# New Quantum Strategy for MIMO System Optimization

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Abstract: Co-channel interference and noise power could affect the performance of the MIMO system and can be evaluated with respect to the user's signal to noise and interference ratio. As a result, the desired transmission rate of the users could be satisfied by consuming more transmit power. Owing to this, a quantum optimization strategy can be utilized in order to minimize the transmit power, as well as to achieve an optimum trade-off within the throughput and the resulting interference and noise. In this study, a constrained quantum optimization algorithm (CQOA) has been implemented in the MIMO-downlink system to reduce the transmit power and computational complexity. An analytical study is conducted along with a comparison between the water filling algorithm-based binary searching algorithm (WFA-BSA), exhaustive algorithm-based water filling algorithm (EWFA), and the CQOA. Finally, simulation results show that the aforementioned methods consume similar total transmit power, however, the computational complexity of the quantum strategy is dramatically low compared to the other methods.

## 1 INTRODUCTION

The next 5G and 6G wireless communication networks are expected to support the massive exponential augmenting number of devices (Eid et al., 2021; Dung et al., 2020). The multiple-input and multiple-output (MIMO), a promising essential method in 5G and 6G wireless communication, boosts system throughput by increasing the number of channels thanks to the adoption of multiple transmit and receive antennas. The MIMO exploits the power of multipath propagation to send and receive simultaneously multiple data signals over the same radio channel and space-time (Ahrens et al., 2014; Marosits et al., 2021).

It is expected that the total number of 5G devices will reach 13.1 million in 2025 (Report, 2021). Merging 5G and MIMO technologies will lead to deploying a massive number of base stations, which will dramatically increase the power consumption by 1000 times (Johnson, 2018). For this sake, information and communication technologies (ICTs) working on leveraging this enormous energy usage. Beside the high-power usage, MIMO systems suffer from high computational complexity as the number of antennas grows (Kyosti and Jamsa, 2007). To that end, new cutting-edge technologies have emerged as alternative solutions for increasing the transmission rate of 5G and 6G wireless technologies, as well as augmenting the signal-to-noise ratio, such as quantum computing, quantum machine learning, etc.

The aim of these newly emerged technologies is to lower the computational complexity and provide an exponential speed over classical computers, as well as increasing the accuracy of the obtained solutions. Quantum computing proposes its capabilities as a new futuristic alternative solution for MIMO systems

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in order to achieve high throughput and reduce both the transmit power and the computational complexity.

In the present study, a constrained quantum optimization algorithm (CQOA) for the downlink MIMO system is implemented in order to minimize the transmit power consumption with respect to the target transmission rate of the user. To validate the efficiency of the proposed quantum strategy, the performance of the CQOA is compared with the water filling algorithm-based binary searching algorithm (WFA-BSA) and the exhaustive search-based water filling algorithm (EWFA) in terms of overall transmit power consumption and computational complexity.

The remainder of the paper is organized as follows: Section 2 describes the downlink MIMO system where the flat fading channel is considered. Section 3 introduces the implementation of the WFA-BSA, EWFA, and CQOA. A computational complexity analysis of the presented algorithms is then conducted. Section 4 estimates the essential stochastic parameter for running the binary searching algorithm (BSA) embedded in the WFA-BSA and CQOA. Section 5 demonstrates the efficiency of the proposed quantum solution using simulation results. Finally, a summary and future plans are included in Section 6.

## 2 MIMO SYSTEM

A downlink MIMO system is considered, where a flat fading is assumed. This model contains one base station equipped with *T* antennas. Assuming that the total number of users is *U*, each of them has *R* receive antennas, as shown in Figure 1. Full knowledge about the channel state information at both the receiver and the transmitter sides is assumed.

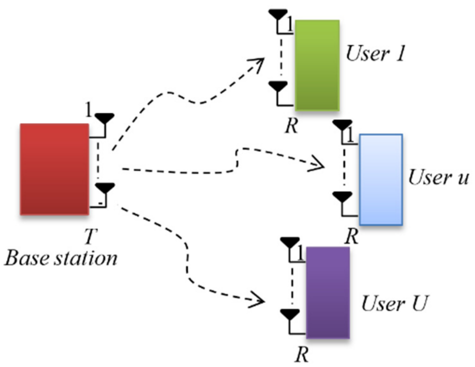


Figure 1: A MIMO system has one base with *T* transmit antennas and *U* users with an *R* receive antennas.

