework for drawing meaningful conclusions and making astute decisions concerning the applicability and performance of the devised UQGA in practical real-world scenarios.

In our comprehensive research study, we conducted three distinct simulations to evaluate different optimization approaches. The first simulation involved an exhaustive search, where we exhaustively explored the entire search space to obtain the optimal solution. This served as a benchmark for evaluating the performance of the subsequent algorithms.

The second simulation revolved around the Unconstrained Classical Genetic Algorithm (UCGA). This conventional optimization method operates on classical computational principles and utilizes genetic operators, including selection, crossover, and mutation, to progressively refine the population towards improved solutions. We meticulously configured the UCGA parameters to ensure a justifiable comparison with alternative methodologies.

The third simulation focused on our pioneering Unconstrained Quantum Genetic Algorithm (UQGA). This algorithm, founded upon quantum computing principles, integrates quantum-inspired methodologies to amplify exploration capabilities and expedite convergence. We meticulously devised and implemented the UQGA to highlight its prospective merits in contrast to exhaustive search methods and the traditional Unconstrained Classical Genetic Algorithm (UCGA).

By performing these three simulations, we obtained valuable insights into the performance and efficiency of each approach. The results of these simulations will be analyzed and compared to shed light on the strengths and limitations of the different optimization methods. This analysis will provide a deeper understanding of the benefits offered by the UQGA and its potential as an advanced optimization tool in various application domains.

6.1.1 Simulation Results Of UCGA And UQGA With Varying Number Of Base Station Antennas Under Fixed Power Levels

Two experiments of different MIMO systems are implemented as follows:

- 4×4 MIMO: This MIMO contains 4 transmit antennas and 4 receive antennas
- 8×8 MIMO: This MIMO contains 8 transmit antenna and 8 receiving antennas.

The chosen values for the possible transmit antenna at the base station are 42, 44, 46 Dbm. It is worth noting that the size of the database grows as the number of transmit antennas at the base station rises, i.e., as the database size increases [25]. For every MIMO system considered, both the UQGA and UCGA were utilized, and subsequently, the total power consumption during transmission was computed for each approach.

The Table 6.1 provides insights into the total power consumption in relation to the number of transmit antennas at the base station. By varying the number of antennas, we observed the corresponding changes in the total power consumption.

MIMO System	**4x4 MIMO**	**8X8 MIMO**
UQGA	63.39	126.791
UCGA	63.39	126.791

Table 6.1: Optimal Power Consumption For Different Numbers Of Transmit Antennas At The Base Station Under Fixed Power Set.

