Power Optimization of Massive MIMO Using Quantum Genetic Algorithm

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***Abstract*—The massive Multiple-Input Multiple-Output (MIMO) is key enabling technology for the 5G and 6G cellular technologies, which allows dramatically improving the energy efficiency of the network, as well as increasing the transmission bit rate. In this paper, we developed a new quantum genetic algorithm for handling non-constrained objective functions. The study aims to compare the performance of the classical genetic algorithm and its newly extended quantum version in minimizing the overall transmit power of the downlink massive MIMO system. In terms of the total number of performed generations and total transmit power, a simulation environment was used to demonstrate the efficiency of the quantum genetic strategy versus the classical one.**

Keywords—genetic algorithm; massive MIMO; quantum computing; quantum extreme value searching algorithm; transmit power.

I. Introduction

At the present, massive multiple-input multiple-output (MIMO) is a fundamental technology that can deliver consistently acceptable service to wireless terminals in areas with significant mobility by using more antennas at both transmission and reception points to capture fragmented waves[1]. A key technology for 5G is massive MIMO, which gives users more reliable connections, better data rates, and an overall improved user experience [2]. It is also highly expected to be involved in 6G [3]. We anticipated that 6G would lead to the evolution of massive MIMO technologies, which will improve our networks' speed, coverage, and general efficiency [4].

In uplink massive MIMO, the active users transmit to the base station (BS) at the same time. Through the utilization of multi-user detection strategies, the access point can recognize and differentiate between the various signals that originate from many users. The base station transmits to all active users simultaneously for the downlink massive MIMO and uses beamforming or precoding methods to significantly divide users [5].

In general, most of the research studies have discussed the power optimization (minimizing transmit power) of massive MIMO. The authors in [6] implemented the Lagrange multiplier method to minimize the downlink power consumption of a cell-free massive MIMO system under the downlink rate constraints of users and the power constraints of per-antenna. The authors in [7] suggested two suboptimal algorithms in order to minimize the transmit power consumption as well as reduce the computational complexity of the non-convex optimization problem in cell-free Massive MIMO networks with considering both the downlink transmit power and the number of active access points. The authors of [8] examine the combined optimization of the transmission strengths and the number of active base station antennas in order to optimize the total power consumption in the downlink of a massive MIMO system, the optimization problem was formulated as a geometric programming language, which can be easily solved by classical computer.

Quantum computing employs the behavior of quantum information to solve a huge number of computational problems that cannot be handled by its classical counterpart [9]–[11]. Quantum computing utilizes novel resilient and efficient quantum algorithms that can only be run on quantum computers. The Grover algorithm, which finds a given item in an unsorted database; quantum phase estimation, which computes the phase of an eigenvalue of a unitary matrix exponentially faster; and Shor's algorithm, which finds the prime factors of an integer, are among the most well-known quantum algorithms in recent decades [12].

Due to the need for a stable and strong quantum error correction framework, the available quantum computer can only work with a small number of qubits. In this way, the current technology for quantum computing limits the applicability of the quantum algorithms in a very large database. It is worth stressing that all the quantum algorithms that have been proposed are limited by the size of the quantum computers that are available right now. For this sake, we focused in this paper on handling this problem by extending the classical genetic algorithm to a quantum one while exploiting the power provided by quantum blind computing [13]. The developed quantum genetic strategy was used to reduce the computational complexity of the computational framework system while also minimizing the overall transmit power consumption of the one-cell massive MIMO system embedded in 5G technology. This work is an extended version of our previous work [14]–[17].

This paper is organized as follows: Section II introduces the problem statement and the essential background to understand the newly developed quantum genetic strategy. Section III proposes our new quantum genetic algorithm for solving an unconstrained optimization problem. Section IV defines a downlink massive MIMO model, where the optimization problem statement related to it is described. Section V compares and evaluates the quantum genetic algorithm's performance with that of the classical genetic algorithm in terms of computational complexity and transmitted power consumed by the transmit antennas. Section VI concludes the manuscript.