Let $\boldsymbol{x}_u$ be the signal transmitted to the user $u$ such as,

$$\boldsymbol{x}_u = [x_1^u, \dots, x_T^u] \tag{1}$$

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

$$\boldsymbol{y}^{(u)} = \boldsymbol{H}_u \boldsymbol{x}_u + \boldsymbol{n} + \gamma \sum_{v \neq u} \boldsymbol{H}_v \boldsymbol{x}_v \tag{2}$$

where,

- $\gamma$ is the scaling factor that describes the interference ratio of the interferer users.
- $\boldsymbol{H}_u$ refers to the channel state that is linked to user $u$. Note that the channel pair is denoted by subscripts $(r, t)$ such that $r$ and $t$ refer to receive and transmit antenna, respectively. The coefficients of the matrix $H_u$ are represented as ${h_{r,t}}^{(u)}$.
- $\boldsymbol{n}$ denotes the noise vector. All channels have an identical power noise denoted $n_0$.
- $\sum_{v \neq u} \boldsymbol{H}_v \boldsymbol{x}_v$ refers to the interference exercises by the other remaining users.

The maximum transmission rate desired by user $u$ is given as,

$$B_{r,t}^{(u)} = D * log_2 \left( 1 + \frac{{g_{r,t}}^{(u)} {p_{r,t}}^{(u)}}{\gamma \sum_{v \neq u} {g_{r,k}}^{(v)} {p_{r,k}}^{(v)} + n_0} \right) \tag{3}$$

where the parameters $D$ and ${g_{r,t}}^{(u)}$ refer to the bandwidth and the channel gain, respectively, such that ${g_{r,t}}^{(u)} = \left|{h_{r,t}}^{(u)}\right|^2$. The parameter ${p_{r,t}}^{(u)}$ denotes the power usage of user *u* in the channel link (*r*,*t*).

One can easily verify that the total bit rate associated with user *u* can be expressed as,

$$B^{(u)} = \sum_{t=1}^{T} \sum_{r=1}^{R} B_{r,t}^{(u)}. \tag{4}$$

Now we are in a position to express mathematically the optimization problem. The aim is to select the best optimum minimum overall transmit power with respect to the bit rate target of the given user $B_{target}^u$,

$$\begin{gathered} min \sum_{t=1}^{T} \sum_{r=1}^{R} {p_{r,t}}^{(u)} \\ subject\ to \quad B^{(u)} \geq B_{target}^u \\ \forall r, t \quad {p_{r,t}}^{(u)} \geq 0 \end{gathered} \tag{5}$$

## 3 ALGORITHMS

In the light of what has been discussed in Section 1. One may conclude that among classical search and optimization methods that have been extensively extended and explored in improving the power consumption of MIMO systems are: the water filling algorithm (WFA), and the exhaustive algorithm (EA). As commonly known, computational complexity stands as a crucial pillar in selecting the best optimization strategy for the given desired optimization problem. This section introduces the CQOA and compares the performance of the aforementioned traditional algorithms with the CQOA in terms of computational complexity.

In the sequel, each optimization strategy was presented, followed by an implementation in the proposed MIMO system.

## 3.1 WFA-BSA Implementation

The problem of reducing the total transmit power usage subject to the desired transmission rate of a certain user $u$ can be solved by iterating over the possible total power transmit using the binary searching algorithm (BSA) (Knuth, 1998), and applying the water filling algorithm with respect to the candidate possible total transmit power selected by the BSA, this new method called water filling algorithm-based binary searching algorithm (WFA-BSA). For this sake, deriving an appropriate solution for (5) using the Karush–Kuhn–Tucker (KKT) conditions is necessary. Reformulates the problem in (5) yields,

$$\begin{gathered} min \sum_{t=1}^{T}\sum_{r=1}^{R} p_{r,t}{}^{(u)} \\ subject\ to \quad -B^{(u)} + B^{u}_{target} \leq 0 \\ \forall r,t \quad -p_{r,t}{}^{(u)} \leq 0 \end{gathered} \tag{6}$$

The optimization problem stated in (6) is convex. Thus, the KTT conditions can be implemented.