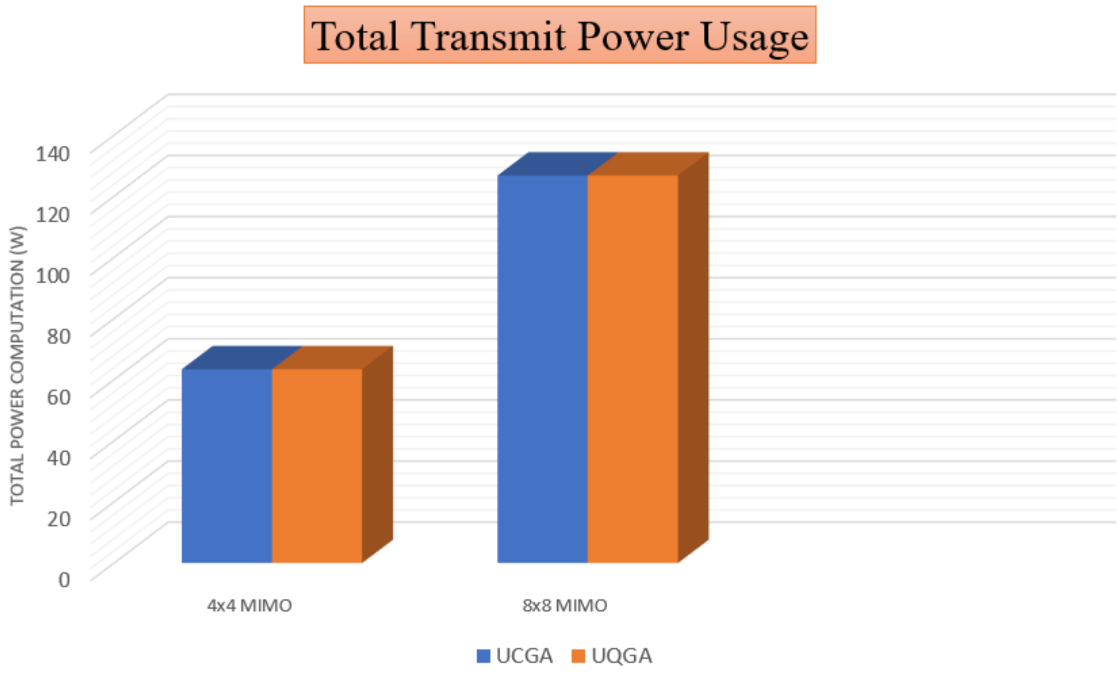

Figure 6.1: Impact Of Different Number Of Transmit Antennas At The Base Station On Total Power Consumption Under Fixed Power Set

Figure 6.1 Illustrates The Impact Of Varying The Number Of Transmit Antennas At The Base Station On The Total Power Consumption. The graph clearly demonstrates that as the number of antennas increases, the optimal power usage also increases. It is noteworthy that both algorithms exhibit comparable power consumption patterns across various massive MIMO systems.

The Table 6.2 presents the average number of generations required for both UCGA and UQGA to converge to the optimal scenario for different MIMO systems. The experiments were conducted by running the algorithm 20 times to ensure statistical reliability.

Average Number of Generations for MIMO System	**4x4 MIMO**	**8X8 MIMO**
UCGA	9.25	15.55
UQGA	1.35	4.45

Table 6.2: The Average Number Of Generations By Different MIMO Systems For Both Algorithms (UCGA, UQGA) With Fixed Power Set.

The x-axis in Figure 6.2 represents the MIMO systems, while the y-axis represents the average number of generations. From the graph, it can be observed that the UQGA consistently outperforms the UCGA in terms of convergence speed across all MIMO systems. The average number of generations required for the UQGA to reach the optimal scenario is significantly lower compared to the UCGA for each MIMO system. This indicates that the UQGA is more efficient in finding optimal solutions within a reduced number of generations, regardless of the specific MIMO system configuration. The superior convergence speed of the UQGA demonstrates its effectiveness in accelerating the optimization process and achieving better solutions. These findings support the notion that leveraging quantum principles can significantly enhance the performance and efficiency of genetic algorithms in solving complex optimization problems.

