Hybrid digital and analog beamforming design using genetic algorithms

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ABSTRACT

Hybrid analog and digital beamforming is gaining attention for its practical application in large-scale antenna systems. It offers significant cost savings, reduced complexity, and lower power consumption compared to entirely digital beamforming, all while maintaining comparable performance. This article proposes a hybrid beamforming architecture aimed at addressing these challenges by using a reduced number of radio frequency (RF) chains while achieving performance comparable to entirely digital schemes. The study demonstrates that matching the number of RF chains to the total number of data streams enables hybrid beamforming to compete effectively with entirely digital beamformers. The adopted approach focuses on computing analog and digital precoders and combiners using the meta-heuristic method of genetic algorithms, in a point-to-point multiple input multiple output (MIMO) system scenario. The objective is to simplify the system and reduce costs by optimizing the number of antennas, RF chains, and data streams, all while maintaining comparable performance to entirely digital beamforming. The study's results show that increasing the number of antennas significantly impacts the quality and capacity of the hybrid massive MIMO beamforming system. Conversely, reducing the number of RF chains has a negligible effect on quality and capacity, but simplifies the design and minimizes costs

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1. INTRODUCTION

The exponential increase in data usage on mobile devices and the increasing demand for high data rate applications have motivated the development of millimeter wave (mmWave) communication systems [1]–[3]. The mmWave communication systems offer a large bandwidth and are capable of providing high data rates. However, the high frequency and high path loss of mmWave signals present significant challenges in the design of efficient communication systems [4]. Nonetheless, the reduced wavelength associated with mmWave frequencies also facilitates the denser arrangement of antennas within a given physical space. This phenomenon paves the way for extensive spatial multiplexing and the implementation of markedly focused beamforming strategies. Consequently, the emergence of the massive multiple input multiple output (MIMO) concept becomes as a defining feature within the domain of mmWave communications. However, the implementation of efficient beamforming techniques for mmWave communications is not without challenges.

Traditional approaches to beamforming, including both digital and analog methods, encounter limitations when applied to mmWave communications. The utilization of digital beamforming in mmWave systems is hindered by the exorbitant expenses and power consumption associated with requiring a dedicated radio frequency (RF) chain for each antenna element [5]–[10]. Analog beamforming, while more energy-efficient, suffers from limitations in adaptability and flexibility, particularly in handling dynamic channel conditions.

Addressing these challenges, researchers have turned their focus towards hybrid beamforming architectures, which combine the strengths of both digital and analog techniques. Within the literature, various hybrid beamforming architectures have been proposed, each with its own advantages and limitations. Among these, the utilization of analog or RF beamforming methodologies, implemented through analog circuitry, has been introduced [11]–[14]. These methodologies predominantly rely on analog phase shifters, which enforce a constant modulus constraint on the beamformer's constituent elements. Consequently, analog beamforming displays inferior performance when compared to entirely digital beamforming designs. An alternate avenue for addressing the RF chain limitation involves antenna subset selection, realized through the application of uncomplicated analog switches [15]–[17]. However, these methods fall short of achieving complete diversity gains in correlated channels, as the antenna selection scheme exclusively engages a subset of channels [18], [19].

Despite the progress in this field, certain critical questions remain. One such question pertains to the relationship between the number of RF chains and data streams in a hybrid beamforming architecture. Interestingly, research has shown that the number of RF chains needs only to scale linearly with twice the total number of data streams to achieve performance comparable to entirely digital schemes. However, challenges arise when the number of RF chains falls short of this threshold, warranting the exploration of heuristic algorithms proposed in [20].

The problem this paper addresses is the design and implementation of efficient beamforming techniques for mmWave massive MIMO systems that can overcome the inherent limitations of both digital and analog beamforming methods. Specifically, it tackles the challenges posed by the high costs and power requirements of digital beamforming, the limited flexibility and adaptability of analog beamforming, and the limitations of heuristic methods. Heuristic methods, while useful, often fail to achieve global optima and can be trapped in local minima, leading to suboptimal performance in dynamic and complex channel conditions.