To solve the problem in (6), the Lagrangian function for the optimization problem in (6) (denoted by $M$) is constructed as,

$$M = \sum_{t=1}^{T}\sum_{r=1}^{R} p_{r,t}{}^{(u)} + a * \left(-B^{(u)} + B^{u}_{target}\right) - \sum_{t=1}^{T}\sum_{r=1}^{R} \beta_{r,t} * p_{r,t}{}^{(u)} \tag{7}$$

where$a$ and $\beta_{r,t}$ refer to the Lagrangian multipliers. Assuming that$p_{r,t}{}^{(u)} \geq 0$, the optimal solution can be expressed as,

$$\begin{gathered} \frac{\partial M}{\partial p_{r,t}{}^{(u)}} = 0 \quad if\ p_{r,t}{}^{(u)} > 0 \\ \frac{\partial M}{\partial p_{r,t}{}^{(u)}} \leq 0 \quad if\ p_{r,t}{}^{(u)} = 0 \end{gathered} \tag{8}$$

According to the complementary slackness $\forall r,t \quad \beta_{r,t} * p_{r,t}{}^{(u)} = 0$ , this states that either $p_{r,t}{}^{(u)} = 0$ or $\beta_{r,t} = 0$, which means that if $p_{r,t}{}^{(u)} > 0$, then $\beta_{r,t} = 0$. This can be easily verified as,

$$p_{r,t}{}^{(u)^*} = \left(aD - \frac{\gamma \sum_{v \neq u} g_{r,k}{}^{(v)} p_{r,k}{}^{(v)} + n_0}{g_{r,t}{}^{(u)}}\right)^+ \tag{9}$$

Let's assume that $I_{r=} \sum_{v \neq u,\ k \neq t} g_{r,k}{}^{(v)} p_{r,k}{}^{(v)}$, where the parameter $I_r$ denotes the co-channel interference resulting from the remaining users $v$. The parameter $p_{r,t}{}^{(u)^*}$ denotes the power usage of user $u$ of the channel link ($r$,$t$). It is considered that all channels have identical power noise called $n_0$. Note that $x^+ := max(x, 0)$.

The value of $a * D$ describes the water level. For finding the optimal minimum power transmission with respect to the transmission rate of the user, the WFA-BSA can be applied, which is explicitly presented as follows,

1. We start with $L = 0$: $P_{min\,1} = P_{min\,0}$, $P_{max\,1} = P_{max\,0}$, and $\Delta P = P_{max\,0} - P_{min\,0}$
2. $L = L + 1$
3. $P_{med\,L} = P_{min\,L} + \left[\frac{P_{max\,L} - P_{min\,L}}{2}\right]$
4. $flag = WFA\left(P_{med,L}\right)$:
   - if $flag = Yes$, then $P_{max,L+1} = P_{med,L}$ $P_{min,L+1} = P_{min,L}$
   - Else $P_{max,L+1} = P_{max,L}$, $P_{min\,L+1} = P_{med\,L}$.
5. If $L < log_2\ (G)$, then go to 2, else stop, then $y_{opt} = P_{opt}$

The function $WFA\left(P_{med,L}\right)$ returns an answer to whether the actual selected candidate for the total transmit power satisfies the target transmission rate of the given user or not given that $G$ denotes the maximum number of steps required to run the BSA. More details about the WFA function will be discussed in Section 3.4.

### 3.2 EA Implementation

To sort out the antenna combination that gives back the optimum minimum overall transmit power of the MIMO system, the exhaustive search method examines all possible solutions resulting from all transmit and receive antenna combinations. The EA gives back an exact and accurate optimum solution. In contrast, the EA iterates over all possible total transmit scenarios which are computationally hard.

A special question arises if one is interested in implementing the EA in the MIMO system described in Section 2. In this case, the EA will be unable to perform an appropriate distribution of power among channels because the optimal decisions are based on the interference and noise resulting from channels. To solve this problem, one may extend the capabilities of the EA by merging the exhaustive search and the WFA. This new algorithm is called the exhaustive search-based water filling algorithm (EWFA). The EWFA iterates over the possible candidate for the total transmit power scenarios and apply the water filling method, the optimum minimum transmit power is selected once the desired transmission rate $B^{u}_{target}$ is met.

