

Budapest University of Technology and Economics

Faculty of Electrical Engineering and Informatics

Department of Control Engineering and Information Technology

Areeba Tabassum Shoaib

MAXIMIZING POWER CONSUMPTION OF MIMO NETWORK USING A NOVEL QUANTUM GENETIC ALGORITHM

SUPERVISOR

Dr. El Gaily Sara

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Areeba Tabassum Shoaib

Summary

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 area throughput and energy efficiency, the 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 massive MIMO. This 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. Yet, the computational complexity of the embedded optimization techniques in MIMO systems remains a problem. Several techniques, such as the Nash equilibrium-based effective water-filling algorithm (WFA), have been developed in an effort to enhance the power allocation system for MIMO.

This thesis focuses on the question of how the power consumption of MIMO systems can be maximized by using a novel Quantum Genetic Algorithm.

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!!!

Sommaire

The text of a ½-1 page long summary goes here in a second language, different of English (German, French, Portuguese, Russian, Finnish, Korean, Chinese, Japanese, Hungarian, etc,). This summary is the translation of the summary in English and has to be also uploaded to the Thesis Portal separately.

Acknowledgement

To be Done!!

# 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:

(

where a and b are complex coefficients, and |0 > and |1 > are the so-called computational basis states , such that,

Two classical states can coexist in one qubit. The outcome of a coin flip can be thought of as an example of a qubit. If we toss a coin (and assume it's fair), we've got an equal chance of getting a head or a tail with a probability of 0.5 for either outcome.

It is important to stress that is a superposition of two states, and the precise formula of (1.1) can be stated as follows:

**Second postulate (Evolution)**

How a quantum state changes over time is described by the second postulate. For those unfamiliar, the quantum gate is just a unitary operator used in quantum computing.

A unitary operator satisfies the following formula:

Moreover, the unit norm of the quantum state is conserved by a unitary transformation. The relation between and is shown as in Figure 1.1, where between is an input quantum state and is the output quantum state after performing the unitary transform U.

Logic gates in digital circuits function similarly to quantum gates in quantum circuits. The manipulation and alteration of qubits is their primary goal. Contrary to logic gates, quantum gates support the idea of reversibility, which allows us to easily convert an input quantum state into an output quantum state and vice versa.

We list some well-known quantum gates here that work with just one qubit,

**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.

**Third postulate (Measurement)**

It is important to note that a quantum state cannot be observed; the only way to ascertain its state is to carryout a measurement. Notice that the measurement of a quantum system can be characterized by measurement operators , where m represents a potential measurement outcome. If the system is in state , then the probability of measuring the potential state m may very well be expressed as:

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.

**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:

While the second and third qubits are respectively described as,

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

### Quantum Entanglement

Quantum entanglement was first discovered in the 1960s and was named after John von Neumann, who discovered quantum mechanics. Quantum entanglement is a logical connection between quantum states in such a way that they are spatially separated but communicating with each other; in other words, there is a certain hidden relationship between the quantum states.. For instance, if two quantum states are separated by a significant distance, the measurement of one quantum state enables instantaneous estimations of the other quantum state. The capacity of quantum entanglement to communicate at speeds greater than the speed of light is perhaps its most crucial function, as it will greatly accelerate the rate at which human society expands.

The most well-known piece of mathematical equipment that can generate entangled states is called a CNOT-gate. One of the inputs of the CNOT gate is used for controlling the device, and the other input is used for feeding it data. One will be used for the output control, while the other will be used for the output data. When we input 0 into the control terminal, the value at the data terminal does not change, which is a crucial point to keep in mind. If we enter 1 into the control terminal, then the value at the data terminal will be averted. For example, if our control terminal is set to 1, and the data terminal is receiving input 1, then the output of the data terminal will be 0.

It is worth noting that the most well-known entangled states are termed Bell states, and they are stated as follows:



Both the Hadamard Gate and the CNOT Gate can be used to produce them. The circuit that produces a Bell state is illustrated in the figure below.

**H**

.

The circuit depicted in Figure 1.2 is responsible for the generation of four distinct entangled pairs of "Bell states." The following is a list of them in order of precedence:

### 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: |0> and |1>. 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). PROOF??