To address these challenges, recent advancements in optimization techniques have introduced meta-heuristic and global methods, which offer the promise of attaining global optima without succumbing to local minima. These methods, though computationally intensive, provide robust solutions to ill-conditioned problems and constraints [21]. It is within this context that we propose the application of the genetic algorithm to the design of hybrid beamformers.

In this paper, the suggested approach involves utilizing a genetic algorithm to develop hybrid beamformers specifically designed for point-to-point massive MIMO systems. The genetic algorithm is employed to optimize both analog and digital precoders and combiners, aiming to maximize spectral efficiency under the assumption of perfect knowledge of channel information (CSI) at both the base station and user level while minimizing implementation costs. This approach leverages the genetic algorithm's robust global optimization capabilities to address the limitations of traditional heuristic methods and improve system performance in diverse scenarios. Employing a genetic algorithm enables the design of hybrid beamformers that demonstrate commendable performance under the following conditions: i) when the number of RF chains is no less than the number of data streams, and ii) in scenarios where an uncorrelated channel matrix assumption holds true.

The results achieved with this approach are significant improvements in spectral efficiency and bit error rate (BER) compared to existing hybrid methods and close to the performance of entirely digital beamforming systems. Detailed simulations and numerical analyses validate the efficacy of the genetic algorithm-based approach, showing superior performance in various configurations, including different numbers of antennas, RF chains, and data streams. For example, the results indicate that spectral efficiency increases as the signal-to-noise ratio (SNR) improves, and an increase in the number of antennas for transmission and reception enhances spectral efficiency and reduces BER. Additionally, the genetic algorithm demonstrates notable efficiency gains, surpassing heuristic methods and achieving near-optimal performance in several key metrics.

2. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a massive MIMO hybrid beamforming multi-user system operating in millimeter-wave frequencies, as depicted in Figure 1. In this setup, a transmitter utilizes an array of N_t antenna elements and N_t^{RF} RF transmission chains to communicate concurrently with K users. Each user employs an array of N_r antenna elements and N_r^{RF} RF chains for transmitting d data streams. To facilitate multi-stream communication, the system must satisfy the following conditions: $d \leq N_r^{RF} \leq N_r$ and $N_s \leq N_t^{RF} \leq N_t$ where $N_s = kd$ [20].

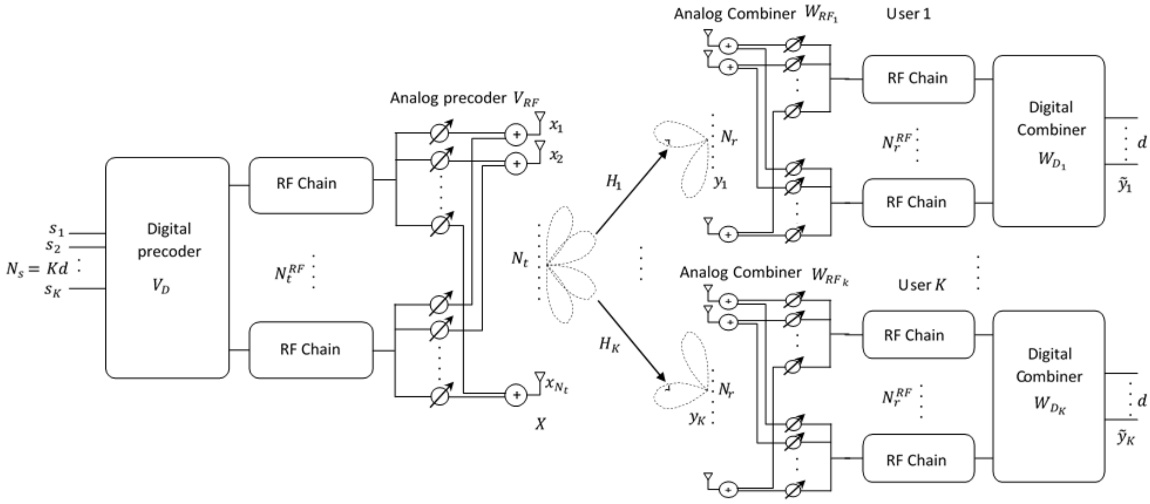

Figure 1. System diagram for the downlink of a multiuser massive MIMO system with hybrid beamforming