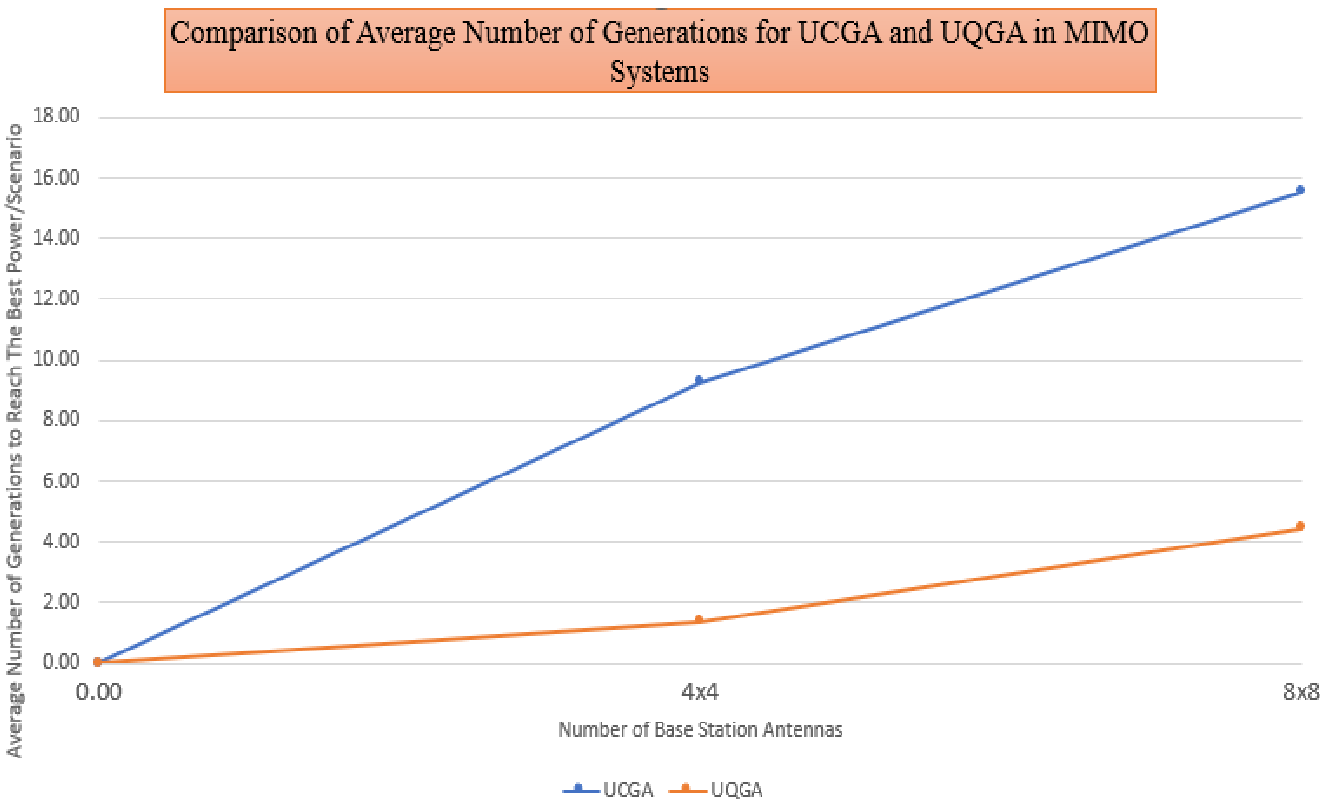

Figure 6.2: Comparison Of Average Number Of Generations For UCGA And UQGA In MIMO Systems With Fixed Power And Varied BS Antennas.

6.1.2 Simulation Results Of UCGA And UQGA With Varying The Available Power Levels Under Fixed Base Station Antennas Fixed

In this simulation, we investigate the behavior of the UCGA and UQGA algorithms while keeping the number of base station antennas fixed and varying the available power levels. The focus is on analyzing how these algorithms perform when the number of base station antennas remains constant.

To assess their performance, three different power sets were considered. The first power set consisted of {42, 44, 46}, with a fixed number of base station antennas at 4. The UCGA and UQGA algorithms were executed to optimize the solution within these power constraints.

Next, the power set was expanded to {42, 44, 46, 48}, while keeping the number of base station antennas unchanged. The UCGA and UQGA algorithms were applied to find the optimal solution within the updated power constraints.

In the third configuration, the power set was further augmented to include {42, 44, 46, 48, 50}, while adhering to a fixed number of base station antennas. The UCGA and the UQGA were harnessed to optimize the solution under these refined power constraints.

Table 6.3 showcases the average count of generations indispensable for the attainment of the optimal solution by both the UCGA and the UQGA. A total of 20 meticulously executed experiments were conducted to guarantee statistical significance and steadfastness of the findings. The figures within the table depict the mean number of generations derived from these iterative trials, thereby imparting valuable discernment into the convergence characteristics exhibited by the algorithms.

It can be observed from the fact that the UQGA exhibits a faster convergence rate compared to UCGA. The UQGA algorithm consistently achieves the optimal solution in fewer generations, indicating its superior performance in reaching convergence within a shorter timeframe.

Power Sets	**{42,22,26}**	**{42,44,46,48}**	**{42,44,46,48,50}**
Average Number Of Generations for UCGA	6.8	8.25	15
Average Number Of Generations for UQGA	1	4.6	5.6

Table 6.3: Convergence Analysis: Average Number Of Generations To Reach Optimal Solution With Fixed Base Station Antenna And Varied Power Sets.