### Quantum Teleportation

The power of quantum entanglement is utilized in the process of quantum teleportation in order to swiftly transport an object from one location to another. The theory of quantum teleportation has been proven, but there are still a lot of obstacles to overcome before it can be used in practice. It is an interesting fact to note that the capabilities afforded by quantum teleportation have been employed as the primary concept for quantum repeaters and communication channels. There are several stages involved in quantum teleportation: the first step is to break the object to be conveyed into smaller pieces (electrons and photons) that are subject to the rules of quantum physics, Second, a classical or quantum channel could be used to send the electrons and photons through, Third, transporting the object across the space and reconstructing it in a different location (another cabin).

Let's say that Alice and Bob want to transport just one qubit between their two locations. They have to carry out a sequence of procedures. The first thing that needs to be done is for Alice and Bob to split their bell pair . After that, Alice needs to do a variety of operations on her qubits (CNOT and Hadamard, etc.). At long last, she is obligated to carry out a measurement. After that, the result that was produced is then transmitted to Bob through the traditional channel. Last but not least, Bob can retrieve the initial qubit (the qubit that was transmitted by Alice) by making use of either the I gate, the ZX gate, the X gate, or the Z gate.

Diagram

Description automatically generated

### Quantum Parallelism

The concept of quantum parallelism is regarded as the fundamental building block of any quantum computation. It permits the execution of activities that have a significantly lower computational complexity than the one that has traditionally been used. Let's say that we have a function that has n inputs but only one output. With the traditional approach, we need 2n-1 steps to get back the output result, while the quantum parallelism strategy just needs one step from us O(1).

A unique quantum gate, known as an f controlled CNOT gate, is responsible for carrying out the quantum parallelism. This gate is formulated as follows:

The following describes the output function obtained by applying the f-controlled CNOT gate:

As can be seen, the evaluation of each and every x is performed in a single step by the function f. The most significant shortcoming is that we are unable to verify the values of any f(x) due to the fact that the measurement equipment returns just a single value. Applying an amplification amplitude so that the probability of the desired outcome reaches one is the approach that needs to be taken in order to solve this challenge.

### Grover’s Algorithm

The Grover algorithm was first developed as an algorithm that could locate a certain item in a database which hadn't been ordered. This quantum tactic has a complexity of , which measures how difficult it is to compute. where N represents the entire size of the database before it was sorted.

I will explain the actions that need to be taken in order to perform a Grover operator as follows:

* The first step involves the use of a Hadamard operator on the upper wire to begin the process of initializing two quantum registers.
* The second phase involves applying the Oracle operator that reduces the probability amplitude of the requested item by a factor of -1 while keeping the original value for the remaining amplitudes.
* The third stage consists of applying the inversion about the the average method in order to increase the likelihood of achieving the desired outcome to 1.
* The fourth step is to use the Grover operator in a recursive manner until the sought-after value or item is located. Below is a breakdown of the required number of optimal evaluations:

A picture containing rectangle

Description automatically generated

## MIMO System

There has been a significant leap forward in communication technology ever since Marconi conducted his first experiments in the late 1800s, a fascination in the opportunities presented by wireless communications. Since then, wireless technology has progressed. The connections that once could only send data at a sluggish and irregular rate have evolved into the high-capacity networks that we see in use today. Numerous fields of application can be found: voice services have become so widespread that they can frequently take the place of fixed line services; wireless local area networks are up and running in many residential, office, municipal, or school buildings; and personal area networks, such as Bluetooth links form wireless connections between various consumer electronics devices. In spite of this, there is a seemingly incessant drive to enhance the capabilities of wireless communications in terms of throughput and/or reliability. Furthermore, there are a wide variety of novel applications and environments for which wireless technology is envisioned. But, despite the continually increasing number of wireless applications, bandwidth is still a very scarce resource, just as it was back in the days of Marconi. The limitation in available bandwidth has driven the development of unique transmission strategies. Out of these novel transmission techniques, MIMO systems have gained a lot of research interest in recent years.

MIMO is an abbreviation that stands for "Multiple Input Multiple Output." This abbreviation describes a method of wireless communication known as MIMO, which makes use of multiple antennas at both the transmitter and the receiver to increase the system's overall performance. For cellular networks of the fourth generation (4G) and the fifth generation (5G), the Multiple Input Multiple Output (MIMO) system is a technique that can boost the throughput and reach the radio channel capacity.