The baseband data streams undergo sequential precoding in a hybrid beamforming system operating at millimeter-wave frequencies. Initially, digital precoding V_D is applied, followed by analog precoding V_{RF} through corresponding RF chains. The analog precoder V_{RF} consists of phase shifters satisfying: $|V_{RF}(m,n)| = 1/\sqrt{N_t}\ \forall m,n$. The hybrid precoder configuration includes $V_D = \left[V_{D,1} \cdots V_{D,k} \cdots V_{D,K}\right] \in \mathbb{C}^{N_t^{RF} \times N_s}$ where $V_{D,k} \in \mathbb{C}^{N_t^{RF} \times d}$ represents the digital precoder matrix for the k-th user, and $V_{RF} \in \mathbb{C}^{N_t \times N_t^{RF}}$. Assuming the initial signal is S, the transmitted signal X is given by (1):

$$X = V_{RF} V_D S = \sum_{l=1}^{K} V_{RF} V_{D_l} S_l \tag{1}$$

where $S = [S_1^T, S_2^T, \cdots, S_K^T\ ]^T \in \mathbb{C}^{N_s \times 1}$, where $s_K^T \in \mathbb{C}^{d \times 1}$ denoting the symbols for the k-th user, satisfying $E[ss^H] = I_{N_s}$, $X \in \mathbb{C}^{N_t \times 1}$ and $\|V_{RF} V_D\|^2 = P_T$ represents the total transmitted power.

For simplification, we assume a block fading narrowband propagation channel, resulting in the received signal vector $y_k \in \mathbb{C}^{N_r \times 1}$ for the k-th user:

$$y_k = H_k V_{RF} V_{D_k} S_k + H_k \sum_{\substack{l=1 \\ l \neq k}}^{K} V_{RF} V_{D_l} S_l + Z_k \tag{2}$$

The channel matrix $H_k \in \mathbb{C}^{N_r \times N_t}$ represents the communication channel for the k-th user, while $Z_k \in \mathbb{C}^{N_r \times 1}$ denotes the noise vector with independent and identically distributed complex Gaussian entries, having zero mean and covariance $\sigma_n^2 I_{N_r}$. Each user k initially processes received signals using an RF combiner $W_{RF_k} \in \mathbb{C}^{N_r \times N_r^{RF}}$, implemented with phase shifters ensuring $|V_{RF}(m,n)| = 1/\sqrt{N_t}\ \forall m,n)$, Subsequently, the signals are down converted to baseband using N_r^{RF} RF chains. Finally, a low-dimensional digital combiner $W_{D_k} \in \mathbb{C}^{N_r^{RF} \times d}$ processes the signals to produce the final processed signals.

$$\check{y}_k = \underbrace{W_{tk}^H H_k V_{tk} S_k}_{\substack{\text{desired} \\ \text{signal}}} + \underbrace{W_{tk}^H H_k \sum_{l \neq k} V_{tl}\, S_l}_{\substack{\text{effective} \\ \text{interference}}} + \underbrace{W_{tk}^H Z_k}_{\substack{\text{effective} \\ \text{noise}}} \tag{3}$$

where $V_{tk} = V_{RF} V_{D_k}$ and $W_{tk} = W_{RF_k} W_{D_k}$.