By examining Figure 6.3, we can gain insights into the performance of the UCGA and UQGA algorithms across different power levels while maintaining a constant number of base station antennas. In this analysis, we investigated the convergence behavior of both algorithms, UCGA and UQGA, by measuring the average number of generations required to reach the optimal solution. The x-axis displays the power sets used in the simulations. These power sets represent different levels of transmit power constraints imposed on the optimization problem. By varying the power sets, we can evaluate the algorithms' performance under different power constraints and observe how it affects their convergence behavior. The y-axis of the graph represents the average number of generations required for the algorithms to converge to the optimal solution. Generations refer to the iterative steps in the evolutionary process, where new candidate solutions are generated and evaluated based on their fitness. The average number of generations provides an insight into the efficiency and convergence speed of the algorithms.

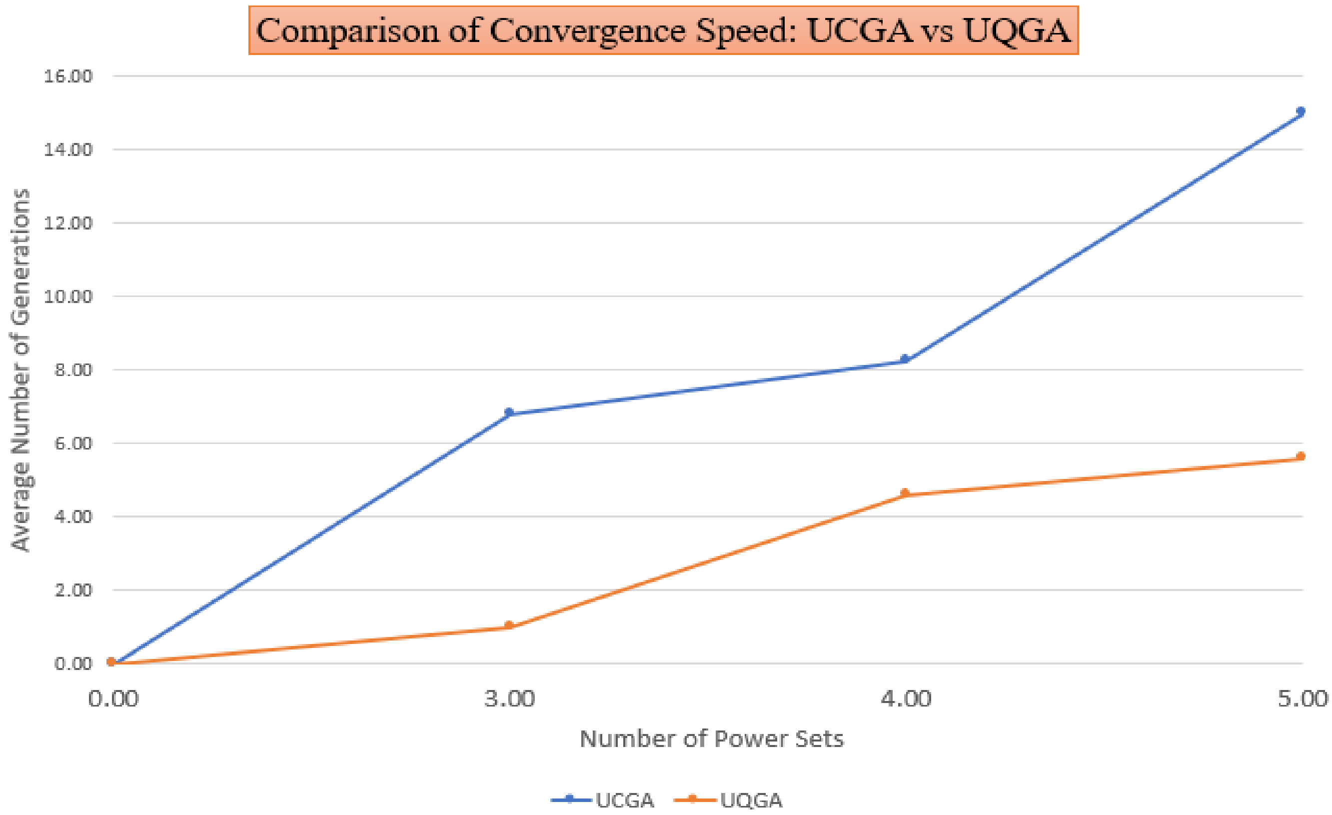

Figure 6.3: Comparison Of Convergence Speed: UCGA Vs UQGA With Fixed Base Station Antenna And Varied Power Sets.