The basic purpose of Multiple Input Multiple Output systems is to improve the quality of communication while simultaneously expanding the capacity of wireless communication channels. MIMO systems include several antennas at both ends of the communication link. The rank of a MIMO system is defined by the total number of antennas. Two broadcast antennas and two receiver antennas are used in a 2x2 MIMO system. Multiple-input multiple-output (MIMO) systems allow the transmitter to convey numerous data streams at once by making use of multiple antennas. The numerous antennas at the receiving end pick up this information since it has been mixed with other streams before transmission. The original data is separated into its component streams and recovered by the receiver using signal processing techniques.

Diagram

Description automatically generatedMIMO systems can significantly increase the capacity of wireless communication systems without increasing the bandwidth or transmit power. This is achieved by transmitting multiple data streams simultaneously through separate antennas, a technique called spatial multiplexing. This capability allows MIMO systems to support higher data rates, which is crucial for bandwidth-intensive applications like video streaming and large file transfers. Due to the fact that an increase in the channel capacity is possible with an increase in the number of transmitting and receiving antennas.

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

MIMO systems are an integral part of modern wireless communication standards, such as 4G (LTE) and 5G. Researchers are exploring ways to integrate MIMO technology with other emerging technologies, such as millimeter-wave communication, massive MIMO, and cooperative communication, to further enhance the performance of next-generation networks.

MIMO (Multiple-Input Multiple-Output) 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 technology can make a big difference in the system's speed, coverage area, and quality of service (QoS). Using MIMO, the best way to send data depends on how the antenna arrays in the sender and receiver are set up. In general, optimizing is a hard and expensive job. So, scientists and engineers have come up with effective ways to optimize MIMO projects so that they can be useful and affordable. In the Cellular Mobile System (CMS), algorithms based on artificial intelligence are used to optimize the way data is sent .

## Organization Of The Dissertation

AT THE END

# Devising A New 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. 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).

On the other hand, metaheuristic algorithms have managed to garner a lot of interest due to the fact that the solutions they provide are considerably more applicable to the real world. In addition, these algorithms are able to produce satisfactory outcomes, in contrast to the deterministic optimization procedures, which are still having trouble arriving at the best possible outcome. Also, in comparison to other heuristic optimization strategies, the metaheuristic approaches are able to produce high-quality solutions in a shorter amount of time than their competitors.

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

**Genetic algorithm (GA):** Genetic Algorithm is a classic metaheuristic search method that is used to solve optimization 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. Here It's important to remember that every time natural selection is done, it's done on random sets.

**Ant Colony Optimization (ANO):** They were inspired by a small species of ant that looks for food by walking around and leaving a trail back to its nest. At first, they follow the path that other ants have made until they find food. If some ants find a good path, most of the others will probably follow in their footsteps. We can see that all of the other ants are following the most recent route. The main idea is to keep going down this path, which helps solve the real problem and makes food cheaper. The problem with the ANO is that it doesn't guarantee coverage and relies mostly on the decision chain, which is pretty much random.

**Particle Swarm Algorithm:** The particle swarm algorithm is a swarm intelligence algorithm that was made by simulating how a flock of birds hunts prey. In the search for load balance, particles share information to improve the search direction of each particle, so that the best solution can be found quickly.

In light of what has been discussed, we can draw the conclusion that traditional optimization algorithms, including heuristic and metaheuristic techniques, suffer from several shortcomings in terms of the amount of computational complexity they require and the results they produce. Also, they are having trouble adapting to the new practical task that has been presented to them. On the other hand, it is important to keep in mind that traditional optimization strategies served as the basis for the creation of the great majority of  advanced approaches that are especially helpful in the complex applications of today.

Genetic algorithms, sometimes known as GAs, are utilized frequently for a variety of purposes. They belong to the category of optimization and search algorithms that are motivated by the concept of natural selection, which gives them the ability to learn and solve difficult problems on their own. GAs are extremely versatile and can perform well in a broad variety of applications, including as optimization, machine learning, scheduling, and game playing, amongst others. GAs explore the search space more effectively than many other optimization methods, which enables them to locate global optima in situations with multiple local optima. Moreover, GAs keep a balance between exploration (looking for new parts of the solution space) and exploitation (improving the best solutions right now), which keeps them from getting stuck in local optima. GAs have a higher efficiency than other approaches because they can explore numerous points in the solution space at the same time, whereas other methods only concentrate on one point at a time.