### 3.3 CQOA Implementation

The CQOA (El Gaily and Imre, 2021) seeks the best extreme value of a constrained goal function (or an unsorted database). Its efficiency stems from the combination of two methods: The BSA and the constrained quantum relation testing (CQRT), which is an extended version of the quantum relation testing function (Imre, 2005; Imre, 2007). The CQRT gives a clear indication into whether there exist at least one or more database entries with respect to the applied optimization problem type (minimization or maximization of the goal function) of the reference value, and the constraint *C* in a certain region of the database. More details are given in (El Gaily and Imre, 2021). The detailed algorithm is explicitly shown below,

1. We start with $S = 0$ : $P_{min\,1} = P_{min\,0}$ , $P_{max\,1} = P_{max\,0}$ , and $\Delta P = P_{max\,0} - P_{min\,0}$
2. $S = S + 1$
3. $P_{med\,S} = P_{min\,S} + \left[\frac{P_{max\,S} - P_{min\,S}}{2}\right]$
4. $flag = CQRT\ (P_{med\,S}, R, C\ )$:
   - if $flag = Yes,$ then $P_{max,S+1} = P_{med,S}$ $P_{min,\ S+1} = P_{min,L}$
   - 
   - Else $P_{max\,S+1} = P_{max\,S}$ , $P_{min\,S+1} = P_{med\,S}$
5. If $S < log_2\ (G)$, then go to 2, else stop and $y_{opt} = P_{med\,S}$

where the CQRT function has the following inputs, which are defined as follows,

- $P_{med\,S}$ : The newly actual updated mean value of the total transmit power selected by the BSA.
- $R$ : The index relation defines the optimization type whether it is unconstraint or constraint optimization. More details about the setup of the symbol $R$ are described in (El Gaily and Imre, 2021). As the optimization problem presented in (5) describes a minimization of the total transmit power of the MIMO system, the index relation $R$ will be assigned the symbol "≤".
- $C$ : The function's constraint parameter. According to the problem defined in (5), $C = B^{u}_{target}$.

The CQRT allows the BSA to be adapted to work with an unsorted database while maintaining high speed and accuracy, which is why the CQOA outperforms its traditional optimization counterpart. The quantum phase estimation approach (Imre, 2005; Imre, 2007; Imre and Balázs, 2005) is used to derive the CQRT's power.

### 3.4 Computation Complexity Analysis

In search and optimization problems, computational complexity plays a crucial role in selecting the best optimization strategy for the given desired problem. Thus, this section is devoted to compare the performance of the WFA, EWFA, and CQOA in terms of computational complexity.

Let $N$ denote the total number of channels, where $N = R * T$. The implementation methodology of the WFA-BSA in the proposed optimization problem is described as follows: First, preparing the search space (database entries), which represents all the possible total transmit power scenarios of the BSA, where the size space refers to the maximum number of steps $G$ needed to run the BSA (The computational complexity of the BSA is $log_2(G)$ steps). The WFA function is then applied. Note that the WFA sorts the channels in an ascending manner with respect to the resulting noise and interference power (The computational complexity of the best classical sorting method is known to be $O\left(Nlog_2(N)\right)$ steps). The WFA selects the best optimum power that satisfies the desired transmission rate$B_{target}^{u}$. For this purpose, it is worthwhile to repeatedly remove the channel with the highest interference and noise power when the $B_{target}^{u}$ is not met and re-apply the WFA function. The computational complexity of this operation is $O(N)$ steps, whereas the computational complexity of the WFA-BSA is $O\left(N^2log_2(N)log_2(G)\right)$ steps.

The EWFA's working methodology is similar to that of the WFA-BSA with the exception that the BSA is replaced by an exhaustive search. One can conclude that the EWFA's computational complexity is $O\left(GN^2log_2(N)\right)$ steps.

The computational complexity of the CQOA is $O\left(log_2(G)log_2{}^3(\sqrt{N})\right)$ (El Gaily and Imre, 2021). On the other hand, the computational complexities of the aforementioned strategies are listed in Table 1.