The combined multiuser channel is defined as: $H = [H_1^T, H_2^T, \cdot\cdot\cdot, H_K^T\ ]^T$. Given Gaussian symbols are transmitted, the achieved spectral efficiency is determined as per reference [22]:

$$R_k = log_2\left|I_{\mathrm{N}_r} + W_{tk} C_k^{-1} W_{tk}^H H_k V_{tk} V_{tk}^H H_k^H\right| \tag{4}$$

The interference plus noise covariance matrix is given by $C_k = W_{tk}^H H_k (\sum_{l \neq k} V_{tl} V_{tl}^H) + H_k^H W_{tk} + \sigma^2 W_{tk}^H W_{tk}$.

This paper aims to maximize total Bandwidth efficiency while respecting total transmit power constraints. We assume perfect knowledge of H_k, focusing on solving the following problem: finding the optimal hybrid precoders at the base station (BS) and optimal hybrid combiners for each user.

$$\underset{\mathrm{V_{RF},V_D,W_{RF},W_D}}{\text{maximize}} \sum_{k=1}^{K} \beta_k R_k \tag{5a}$$

$$T_r(V_{RF}V_DV_D^HV_{RF}^H) \leq P_T \tag{5b}$$

$$|V_{RF}(i,j)|^2 = 1, \forall i,j \tag{5c}$$

$$\left|W_{RF_k}(i,j)\right|^2 = 1, \forall\, i,j,k \tag{5d}$$

where P_T is the power at the base station, and the weight β_k represents the priority of user k, i.e., $\frac{\beta_k}{\sum_{l=1}^{k}\beta_l}$ the larger it is, the higher the priority of user k.

2.1. Hybrid beamformer design for massive MIMO systems with single user

This section centers on the development of hybrid beamformers. We start by examining a massive MIMO system where a base station equipped with N_t antennas transmit N_s data symbols to a user with N_r antennas. To simplify notation, we assume an equal number of RF transmission and reception chains, denoted as $N_t^{RF} = N_r^{RF} = N_{RF}$. In this hybrid system configuration, the bandwidth efficiency expression in (4) can be simplified as (6):

$$\mathrm{R} = \log_2\left|I_{\mathrm{N}_r} + \frac{1}{\sigma^2}W_t(W_t^HW_t)^{-1}W_t^HHV_tV_t^HH^H\right| \tag{6}$$

where $V_t = V_{RF}V_D$ and $W_t = W_{RF}W_D$.

In this section, our initial focus is on designing hybrid beamforming systems where the number of RF chains equals the number of data streams, i.e. $N^{RF} = N_s$. We propose a meta-heuristic algorithm that achieves near-capacity rates under this condition. Extending our approach, we demonstrate that the algorithm developed for $N^{RF} = N_s$ can also be applied when $N_s < N^{RF} < 2N_s$.

The efficiency maximization problem in (5) requires joint optimization of precoders and hybrid combiners. However, simultaneously optimizing the transmit-receive matrix for such constrained problems is generally challenging [23]. Additionally, constraints on the elements of analog beamformers in (5c) and (5d) suggest that developing a low-complexity algorithm for finding the exact optimal solution remains difficult [24]. Therefore, this section adopts the following strategy: we initially focus on creating hybrid precoders assuming an optimal receiver design. Subsequently, our objective shifts to designing the hybrid transmitter combiner.

The problem of hybrid precoder design can be broken down into two steps as follows [20]:

$$\max_{V_{RF},V_D} log_2\left|I_{N_r} + \frac{1}{\sigma^2}HV_{RF}V_DV_D^HV_{RF}^HH^H\right| \tag{7a}$$

$$s.t.\ (T_r(V_{RF}V_DV_D^HV_{RF}^H) \leq P \tag{7b}$$

$$|V_{RF}(i,j)|^2 = 1, \forall i,j \tag{7c}$$

This section introduces a genetic algorithm aimed at finding an effective solution to problem (7). Initially, we derive the solution for the digital precoder given a fixed RF precoder, V_{RF}, as outlined in problem (7). Subsequently, with the digital precoder established, we propose using the genetic algorithm to identify an optimal global RF precoder.