II. Problem Statement and Background

One of the most remarkable issues in optimization is the unsorted search. Classically, to search for the extreme result of an objective function, the traditional algorithm must evaluate the function $N = 2^n$ times, which means that the computational complexity in the worst case is $O(N)$ steps. Even if we applied a randomized algorithm, it requires at least $\frac{N}{2}$ times. From a quantum computing point of view, there is an efficient quantum method called the quantum extreme value searching algorithm (QEVSA) that finds the minimum (or maximum) in an unstructured database exponentially faster than any classical optimization method. Its computational complexity needs $O\left(log_2(G)log_2{}^3(\sqrt{N})\right)$ steps [18], [19], where G denotes to the maximum number of iterations required to execute the binary searching algorithm (BSA) embedded in the QEVSA. This quantum strategy can be run on a universal quantum machine. The available quantum computer can only work with small and limited size of qubits due to the need for a stable and robust quantum error correction framework. To that end, the applicability of the QEVSA in a massive database size is restricted by the existing quantum computing technology. It is interesting to note that all the developed quantum algorithms are restricted by the size of the currently available quantum computers.

In the last decade, a new buzz word appeared in the quantum world so-called quantum blind computing (QBC) which aims to secure computation rather than the communication channel [13]. The QBC is a type of computing in which a user can dispatch multiple computational tasks to other quantum nodes, the latter cannot reveal any information about the input or output of the computation to the owner of the quantum computer (server/sender).

In light of what has been discussed, performing search optimization in a massive unsorted database still poses a challenge due to the limited size of the available universal quantum computers. For this sake, we suggested a new quantum genetic algorithm that takes advantage from the concepts (QEVSA and QBC) and searches for the extreme result in an enormously large database where no current available quantum or classical machine may handle it. Before delving into introducing the new QGA, it is necessary to present the essential background needed to understand the suggested quantum genetic strategy. First, let's present the working procedure of the QEVSA, Next, describe the operational working scheme of the QBC. Finally, giving in detail the working steps of a general classical genetic algorithm (GA) [20].

The QEVSA is a quantum method that is designed to find the optimal solution among a set of possible solutions (the structure of the database can be unstructured). The power of the QEVSA relies on the principle of quantum parallelism for the simultaneous evaluation of multiple values of a function. The QEVSA merges two concepts, one of them is the classical so-called binary searching algorithm, (which finds a certain searched element in a sorted database) [21], and the other one is a quantum one, named quantum existing testing (QET), (which is a function that gives back an answer whether the given database contains the searched element or not) [18][19]. The algorithm is presented in detail in **Algorithm 1**.

The unconstrained objective function is denoted by F. The parameter $F_{med\,s}$ refers to the newly actual updated mean value of the function F selected by the BSA.

Algorithm 1: Quantum extreme value searching algorithm

1	We start with $s = 0$: $F_{min\,1} = F_{min\,0}$, $F_{max\,1} = F_{max\,0}$, and $\Delta F = F_{max\,0} - F_{min\,0}$
2	$s = s + 1$
3	$F_{med\,s} = F_{min\,S} + \left[\frac{F_{max\,s} - F_{min\,s}}{2}\right]$
4	$flag = QET\ (F_{med\,s})$:
5	• if $flag = Yes,$ then $F_{max\,s+1} = F_{med\,s}$, $F_{min\,s+1} = F_{min\,s}$
6	• Else $F_{max\,s+1} = F_{max\,s}$, $F_{min\,s+1} = F_{med\,s}$
7	If $S < log_2\ (G)$, then go to 2, else stop and $y_{opt} = F_{med\,s}$

The working process of quantum blind computing involves using quantum strategies and protocols to perform universal quantum computations on encoded data without the need to decode the data first, i.e., it allows computations to be performed directly on the encrypted data). This is achieved by delegating calculations to remote quantum nodes while the data remains encrypted throughout the entire process preserving privacy.

Here is an overview of the working mechanism of the QBC:

1. The data to be processed is first encrypted using a quantum encryption technique, such as quantum key distribution (QKD).
2. The encrypted data is then sent to a quantum node/server/processor.
3. The quantum node performs the desired computation on the encrypted data using a quantum encryption strategy.
4. The outcome of the computation is also returned in encrypted form.

5. The data user/sender can then decrypt the received processed data using its private key to get the result of the computation.