Table 1: The computational complexities of the aforementioned optimization algorithms.

| Methods | Computational complexity |
|---|---|
| EWFA | $O\left(GN^2log_2(N)\right)$ |
| WFA-BSA | $O\left(N^2log_2(N)log_2(G)\right)$. |
| CQOA | $O\left(log_2(G)log_2{}^3(\sqrt{N})\right)$. |

## 4 CONFIGURATION OF THE BSA

In the previous section, it was demonstrated that estimating the value of $G$ is very important for running the BSA (embedded in the WFA and CQOA) and the EA. This study estimates the value of $G$ where the co-channel interference is neglected. The stochastic parameter $G$ is strongly connected to the maximum transmission power $P_{max}$ that can be consumed by the MIMO system, as well as the minimum difference between two different possible transmit power scenarios denoted $\alpha$. One reads the value of $G$ as,

$$G = \frac{P_{max} - P_{min}}{\alpha} \quad (10)$$

where $P_{min}$ denotes the minimum transmit power consumed by the MIMO system. The parameter $\alpha$ can be expressed as,

$$\alpha = \min_{i,j}\left|P_i - P_j\right|, \quad (11)$$

where $P_i$and $P_j$ refer respectively to the total transmit power of the possible scenarios $i$ and $j$ . The expression of $P_i$ can be given as,

$$P_i = \sum_{r_i}\sum_{t_i}\left(\lambda_i - \frac{n_0}{g_{r_i,t_i}}\right), \quad (12)$$

where $\lambda_i$ is the water level of the possible transmit power of the $i^{th}$ scenario, note that $\lambda_i = a_i * D$ , where $a_i$ refers to the obtained Lagrangian coefficient of the $i^{th}$ scenario. On reads the expression of $\alpha$ as,

$$\alpha = \min_{i,j}\left|\sum_{r_i}\sum_{t_i}\left(\lambda_i - \frac{n_0}{g_{r_i,t_i}}\right) - \sum_{r_j}\sum_{t_j}\left(\lambda_j - \frac{n_0}{g_{r_j,t_j}}\right)\right|, \quad (13)$$

It is important to note that the power noise summarized in the coefficient $\frac{n_0}{g_{r_i,t_i}}$ of the channels are sorted, before applying the $WFA\left(P_{med,L}\right)$ function described in Section 3.1. Moreover, it is worth mentioning that the selected channels for each scenario depend tightly on the coefficient$\frac{n_0}{g_{r_i,t_i}}$.

Let $S_i$ and $S_j$ be the set of channels chosen respectively in the $i^{th}$ and $j^{th}$ scenarios. We consider $S^c$ the complement of $S$, such as $S = S_i \cap S_j$. One can define $P_i - P_j$ as,

$$P_i - P_j = \sum_{r_i}\sum_{t_i}\lambda_i - \sum_{r_j}\sum_{t_j}\lambda_j + \sum_{r_j}\sum_{t_j}\frac{n_0}{g_{r_j,t_j}} - \sum_{r_i}\sum_{t_i}\frac{n_0}{g_{r_i,t_i}} \quad (14)$$

It is clearly noticed that the coefficient $\sum_{r_i}\sum_{t_i}\lambda_i$ describes the number of channels for the $i^{th}$ scenario multiplied by $\lambda_i$. One then reads,

$$\sum_{r_i}\sum_{t_i}\lambda_i = n_i\,\lambda_i \quad (15)$$

where $n_i$ refers to the total number of channels in the case of the $i^{th}$ scenario. In addition, it can be noticed that the expression given in (16) is connected to constant coefficients such as $n_0$, $g_{r_i,t_i}$, and $g_{r_j,t_j}$.

$$\sum_{r_j}\sum_{t_j}\frac{n_0}{g_{r_j,t_j}} - \sum_{r_i}\sum_{t_i}\frac{n_0}{g_{r_i,t_i}} \quad (16)$$

Eq. (16) can be reformulated as the sum of coefficients $\frac{n_0}{g_k}$ belonging to $S^c$ channels set. The expression of $P_i - P_j$ can be re-expressed as,

$$P_i - P_j = n_i \lambda_i - n_j \lambda_j + \sum_{k \in S^c} \frac{n_0}{g_k} \quad (17)$$

where $g_k$ represents the $k^{th}$ channel belonging to $S^c$ set. To estimate the value of $\alpha$, we utilized the lower bound of $|P_i - P_j|$. One can check that the lower bound of $|P_i - P_j|$ can be expressed as,