2.1.1. Design of a digital precoder for $N_{RF} = N_s$

The initial step of the algorithm focuses on the design of V_D, assuming that V_{RF} remains constant. When the RF precoder is fixed, the effective channel $H_{eff} = HV_{RF}$ can be treated as the channel of interest. Consequently, the task of designing the digital precoder can be formulated in the following manner:

$$\max_{V_D} log_2\left|I_{N_r} + \frac{1}{\sigma^2}H_{eff}V_DV_D^HH_{eff}^H\right| \tag{8a}$$

$$s.t.\ T_r(QV_D V_D^H \leq P) \tag{8b}$$

where $Q = V_{RF}^H V_{RF}$

- Genetic algorithm optimization

In combinatorial optimization, genetic algorithms are employed to solve problems by introducing random variations in the chromosomes of the population. Chromosomes with higher fitness values are more likely to survive and propagate to the next generation [25]. As generations pass, the chromosomes that remain in the population tend to have high fitness values, representing sub-optimal solutions. Three basic operations of genetic algorithms—selection, crossover, and mutation—will be described in later sections.

The genetic algorithm requires defining a function that assesses the relevance of potential solutions based on the quantities to be optimized. This is known as the objective function (or cost function or fitness function), which establishes a link between the physical problem and the optimization process. The fitness function is a tool used to express the optimization goal and serves as a means to develop chromosomes. The fitness function must mathematically translate the user's objectives.

Mathematically, the problem involves searching for the digital encoding law V_D applied to the system input to maximize the spectral efficiency, given by (9):

$$R1 = \log_2 \left| I_{\mathrm{N}_r} + \frac{1}{\sigma^2} H_{eff} V_D V_D^H H_{eff}^H \right| \tag{9}$$

In the context of the genetic algorithm, the digital encoding law V_D is likened to a chromosome, with genes representing the values of this vector (V_{Di} in this case).

The initial phase of the genetic algorithm involves creating a population of individuals randomly in the form of a binary matrix, which contains an $L \times C$ number of 0s and 1s as follows: C denotes the number of columns, which is the product of the number of parameters in vector V_D and the number of bits in the binary code used. L represents the number of rows, corresponding to the total number of individuals in the population. Following this, the fitness of individuals within the population is assessed by computing the fitness function for each individual. This process includes decoding the chromosome associated with each individual in the population, which reverses the encoding operation. The formula (10) is utilized to decode N-bit genes for this purpose:

$$P = \frac{P_{max} - P_{min}}{2^N} \sum_{i=0}^{N-1} 2^i b_i + P_{min} \tag{10}$$

P_{max} and P_{min} denote the maximum and minimum limits of the parameter value range, respectively, while b_i represents the i-th bit within the gene associated with parameter P (where P may include one or more parameters, such as V_{Di}).

The resulting vector P is subsequently inputted into function R_1 to to evaluate the fitness of this individual:

$$Fitness\ Function = R_1 \tag{11}$$

An elitist strategy that ensures the presence of the best individual in the future generation is utilized. For this, a ranking-based selection method known as ranking is employed. The crossover method used is the one-point crossover.

2.1.2. Design of an RF precoder for $N_{RF} = N_s$

Now, our objective is to design the RF precoder while assuming $V_D V_D^H \approx \gamma^2 I$. The given assumption ensures that the transmitter power constraint in (8b) is automatically met regardless of the design of V_{RF}. Consequently, the RF precoder can be acquired by resolving the subsequent problem:

$$\max_{V_{RF}} log_2 \left| I + \frac{\gamma^2}{\sigma^2} V_{RF}^H F_1\, V_{RF} \right| \tag{12a}$$

$$s.t. |V_{RF}(i,j)|^2 = 1,\ \forall i,j \tag{12b}$$

where $F_1 = H^H \times H$.