The Figure 6.4 illustrates the performance comparison between UCGA and UQGA algorithms for a 4x4 MIMO system, where the power sets were varied. Initially, the power set consisted of 3 different power levels, and then it was increased to 4 and further to 5. The objective was to identify the optimal power level that minimizes the overall power consumption while maintaining reliable communication. The values are given in Table 6.4:

Power Sets	**{42,22,26}**	**{42,44,46,48}**	**{42,44,46,48,50}**
UCGA	42 (63.39)	42 (63.39)	42 (63.39)
UQGA	42 (63.39)	42(63.39)	42 (63.39)

Table 6.4: Optimal Transmit Power Used By 4x4 MIMO With Varying Power Sets.

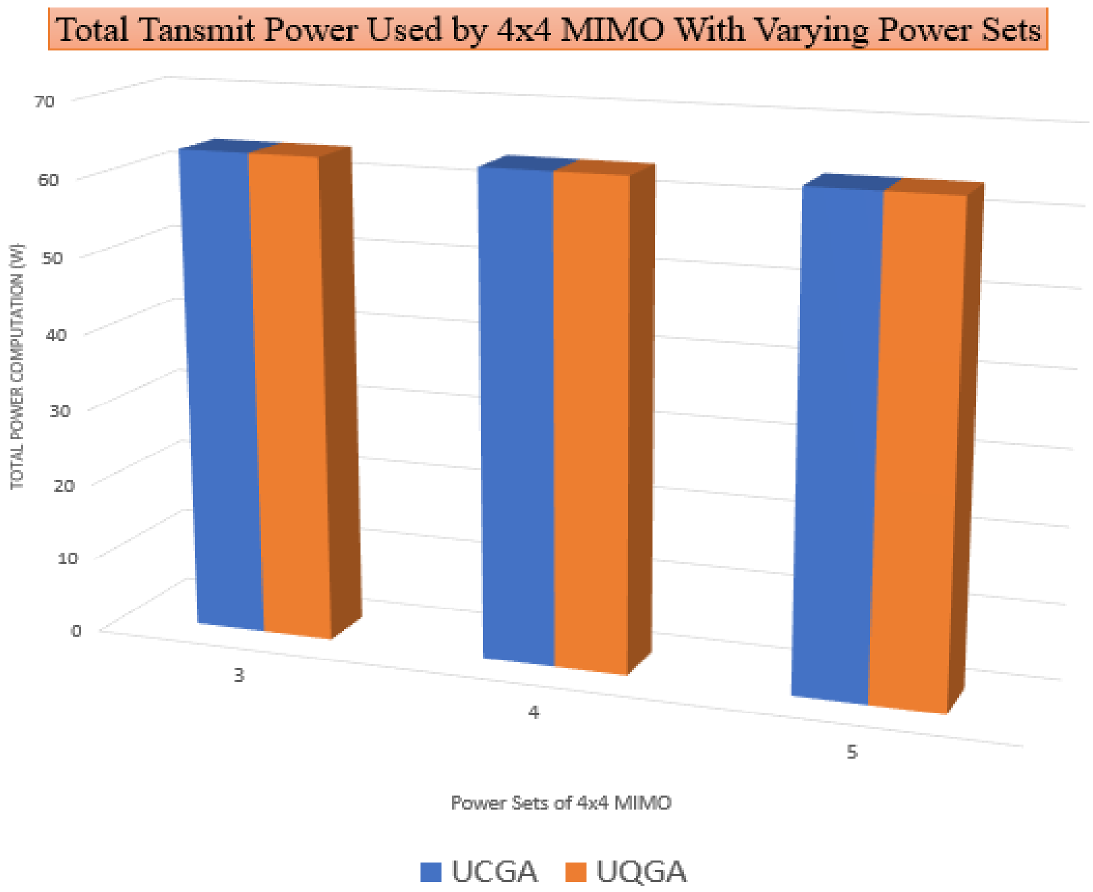

Figure 6.4: Optimal Transmit Power Used By 4x4 MIMO With Varying Power Sets.