$$|n(\lambda_i - \lambda_j)| \leq |P_i - P_j| \quad (18)$$

where $n = n_i = n_j$. Note that if the value of $\alpha$ is very small, it will not affect the search process of the BSA, i.e., the logarithmic operation allows a high reduction in terms of the total number of database entries. A new lower bound of $|P_i - P_j|$ can be seen as,

$$|(\lambda_i - \lambda_j)| \leq |P_i - P_j| \quad (19)$$

Consequently, the expression of the parameter $\alpha$ can be written as,

$$\alpha = \min_{i,j} |\lambda_i - \lambda_j| \quad (20)$$

According to (20), the value of $\alpha$ is strongly connected to $\lambda_i$ and $\lambda_j$ of the $i^{th}$ and $j^{th}$ scenarios.

# 5 SIMULATIONS

To demonstrate the efficiency of the proposed CQOA, a simulation environment was built to compare the performance of the proposed CQOA with the WFA-BSA and the EWFA.

To this end, three simulation environments were built, where each one of them considers a MIMO system type: MIMO $2 \times 2$, MIMO $4 \times 4$, and MIMO $8 \times 8$. It is interesting to note that the simulation experiments aim to evaluate and compare the performance of the CQOA, EWFA, and WFA-BSA in terms of overall transmit power consumption of the MIMO system and computational complexity.

We considered in every MIMO system type the following:

- The total number of users is 32, where we assumed that the channels of the 31 users interfere with the last reference user.
- The channel gain is random, it depends on channel fading, path loss, and the distance between users.
- Path loss equals 4 dB.
- The distance between every two users equals 1000 meters.
- The desired target transmission rate of the reference user is $B^u_{target} = 60$ Mbps.
- The target transmission rate of 16 users is similar and equals 50 Mbps.
- The target transmission rate of the remaining 15 users is similar and equals 55 Mbps.
- The used bandwidth $D = 10^6$ Hz and $\gamma = 0.001$.
- The transmitted data is one signal.
- The power noise of all channels is identical.
- The interference between channels belonging to the reference user is not assumed (there is no self-interference of the desired user).

As it is already discussed, the step size is a very important parameter for running the algorithms. For this sake, it is considered that $\alpha = 0.0002$, and the maximum transmit power that can be reached by a MIMO system type is $P_{max} = 0.02$ Watt.

We repeat every simulation for different channel gains for the aforementioned optimization strategies (EWFA, WFA-BSA, and CQOA).

For each MIMO system type (MIMO $2 \times 2$, MIMO $4 \times 4$, and MIMO $8 \times 8$), the simulations were repeated 100 times. the average of the overall transmit power consumption was then calculated, as well as the power gain of every MIMO type versus another MIMO type for each strategy, i.e., the CQOA, EWFA, and WFA-BSA. Moreover, to show the influence of the interference power resulting from the other 31 users on the optimum power usage of the reference user, the simulation is repeated with and without considering the interference of users.

Figure 2 illustrates the total transmit power consumption of the CQOA, EWFA, and WFA-BSA, where the resulting interference power of users is assumed. It is clearly noticeable that the three optimization strategies consume the same optimum minimum average total transmit power in each MIMO system type. Also, one may observe that the optimum total transmit power decreases when the number of antennas of the MIMO system increases.

Figure 3 presents the influence of the interference and noise power resulting from other 31 users on the reference user. It is noticed that the optimum total transmit power consumed before and after considering interference of users is approximately similar. This shows that the resulting interference from the other 31 users has no significant effect on the power usage of the reference user.

Table 2 shows the power gain of every MIMO type versus another MIMO type. It is obvious that the average optimum minimum power value decreases with a higher number of antennas. For example, the optimum power consumed in MIMO 8 x 8 compared with MIMO 2 x 2 and MIMO 4 x 4 is much less by 41% and 10%, respectively.

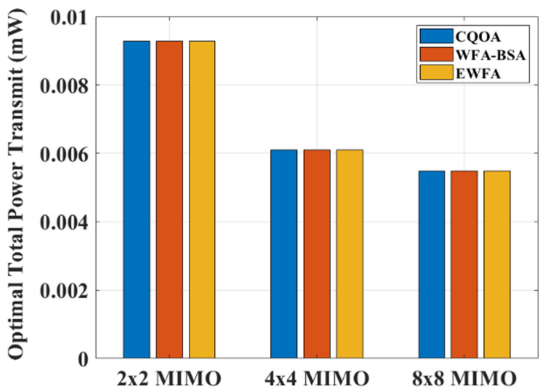


Figure 2: The total transmit power consumed by the WFA_BSA, EWFA, and CQOA, in the case of MIMO 2 × 2, MIMO 4 × 4, and MIMO 8 × 8.