A classical genetic algorithm (GA) is a metaheuristic method for solving complex optimization problems using techniques inspired by natural biological evolution. The basic steps of a GA are summarized as follows:

1. Initialization step: Generate a random candidate solution (chromosome) called the "initial population". Note that each chromosome is composed of small information pieces called genes.
2. Evaluation: Evaluate the fitness function of each possible solution in the population, which is a measure of the quality of the chromosomes.
3. Selection: Select candidate solutions from the current population to generate the next generation. Typically, this is accomplished by selecting individuals with a high fitness function. There are several selection strategies[22].
4. Crossover: merge the genetic information at random positions of two selected chromosomes to create new individuals for the next generation. There are several crossover operations types [22].
5. Mutation: exchange and modify a randomly selected gene from the chromosome to generate a new chromosome. There are several crossover operations types [22].
6. Repeat steps 2 to 5 for a number of generations until converging on an optimal solution.

In real-world applications, several classical genetic algorithms have been devised with respect to the requirements of the application. In this paper, we suggested the following classical genetic algorithm, which is presented in detail in **Algorithm 2**.

Algorithm 2: Classical genetic algorithm	
1	Start with $step = 0$. Set the size of the database N. Set the size initial population S.
2	Generate randomly initial population P_{step}.
3	Apply the best-known sorting algorithm in order to select the first half of the population (parent set).
4	Apply the crossover and mutation to the parent set in order to generate the offspring set.
5	Unify the parent and offspring sets to produce the new population P_{step+1}.
6	If the optimum solution F_{opt} is obtained, then stop, else go to 3.

III. UNCONSTRAINED QUANTUM GENETIC ALGORITHM

Returning to our problem statement described in the previous section, we took advantage of the possibilities provided by quantum blind computing by delegating computation to other untrustworthy quantum nodes in developing a new quantum genetic method for solving unconstrained optimization, where the size of the unsorted database is enormous and no existing classical or quantum machine can handle it.

The computational framework is made up of a number of several quantum nodes/computers and a central quantum server. It is worth stressing that the quantum server's capacity/size is the same as that of the quantum node. As it is known, the convergence speed of the genetic method depends heavily on the quality of the generated initial candidate solutions at the initial stage. To that end, we replaced the classical heuristic initialization step with a quantum one. The suggested QGA surpasses the one presented in the previous section by two significant stages:

1. The heuristic generation of the initialization step is substituted by a quantum one, wich is realized by selecting random regions (sets of chromosomes/sub-databases). The central quantum server dispatches sub-databases into quantum computing units, and the later applies the stochastic method QEVSA in order to extract the best chromosomes/individuals. Note that the size of the population is denoted by S, while the sizes of the regions are equivalent, it equals R.
2. The classical selection procedure is substituted by a quantum one: the QEVSA is executed $\frac{S}{2}$ times in order to identify the best half-individuals/parent of the current population.

This paper does not study the physical implemental of the developed quantum genetic strategy as it is assumed well-known. The proposed quantum genetic strategy is presented in detail in **Algorithm 3**.

Algorithm 3: Quantum genetic algorithm	
1	Start with $step = 0$. Set the size of the database N, initial population S, size of the region R.
2	Generate the S regions.
3	Apply the QEVSA in each region in order to generate the initial population P_{step}.
4	Select the first half of the population (parent set) by applying the QEVSA $\frac{S}{2}$ times.
5	Apply the crossover and mutation to the parent set in order to generate the offspring set.
6	Unify the parent and offspring sets to produce the new population P_{step+1}.
7	If the optimum solution F_{opt} is found, then stop, else go to 4.

Let us investigate the computational complexity of the QGA. First, let us estimate the number of steps needed to execute the quantum initialization step. Then, the quantum selection stage.