Genetic algorithms (GAs) have numerous benefits, but they also have significant limitations that might hinder their performance and make them unsuitable for solving specific types of problems. The main problem with the GA is that it is hard to implement and has a high computational complexity. It needs steps, where is the number of steps the GA needs, is the total time, and is the size of each individual's assignment. It can take a while for GAs to converge on the best solution, which is especially the case in search spaces that are big, complex, and high-dimensional. Because of this, they may be less effective than several other optimization strategies in certain circumstances. GAs can sometimes converge to less-than-ideal solutions (called "local optima") instead of the "global optimum," especially if the population isn't diverse enough or there isn't enough exploration.

This research will focus on enhancing the search capability of Genetic Algorithm by merging Quantum Computing in the Genetic Algorithm framework. In order to gain a deeper understanding of the newly devised algorithm, it is essential to have the necessary background in certain algorithms, which includes knowledge of Quantum Extreme Value Searching (QEVSA), Classical Genetic Algorithm (CGA), Quantum Genetic Algorithm (QGA), which are presented in the following subsections.

## Quantum Extreme Value Searching Algorithm (QEVSA)

The Quantum Extreme Value Search algorithm (QEVSA), proposed by Sándor Imre, is a quantum computing algorithm designed to find the extreme value (minimum or maximum) of a given function within a specified domain. Unlike classical optimization algorithms, QEVSA leverages the principles of quantum mechanics to achieve faster and more efficient search.

The QEVSA determines the extreme (maximum or minimum) value of an objective function with no constraints. This quantum technique combines two methods:

* The traditional approach, the so-called logarithmic searching algorithm, searches an ordered (sorted) database for a specified database entry (item).
* The quantum algorithm, also referred to as Quantum Existence Testing (QET), is a subset of the more general concept of quantum counting. It provides a response, either true or false, on whether or not a particular database entry exists in a database that is not ordered.

The QEVSA is represented as follows:

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 T indicates the maximum number of steps that must be taken in order to execute the QEVSA's logarithmic searching algorithms, and the value G 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 logarithmic search algorithm uses 𝑂(log2(𝑇) steps, where T denotes the maximum number of steps needed to run the logarithmic algorithm integrated into the QEVSA.
* The QET requires steps and 𝑁 refers to the total number of entries in the unsorted database. According to our study case, the parameter N refers to the overall possible distribution scenarios.

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## Classical Genetic Algorithm (CGA)

A Classical Genetic Algorithm (GA) is a search heuristic and optimization method inspired by the natural process of evolution. Genetic algorithms are used to find approximate solutions to optimization and search problems, such as function optimization, machine learning, and scheduling problems. 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.

Here is a high-level overview of the Classical Genetic Algorithm:

* Initialization: Create an initial population of candidate solutions (usually generated randomly). Each candidate solution is referred to as an individual or a chromosome and is encoded as a data structure, such as a binary string, representing the problem's variables.
* Evaluation: Assess the quality of each individual in the population using a fitness function. The fitness function quantifies how well a solution solves the problem or meets the desired criteria.
* Selection: Choose individuals from the current population to act as parents for the next generation. The selection process is biased towards individuals with higher fitness values, simulating the "survival of the fittest" concept from natural evolution.
* Crossover: Generate offspring (new individuals) from the selected parents by combining their genetic material. This process, also known as recombination, typically involves selecting a crossover point and exchanging parts of the parent chromosomes to create new chromosomes for the offspring.
* Mutation: Apply random modifications to the offspring's genetic material with a certain probability. Mutation introduces diversity into the population and helps prevent the algorithm from getting stuck in local optima.
* Replacement: Replace the old population with the newly generated offspring. Different strategies can be used for replacement, such as generational replacement (replacing the entire population) or steady-state replacement (replacing a portion of the population).
* 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.

The best individual found during the algorithm's execution represents the approximate solution to the optimization problem. Genetic algorithms are particularly useful for problems with large, complex, and poorly understood search spaces, where traditional optimization techniques might struggle to find a good solution. However, they do not guarantee finding the global optimum and can require significant computational resources for complex problems.

## Quantum Genetic Algorithm (QGA)

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.

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Annex