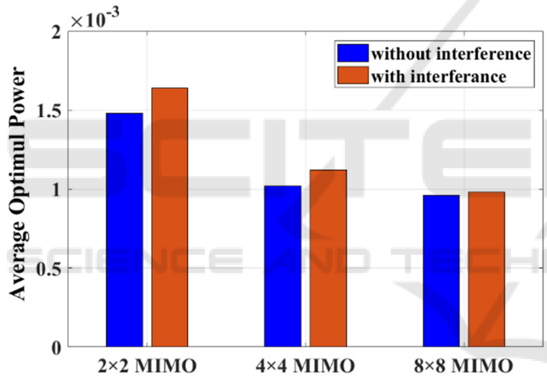


Figure 3: The total transmit power consumed with and without considering interference of users on the reference user, in the case of MIMO $2 \times 2$, MIMO $4 \times 4$, and MIMO $8 \times 8$.

Table 2: The power gain of each MIMO type versus another MIMO type.

| | Average_ Power | Power gain vs. MIMO 2 x 2 | Power gain vs. MIMO 4 x 4 | Power gain vs. MIMO 8 x 8 |
|---|---|---|---|---|
| MIMO 2 x 2 | 0.00928 | * | 34% | 41% |
| MIMO 4 x 4 | 0.00610 | -34% | * | 10% |
| MIMO 8 x 8 | 0.00548 | -41% | -10% | * |

To demonstrate the efficiency of the proposed CQOA, another simulation experiment was implemented to compare the performance in terms of the computational complexity of the proposed CQOA with other optimization algorithms. As it can be seen from Figure 2, the CQOA, EWFA, and the WFA-BSA require the same amount of transmit power in each MIMO system type. However, from the perspective of computational complexity (Figure 4), it is clearly noticeable that the total number of steps needed to identify the optimum transmit power consumption of the CQOA is very low compared to the other reference algorithms. For instance, the WFA_BSA requires roughly $6.7 \times 10^8$ steps in MIMO 64 x 64, whereas the CQOA only requires 717 steps. In addition, it is apparent that as the total number of transmit antennas increases, the computational complexity of the WFA_BSA and EWFA grows exponentially, while the CQOA retains a low computational complexity as the number of transmit antennas grows.

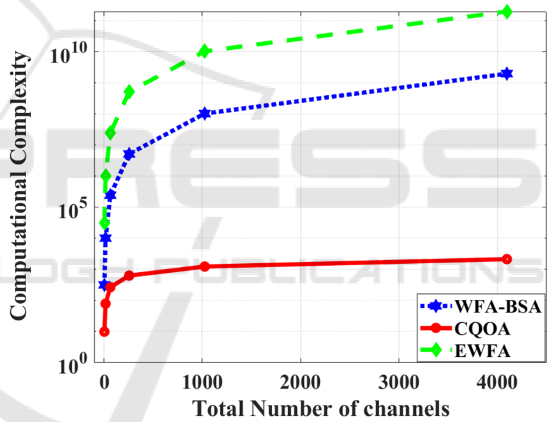


Figure 4: The computational complexity of CQOA and WTA_BSA.

## 6 CONCLUSIONS

This work investigated the reduction of the total transmit power for different MIMO-downlink systems by taking into consideration the transmission bit rate target of the users. The implementation of the WFA-BSA, EWFA, and CQOA is also studied. It is proved by simulation environment for different MIMO systems that the CQOA reduces the power consumption with high exponential speed and accuracy. While the WFA-BSA and EWFA consume similar power as the CQOA with the price of high computational complexity. In future work, the plan is to expand the MIMO model by considering multiple users and multiple base stations, as well as embedding the orthogonal frequency-division multiplexing (OFDM) technique in the MIMO system. In addition, the maximum number of steps needed to run the BSA with respect to the resulting interference and noise power required to run the CQOA can be estimated.

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