- Quantum initialization step: at this stage, the algorithm selects randomly sets of chromosomes, where the size their size can be similar or not. The quantum server assigns the selected sub-databases into quantum computing units (the computational complexity of this procedure requires S steps). The later perform the QEVSA in order to release the best individual (the computational of this operation needs $O\left(log_2(G)log_2{}^3(\sqrt{R})\right)$ steps). In summary, the computational complexity required to create the initial quantum population of the QGA is $O\left(S.log_2(G)log_2{}^3(\sqrt{R})\right)$ steps.
- Quantum selection step: most of classical genetic algorithm uses the best classical sorting algorithm to extract the best parent set. The computational complexity of the best classical sorting strategy equals $O(S.log_2(G))$ steps. Instead of utilizing a conventional sorting method repeatedly, we run the QEVSA $\frac{S}{2}$ times, the overall computational complexity of this process is $O\left(\frac{S}{2}log_2(G)log_2{}^3(\sqrt{S})\right)$ steps.

The QGA has a resemblance to the GA. The only distinction is displacing the heuristic initialization step of the chromosome population of the GA with a stochastic quantum initialization step and the traditional selection procedure (traditional sorting strategy) with a quantum selection procedure (Utilizing $\frac{S}{2}$ times the QEVSA to retrieve the parent set).

IV. Massive MIMO Model

A downlink massive MIMO with a flat fading assumption is considered. This model has a single base station with T transmit antennas. Assuming there are K users in total, each user has R receive antennas, as seen in Figure 1. On both the receiver and transmitter sides, it is assumed that full knowledge of channel status information exists.

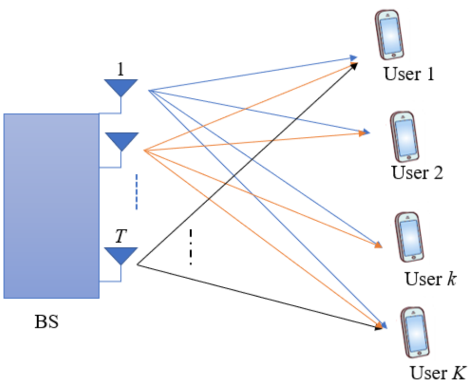

Fig. 1. Massive MIMO model with K active users and one base station with T transmit antennas.

The user k receives the signal $\boldsymbol{y}^{(k)}$,

$$\boldsymbol{y}^{(k)} = \boldsymbol{H}_k\boldsymbol{x}_k + \alpha\sum_{u\neq k}\boldsymbol{H}_u\boldsymbol{x}_u + \boldsymbol{n} \quad (1)$$

where,

- $\boldsymbol{H}_k$ indicates the channel state matrix that corresponds to the user k. The channel pair is illustrated by the notation (r,t), where r and t represent the receive and transmit antenna indexes, respectively. The channel matrix parameters are described as $h_{r,t}{}^{(k)}$.
- $\boldsymbol{x}_k$ denotes the transmitted signal to the user k such as, $\boldsymbol{x}_k = [x_1^k, \dots, x_T^k]$.
- α indicates the scaling coefficient that specifies the interference ratio of the interferer active users.
- $\boldsymbol{n}$ stands for the noise vector, with n_0 represents the power noise value utilized across all channels.
- $\sum_{u\neq k}\boldsymbol{H}_u\boldsymbol{x}_u$ is the interference applied by the remaining active users.

The transmission rate required by the user k can be expressed as,

$$R_{r,t}^{(k)} = BW * log_2\left(1 + \frac{\left|h_{r,t}{}^{(k)}\right|^2 p_{r,t}{}^{(k)}}{\alpha\sum_{u\neq k}\left|h_{r,t}{}^{(u)}\right|^2 p_{r,k}{}^{(u)} + n_0}\right) \quad (2)$$

where $p_{r,t}{}^{(k)}, BW$, and $\left|h_{r,t}{}^{(u)}\right|^2$ represent the power usage of user k, the bandwidth, and the channel gain, respectively.

One may confirm that the total data rate for the user k can be stated as,

$$R^{(k)} = \sum_{t=1}^{T}\sum_{r=1}^{R} R_{r,t}^{(k)}. \quad (3)$$

One may represent the transmit power scenarios that corresponds to signal $\boldsymbol{x}$ as $P^i = \left[p_1^i, p_2^i, \dots, p_v^i, \dots, p_T^i\right]$. The values of p_v^i are chosen from a set of powers defined by the engineer.