The Figure 6.5 represents the computational complexity of the classical selection and quantum selection stages of the UCGA and UQGA, respectively. The blue line plot represents the number of steps exhibited by the classical selection step, while the red line plot refers to the quantum one. As can be seen, as the value of M increases, the output of the computational complexity also increases, although the rate of increase varies between the two algorithms, i.e., the classical sorting and QEVSA. The slope of the blue line is steeper than that of the red line, indicating a faster growth rate for the classical selection. The graph unmistakably demonstrates that quantum selection surpasses classical selection.

The graph provides insights into how the output values change as M varies and demonstrates the logarithmic growth behavior of the functions. It can be used to analyze and compare the output of the two functions for different values of M.

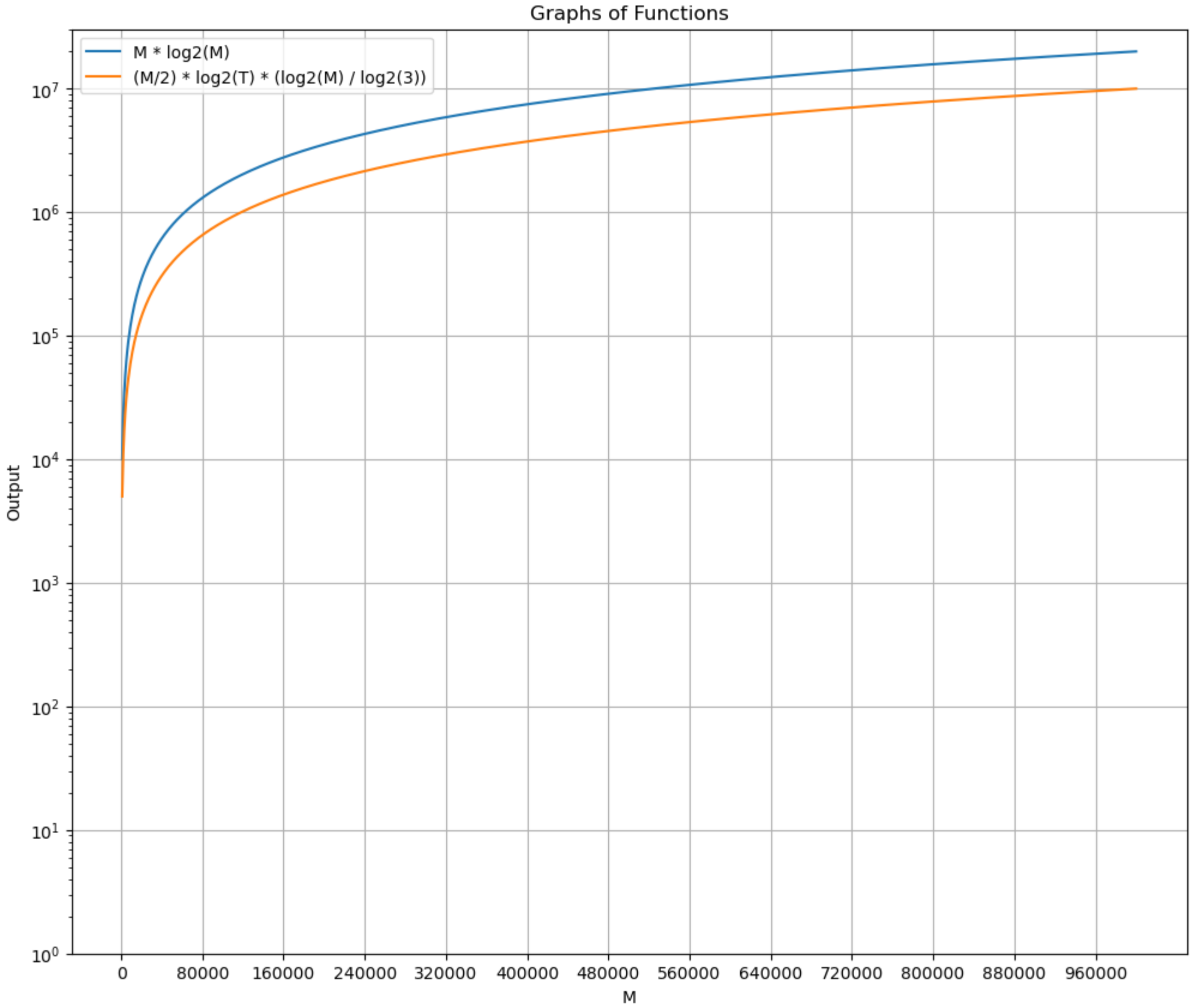

Figure 6.5: Quantum And Classical Selection Stages Of The Genetic Algorithms

Chapter 7

Conclusion

7.1 Summary of Research

This thesis aimed to address the challenge of minimizing power consumption in MIMO (Multiple-Input Multiple-Output) networks by applying a novel approach called Unconstrained Quantum Genetic Algorithm (UQGA).

Chapter 2 took us on a captivating journey into the realm of quantum computing and communication. We unraveled the mysteries of quantum entanglement and delved into the mind-boggling concept of quantum teleportation. These foundational concepts provided a solid background for the subsequent chapters.

Moving on to Chapter 3, we explored the fascinating world of Multiple-Input Multiple-Output (MIMO) technology. We discovered the benefits of MIMO systems in wireless communication, including increased data rates, improved reliability, and spatial multiplexing. This chapter laid the groundwork for understanding the practical applications of MIMO technology.

Chapter 4 marked a significant milestone with the introduction of the groundbreaking UQGA. We witnessed the fusion of quantum computing and genetic algorithms, revolutionizing the search process. The utilization of quantum blind computing and the quantum extreme value searching algorithm showcased the algorithm's potential for optimization.

