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

B.Sc. Dissertation

by

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Abstract

Quantum computing is one of the most promising approaches to addressing the problems of computational complexity, data storage, and power consumption because of its extremely fast performance. Applying the principles of quantum computing to the development of optimization algorithms is a rapidly growing field of study.

With its ability to provide improvements in throughput and energy efficiency, multiple-input multiple-output (MIMO) system offers significant potential for 5th generation (5G) wireless communication systems. The number of antennas used by the base station is increased in the MIMO. This new technology has several advantages, including an array gain that may be utilized to expand coverage, favorable propagation that makes user separation easier, and channel hardening that makes the system more robust and stable. One of the main challenges facing the massive MIMO systems is the high computational complexity of the embedded optimization techniques. Several optimization techniques have been implemented, such as the Nash equilibrium-based effective, water-filling algorithm (WFA), genetic algorithm (GA), particle swarm optimization (PSO) have been employed to enhance the power allocation system for the MIMO system.

This thesis focuses on exploiting unconstrained quantum genetic algorithm for minimizing the power consumption of downlink MIMO system, inspired by the need of handling the search for an optimum result in a massive and unsorted database \_in which no traditional or quantum server can deal with this type of optimization problems\_.

In the first Chapter, ….

In this research , we implemented a quantum optimization technique known as the Quantum Extreme Value Searching Algorithm (QEVSA) to Develop a new Unconstrained Quantum Genetic Algorithm (UQGA). Not Completed!!! DO AT THE END!!

STUDENT DECLARATION

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...…………………………………………….

Areeba Tabassum Shoaib

Acknowledgement

To be Done!!

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# 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 or power. 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.

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.

MIMO technology has revolutionized wireless communication, but it remains difficult to optimize power consumption and energy efficiency. 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 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.

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. This chapter thoroughly examines the state-of-the-art classical optimization algorithm metaheuristics and deterministic approaches, highlighting their principles, strengths, limitations, and diverse applications. It also introduces quantum extreme value searching algorithm and quantum blind computing as innovative cornerstones for advancing optimization processes.

In the fifth chapter, the developed unconstrained quantum genetic algorithm is applied to a downlink MIMO system. This practical application showcases the UQGA's effectiveness in minimizing power consumption and computational complexity. Furthermore, the chapter presents a methodology for estimating stochastic parameters of the UQGA, enhancing its optimization capabilities. By demonstrating the UQGA's real-world performance and addressing important metrics, this chapter provides valuable insights into the algorithm's practical implications and benefits.

In the sixth chapter, detailed simulations are conducted to analyze the effectiveness of the unconstrained quantum genetic algorithm in reducing power consumption in MIMO systems. The study encompasses the simulation setup, methodologies used, and performance evaluation metrics. Through a comprehensive analysis of simulation results, valuable insights are gained regarding the algorithm's feasibility and its potential for efficient power optimization.

The seventh chapter of the dissertation serves as a succinct summary of the notable findings and contributions made throughout the research. Additionally, it delves into an examination of potential limitations, implications of the findings, and suggests promising avenues for future research exploration.

# Introduction

## 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:

### 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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.1) |

Where and are complex coefficients, and and are the so-called computational basis states:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.2) |

such that,

|  |  |  |
| --- | --- | --- |
|  | . | ( 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 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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 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 . The fundamental characteristic of a unitary operator is that it adheres to a specific formula, which can be stated as follows:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.5) |

Where, denotes the conjugate transpose (also known as the adjoint or Hermitian conjugate) of the unitary operator U, and 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 is the input quantum state and is the output quantum state obtained after applying the unitary transform (as depicted in Figure 2.1), the relationship between and can be described as follows:

|  |  |  |
| --- | --- | --- |
|  | , | ( 2.6) |

Input

Quantum

States

Output

Quantum

States

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 to produce the output state .

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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 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 and states.

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.8) |

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

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.9) |

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

|  |  |  |
| --- | --- | --- |
|  |  | ( 210) |

* **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.

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.11) |

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

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.12) |

And,

|  |  |  |
| --- | --- | --- |
|  |  | ( 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 , where represents a potential measurement outcome. The probability of obtaining the measurement outcome when the quantum system is in the state can be expressed as follows:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.14) |

where the adjoint of is denoted by and the adjoint of is denoted by . 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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.15) |

**Fourth postulate (Composite systems)**

The 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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.16) |

While the second and third qubits are respectively described as,

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.17) |
|  |  | ( 2.18) |

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

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.19) |

### 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:

|  |  |  |
| --- | --- | --- |
|  |  | ( 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.