Our objective is to determine the optimal minimal overall transmit power assuming that all the transmit power scenarios meet the transmission rate required by the active users, one can mathematically represent this optimization problem as,

$$\min \sum_{t=1}^{T}\sum_{r=1}^{R} p_{r,t}{}^{(k)} \quad (4)$$
$$\forall\, r,t \;\; p_{r,t}{}^{(k)} \geq 0$$

V. Simulation Results

To prove the high performance of the devised QGA, a simulation was performed in order to investigate and compare the efficiency of both algorithms, i.e., (QGA and GA). Notably, both the QGA and the GA were evaluated based on a variety of metrics, including the overall transmit power and the total number of generations.

It's worth noting that the simulation's overarching objective is to compare the two algorithms (QGA and GA) in terms of the overall transmit power and the total number of generations by choosing the ideal user to transmit power for different massive MIMO systems (32x32, 64x64, 128x128, 256x256, and 512x512 M-MIMO).

The simulation environment hosts a base station with a fixed number of active users ($K = 50$). The chosen values for the possible transmit power at the base station are 0, 2, 4, and 6 dBm. The interference and the intraference are assumed. 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. The total power consumption and number of generations are computed for transmit antennas with varying numbers at the base station ($T = 32$, $T = 64$, $T = 128$, $T = 256$, and $T = 512$). The considered value of the BW equals 10 MHz, while the value of the parameter α equals 0.001.

Figure 2 presents the effect that increasing the number of transmit antennas at the base station T on the total power consumption. As depicted in Figure 2, the optimal value of power usage increases as the total number of antennas at the base station increases. In addition, both algorithms consume similar quantity of power for every massive MIMO system.

Figure 3 shows that the QGA executes lower number of generations compared to the classical GA. Additionally, one may observe that although the changes of the number of transmit antennas, the QGA executes a low number of generations. Consequently, the QGA maintains a lower computational complexity than the GA when the value of T increases.

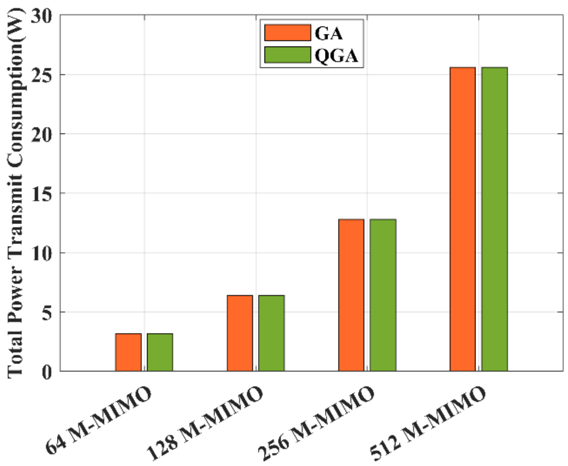

Fig. 2. The overall transmit power usage consumed by different massive MIMO systems for both algorithms (QGA and GA).

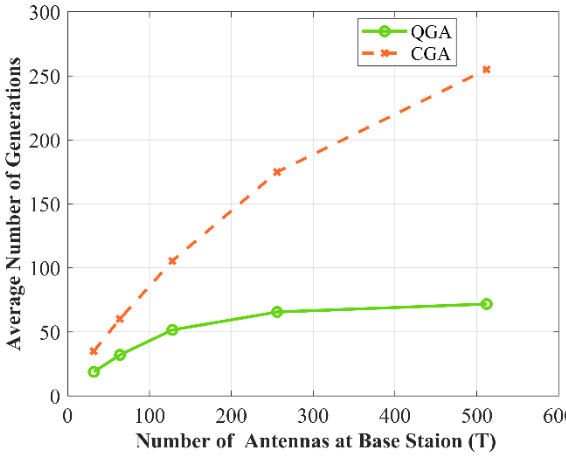

Fig. 3. The number generations performed by the QGA and GA for different massive MIMO systems.

VI. Conclusion

In this paper, we incorporated a novel quantum genetic algorithm (QGA) based on the quantum extreme value searching algorithm (QEVSA) in the computational framework of the downlink massive MIMO system in order to minimize the transmit power of the downlink massive MIMO system. Simulation results shows that the developed quantum genetic strategy conserves a low consumption of power as well as a low reduction in terms of computational complexity, although rising the number of transmit antenna at the base station.

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