In the illustrious fifth chapter, the pragmatic implementation of UQGA unfurled within the intricate framework of a downlink MIMO system. The UQGA unveiled its prodigious prowess by proficiently mitigating power consumption while simultaneously orchestrating the intricate dance of optimizing computational complexity. Delving deeper into the realms of algorithmic excellence, a meticulous methodology for estimating the stochastic parameters materialized, further amplifying the algorithm's dexterity in the realm of optimization.

Chapter 6 focused on detailed simulations to analyze the UQGA's performance in reducing power consumption in MIMO systems. We meticulously designed the simulation setup, employing various methodologies and evaluation metrics. The results provided valuable insights into the feasibility and potential of the UQGA for efficient power optimization.

Collectively, these chapters unveiled a captivating journey of knowledge and innovation. From the foundations of quantum computing to the practical applications in MIMO power optimization, we delved into cutting-edge concepts and real-world implications. The thesis provided a comprehensive exploration of the subject matter, leaving a lasting impact in the field of power consumption minimization in MIMO networks.

7.2 Future Directions

While this scholarly thesis has achieved commendable strides in the realm of power optimization within Multiple-Input Multiple-Output (MIMO) networks through the application of the Unconstrained Quantum Genetic Algorithm (UQGA), there exist promising avenues for future research and development:

- ❖ Algorithmic Refinements: The refinement of the UQGA holds the potential for bolstering its overall performance and expediting convergence. This pursuit may encompass the exploration and elucidation of sophisticated quantum-inspired methodologies, adaptive strategies, and hybrid algorithms synergistically amalgamating quantum and classical optimization techniques.
- ❖ Real-world Deployments: The empirical examination and validation of the proposed algorithm in authentic MIMO network scenarios assumes paramount importance. By accounting for the intricate constraints imposed by practical considerations, the vagaries associated with channel dynamics, and the manifold challenges encountered during system deployment, a comprehensive assessment of the algorithm's efficacy in real-world operational environments can be realized.

The pursuit of these research trajectories will pave the way for notable advancements in the domain of power optimization within MIMO networks, thereby broadening the horizons of knowledge and facilitating the practical adoption of cutting-edge algorithmic solutions.

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