**H**

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.

|  |  |  |
| --- | --- | --- |
|  |  | ( 2.21) |
|  |  | ( 2.22) |
|  |  | ( 2.23) |
|  |  | ( 2.24) |

### No-cloning Theorem

According to the no-cloning theorem, it is not possible to clone unknown quantum states in the universe of quantum mechanics. However, it is possible to clone either recognized quantum states as well as orthogonal quantum states. Due to the fact that identical backups of quantum states cannot be created in advance in quantum computing, the "no-cloning theorem" rules out the use of conventional error correcting techniques on quantum states. Let's offer an example. Consider for a moment that there are two possible quantum states:  and . It is not difficult to check whether or not the inner product of these two states is equal to zero. As a result, the quantum states 0 and 1 are orthogonal to one another. We are consequently able to clone them. Because of the no-cloning theorem, it is impossible to fix errors in quantum states by using the more conventional methods that were previously utilized. There is no way to build backup copies on the quantum states in the middle of the computation and check for mistakes in those copies.

The no-cloning theorem can be useful in a variety of situations. For example, quantum key distribution (QKD) is a method of communicating between two parties that is safer and more secure because it does not rely on cloning power (the generated key cannot be cloned by eavesdroppers).

### 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 mechanics enable the transfer of information or properties from one location to another, offering unique possibilities for secure and efficient communication.

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.
* **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.

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 |𝛽00⟩. 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.

A picture containing text, diagram, plan, technical drawing

Description automatically generated

Figure 2.4: The teleportation scenario

### 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. In contrast to classical searching methods that require steps to find the target, Grover's algorithm achieves the same outcome in just steps, representing a significant speedup. It's worth noting that any quantum algorithm consists of three key components:

* 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.

A picture containing rectangle

Description automatically generatedThe 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. 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 , where represents the total number of items in the database, and corresponds to the number of occurrences of the searched item.

## 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.

Moreover, wireless technology is envisioned to find new applications and thrive in diverse environments. However, despite the growing number of wireless applications, bandwidth remains a limited resource, as it was during Marconi's time. This scarcity of available bandwidth has spurred the exploration of innovative transmission strategies. Among these emerging techniques, there has been a surge of research interest in Multiple-Input Multiple-Output (MIMO) systems in recent years.

MIMO, short for "Multiple Input Multiple Output," refers to a wireless communication technique that utilizes multiple antennas at both the transmitter and receiver ends to enhance overall system performance. Specifically, in 4G and 5G cellular networks, MIMO systems have proven effective in increasing throughput and expanding the capacity of the radio channel.

The primary objective of MIMO systems is to enhance communication quality and expand the capacity of wireless channels. 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. 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.

MIMO technology offers several advantages in wireless communication. Firstly, it enhances the overall system capacity by allowing multiple data streams to be transmitted simultaneously through separate antennas as shown in figure 2.6. This leads to increased data rates, improved spectral efficiency, and the ability to support more users. Secondly, MIMO provides spatial diversity, which helps mitigate fading and interference, resulting in improved reliability and coverage. Additionally, MIMO systems can achieve higher signal quality and reduced error rates, leading to enhanced communication performance. Overall, MIMO technology plays a crucial role in maximizing the efficiency, capacity, and reliability of wireless communication systems.

Diagram

Description automatically generated

Figure 2.6: Multiple-input multiple-output (MIMO) link, in which the transmitting base station directs three separate spatial beams at the receiver..

MIMO systems have been an important area of research due to the numerous advantages they offer and their significant impact on wireless communication systems. Researchers have been exploring various aspects of MIMO technology to further improve its performance, enhance system capacity, and devise more efficient algorithms.

# MIMO System

This chapter presents an overview of massive MIMO, its benefits, and the importance of massive MIMO for 5G networks.

Diagram, line chart

Description automatically generatedMIMO 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. MIMO has been widely used in various communication standards, including Wi-Fi, WiMAX, HSPA+, and LTE. A basic structure of a MIMO system is shown in Figure 3.1.

## History of MIMO

The first description of 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. 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 the 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 standard were developed in later years: IEEE 802.11n (2006), IEEE 802.11e WiMAX (2006), and 3GPP HSDPA, LTE standards (2008).

### MIMO Basic Antenna Configuration

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

1. SISO

A picture containing graphical user interface

Description automatically generated 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. A SISO antenna configuration is shown in Figure 3.2

(b) SIMO

The Single Input Multiple Output (SIMO) has one antenna on the transmitter side and multiple antenna on the receiver side. The SIMO antenna configuration is also known as the receive diversity. In SIMO, the transmitted signals are combined at the receiver, which reduces the effect of fading and interference, but it requires simple processing at the receiver. A SIMO antenna configuration is shown in 3.3.

(c) MISO

Chart, line chart

Description automatically generatedA picture containing text, device, meter

Description automatically generatedThe Multiple Input Single Output (MISO) configuration has multiple antenna 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. A MISO antenna configuration is shown in 3.4

(d) MIMO

The MIMO configuration has multiple antenna 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 antenna used. A basic 2 x 2 MIMO antenna configuration is shown in Figure. 3.5. Some of the advantages of the MIMO system are:

* + Higher capacity
  + Increased data rate
  + Expansion of coverage
  + Improvement in user tracking
  + Low error rate
  + Improved reliability
  + Higher spectral efficiency

Chart, line chart

Description automatically generated

# Devising A New Unconstrained Quantum Genetic Algorithm (UQGA)

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. By finding the best way to do things, we can reach our goals while wasting the least amount of time and being as productive as possible.
* **Decision-making:** Many problems in the real world require people to make choices when they are limited or unsure of what to do. Optimization helps find the best course of action, weigh the pros and cons of different options, and reach goals.
* **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.

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.
* **Model Limitation:** Optimization relies on mathematical models to show how a problem works. But these models might not always show the full complexity of the real-world system, which could lead to less-than-ideal solutions.

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. 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. 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 , indicating its time complexity in relation to the problem size.

**Particle Swarm Algorithm:** 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 , where , is the number of particles and , is the problem's dimensionality. 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. 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 steps for a genetic algorithm, where represents the population size, indicates the size of the individuals (genomes), and 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.

## Necessary Background for the UQGA

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 UQGA, it is essential to have prior knowledge of related algorithms, including classical genetic algorithm (CGA), quantum extreme value searching (QEVSA), and quantum genetic algorithm (QGA). These algorithms will be thoroughly discussed in subsequent subsections to provide the necessary background for comprehending the advancements introduced by the UQGA.

### Unconstrained Classical Genetic Algorithm (UCGA)

The unconstrained classical genetic algorithm (UCGA) is a variant of the genetic algorithm (GA) that is specifically designed to solve optimization problems without explicit constraints on the variables or solution space. In the UCGA framework, a population of potential solutions, represented as individuals or chromosomes, is randomly initialized, or generated using a specific method. Each individual represents a potential solution to the optimization problem.

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, selected individuals undergo genetic recombination, where segments of their genetic material are exchanged to create offspring. This mimics the concept of mating and inheritance in biological evolution. The aim is to combine advantageous characteristics from different individuals, potentially leading to improved solutions.

The mutation phase introduces small random changes in the genetic material of the offspring. 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 process continues for multiple generations until a termination criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory solution.

The UCGA is particularly well-suited for optimization problems where there are no explicit constraints on the variables or solution space. It finds applications in various fields, including engineering, computer science, finance, and more. By effectively combining selection, crossover, and mutation, the UCGA explores the solution space and gradually A picture containing text, screenshot, receipt, design

Description automatically generatedconverges towards better solutions over time. The working flowchart of UCGA is depicted in figure 4.1

Figure 4.1: The working methodology of UCGA

### Quantum Extreme Value Searching Algorithm (QEVSA)

QEVSA, the quantum extreme value searching algorithm, is an innovative approach to quantum optimization that excels in locating the maximum or minimum value of an unconstrained objective function. This groundbreaking method seamlessly integrates two key elements: the ingenious binary search algorithm and the extraordinary power of quantum existing testing (QET). QET, a remarkable variant of quantum counting, not only provides a reliable answer on the presence or absence of a specific item within a database but also contributes to the exceptional capabilities of QEVSA.

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

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

In summary, QET plays a crucial role within the Quantum Extreme Value Searching Algorithm (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 follow:

1. We start with ： = , = , 𝑎𝑛𝑑
2. is incremented by 1, where is equal to
3. :
   * If the flag is YES then , ,
   * or else ,
4. If then it goes to step 2 else stop, and the result is

The parameter indicates the maximum number of steps that must be taken in order to execute the QEVSA's logarithmic searching algorithms, and the value indicates the unconstrained objective function.

The function has one variable which denotes the value of the point that divides the database horizontally into two subregions

The computational complexity (CC) of QEVSA depends on two aspects:

* The computational complexity of the Binary Search Algorithm (BSA) incorporated within the QEVSA is expressed as .
* The computational complexity (CC) of the Quantum Existing Testing (QET) algorithm is represented by , where is the entry size of the database. In this case, , where represents the total number of required qubits relative to the size of the database..

**A**

**1 2 3 4 5 6 7 8 9 10 11 12 13**

**6**

**5**

**4**

**3**

**2**

**1**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**B**

**1 2 3 4 5 6 7 8 9 10 11 12 13**

**6**

**5**

**4**

**3**

**2**

**1**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**C**

**1 2 3 4 5 6 7 8 9 10 11 12 13**

**6**

**5**

**4**

**3**

**2**

**1**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**D**

**1 2 3 4 5 6 7 8 9 10 11 12 13**

**6**

**5**

**4**

**3**

**2**

**1**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

**X**

### Unconstrained Quantum Genetic Algorithm (UQGA)

A Quantum Genetic Algorithm (QGA) is an optimization method that combines concepts from classical genetic algorithms with principles of quantum computing. QGAs aim to improve the efficiency and performance of classical genetic algorithms by leveraging the unique properties of quantum mechanics, such as superposition and entanglement.

In a QGA, the chromosomes (candidate solutions) are represented using qubits instead of classical bits. This allows a qubit to be in a superposition of both 0 and 1 simultaneously, meaning that each chromosome can represent multiple solutions at once. This feature enhances the exploration capabilities of the algorithm and can potentially help avoid getting trapped in local optima.

Here is a high-level overview of a Quantum Genetic Algorithm:

* Initialization: Create an initial population of candidate solutions, with each solution represented by a quantum chromosome (an array of qubits). Apply Hadamard gates to each qubit to create an equal superposition of all possible solutions.
* Evaluation: Measure the quantum chromosomes to obtain classical bitstrings, which represent candidate solutions. Then, evaluate the quality of each solution using a fitness function.
* Selection: Select individuals from the current population to act as parents for the next generation. This process is similar to classical genetic algorithms, with the selection biased towards individuals with higher fitness values.
* Quantum Crossover: Generate offspring (new individuals) from the selected parents by applying quantum gates that entangle the parent qubits and create new quantum chromosomes for the offspring. This process mimics classical crossover but takes place in the quantum domain.
* Quantum Mutation: Apply quantum gates (e.g., Pauli-X gates) to the offspring's qubits with a certain probability. This introduces diversity into the population, similar to mutation in classical genetic algorithms.
* Replacement: Replace the old population with the newly generated offspring. The replacement strategy can be similar to classical genetic algorithms, such as generational replacement or steady-state replacement.
* Termination: If a stopping criterion is met (e.g., a maximum number of generations, a satisfactory fitness level, or no significant improvement over a number of generations), the algorithm stops. Otherwise, return to step 2 (Evaluation) and continue iterating.

Quantum Genetic Algorithms have the potential to outperform classical genetic algorithms due to their ability to explore multiple solutions simultaneously and exploit quantum parallelism. However, it's important to note that the practical implementation of QGAs is currently limited by the state of quantum computing hardware and the challenges associated with building large-scale, fault-tolerant quantum computers.

# MIMO System

This chapter presents an overview of massive MIMO, its benefits, and the importance of massive MIMO for 5G networks.

Diagram, line chart

Description automatically generatedMIMO is a technology that uses multiple antenna at both transmitter and receiver to exploit multipath propagation that increases the data capacity of the radio frequency (RF) link. MIMO has been widely used in various communication standards, including Wi-Fi, WiMAX, HSPA+, and LTE. A basic structure of a MIMO system is shown in Figure 3.1.

## History of MIMO

The first description of 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. 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 the 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 standard were developed in later years: IEEE 802.11n (2006), IEEE 802.11e WiMAX (2006), and 3GPP HSDPA, LTE standards (2008).

### MIMO Basic Antenna Configuration

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

1. SISO

A picture containing graphical user interface

Description automatically generated 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. A SISO antenna configuration is shown in Figure 3.2

(b) SIMO

The Single Input Multiple Output (SIMO) has one antenna on the transmitter side and multiple antenna on the receiver side. The SIMO antenna configuration is also known as the receive diversity. In SIMO, the transmitted signals are combined at the receiver, which reduces the effect of fading and interference, but it requires simple processing at the receiver. A SIMO antenna configuration is shown in 3.3.

(c) MISO

Chart, line chart

Description automatically generatedA picture containing text, device, meter

Description automatically generatedThe Multiple Input Single Output (MISO) configuration has multiple antenna 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. A MISO antenna configuration is shown in 3.4

(d) MIMO

The MIMO configuration has multiple antenna 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 antenna used. A basic 2 x 2 MIMO antenna configuration is shown in Figure. 3.5. Some of the advantages of the MIMO system are:

* + Higher capacity
  + Increased data rate
  + Expansion of coverage
  + Improvement in user tracking
  + Low error rate
  + Improved reliability
  + Higher spectral efficiency

Chart, line chart

Description automatically generated

### MIMO Channel Model and Capacity

The MIMO system consists of a single base station outfitted with T transmit antennas. In this scenario, there is only one user who possesses R receive antennas, as depicted in Figure 1. The channel state information is assumed to be accurately known by both the receiver and the transmitter.

Diagram

Description automatically generatedLet L represent the total number of MIMO channels, with L equal to the product of R and T (L = R × T).

The transmitted signal is represented by , and the primary objective is to optimize the power consumption of this signal. This optimization takes into consideration the user's bit rate. For this purpose, it's crucial to establish the following assumptions:

* The transmit power, represented by , corresponds to a specific assignment scenario for the transmitted symbol . It should be noted that the value of can vary based on the chosen transmit power set/range, which is determined by the requirements of the application.
* The target bit rate that the user aims to achieve is represented by .

The transmission power of the signal , based on assignment scenario , is expressed as .

The service provider suggests the power transmission set or range, which is defined under a certain standard as follows: . Here, . The symbol represents the total count of elements in set . It's important to note that one value from set is designated to the transmitted symbol.

Scenario  pertains to a specific power level used in the transmission of the vector . For instance, in scenario , the power assigned to transmitted symbols can be represented as . The total number of these distribution scenarios is symbolized by , with being equal to .

During the process of signal transmission, the transmitted signal experiences attenuations or reductions, leading to a portion of the transmitted power signal being lost due to reflections, diffractions, or absorptions. In simpler terms, the signal received is a weakened version of the original transmitted signal.

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

where:

- stands for the received vector, which has dimensions of (R × 1).

- is the channel matrix, having dimensions of (R × T). It consists of independently and identically distributed (i.i.d.) random variables, each of which originates from a circularly symmetric complex Gaussian distribution with zero mean and unit variance, denoted as . The elements of , expressed as , take into account Rayleigh fading. The channel pair is signified by the subscripts , where and stand for the receive and transmit antennas respectively.

- represents the signal transmitted, with dimensions of .

- is the complex baseband additive white Gaussian noise vector, with dimensions of .

To simplify, this equation models how a signal sent from a base station is received by a user. The signal undergoes changes due to the channel conditions (represented by ) and is also affected by noise (represented by N).

Furthermore, it's assumed that there is no delay spread affecting the transmitted signal (meaning the signal is not delayed during transmission), and there is no inter-symbol interference.

The equation provided sets an upper limit for the actual bit rate, representing the capacity of the system. At this stage of the model, the capacity is used as a stand-in for the bit rate, meaning we're assuming it's achievable through the use of channel coding.

The channel related to the distribution assignment is described by a particular formula:

In this context, signifies the channel gain, where . The symbol represents the bandwidth in use.

It's also worth noting that the component in the formula stands for the signal-to-noise ratio (SINR).

We are now prepared to mathematically formalize the optimization problem. The aim is to determine the optimal transmit power, denoted by, in a way that meets the target bit rate for the specific user, labeled .

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Annex