The problem of designing an analog precoder can be translated into an optimization problem that enhances the bandwidth efficiency R_2 given by (13):

$$R_2 = log_2 \left| I + \frac{\gamma^2}{\sigma^2} V_{RF}^H F_1 \, V_{RF} \right| \tag{13}$$

In the genetic algorithm, the digital encoding law V_{RF} is like a chromosome, with genes representing its values. Initially, a population is created randomly as a binary matrix of size. $L \times C$, where L is the number of individuals and C is the product of the number of parameters in vector V_{RF} and the number of bits in the binary code. Each individual's fitness is evaluated by decoding their chromosome using a specific formula, which considers the bounds of the parameter value interval. The decoded vector P is then used in function R_2 to assess the individual's fitness.

$$Fitness\ Function = R_2 \tag{15}$$

An elitist strategy that ensures the presence of the best individual in the future generation is utilized. For this, a ranking-based selection method known as ranking is employed. The crossover method used is the one-point crossover.

2.1.3. Design of hybrid combiners for $N_{RF} = N_s$

Finally, our objective is to create hybrid combiners that optimize the total bandwidth efficiency in (6), given that hybrid precoders have already been designed. When $N_{RF} = N_s$, the digital combiner becomes an unconstrained square matrix. Hence, without compromising optimality, we can separate the design of W_{RF} and W_D by initially designing the RF combiner assuming an optimal digital combiner. Subsequently, we can determine the optimal digital combiner for this RF combiner. Consequently, the problem of RF combiner design can be expressed as follows:

$$\max_{W_{RF}} \log_2 \left| I + \frac{1}{\sigma^2} (W_{RF}^H W_{RF})^{-1} W_{RF}^H F_2 W_{RF} \right| \tag{16a}$$

$$s.t.\ \ |W_{RF}(i,j)|^2 = 1, \forall i, j \tag{16b}$$

where $F_2 = \mathrm{H}\, V_t V_t^H H^H$.

This issue bears resemblance to the RF precoder design issue described in (12). Consequently problem (16) can be approximated by adopting the RF precoder design problem from (12). To design W_{RF}, the genetic algorithm can be employed, substituting F_2 with F_1 and $\frac{1}{N_r}$ with γ_2.

$$\max_{W_{RF}} \log_2 \left| I + \frac{1}{N_t \sigma^2} W_{RF}^H F_2 W_{RF} \right| \tag{17a}$$

$$s.t. |W_{RF}(i,j)|^2 = 1, \forall i, j \tag{17b}$$

The problem of designing an analog combiner can be translated into an optimization problem focused on maximizing spectral efficiency R_3 given by (18):

$$\mathrm{R}_3 = \log_2 \left| I + \frac{1}{N_t \sigma^2} W_{RF}^H F_2 W_{RF} \right| \tag{18}$$

In the genetic algorithm, the digital encoding law W_{RF} functions like a chromosome with genes as its values. A population is created randomly as a binary matrix of size $L \times C$. Each individual's fitness is assessed by decoding their chromosome and evaluating the resulting vector P using function R_3.

$$Fitness\ Function = \mathrm{R}_3 \tag{20}$$

An elitist strategy that ensures the presence of the best individual in the future generation is utilized. For this, a ranking-based selection method known as ranking is employed. The crossover method used is the one-point crossover. Finally, When every other beamformer has been fixed, the best digital combiner is found when presented in [20]:

$$W_D = J^{-1} W_{RF}^H H V_t \tag{21}$$

where $J = W_{RF}^H H V_t V_t^H H^H W_{RF} + \sigma^2 W_{RF}^H W_{RF}$

2.2. Design of hybrid beamforming for $N_s < N_{RF} < 2N_s$

In this section, we introduced a meta-heuristic algorithm for designing hybrid beamformers initially for $N_{RF} = N_s$. We then shifted focus to cases where $N_s < N_{RF} < 2N_s$. Even in scenarios with $N_s < N_{RF} < 2N_s$, the transmitter design problem remains defined by (7). Given a fixed RF precoder, the optimal digital precoder is determined using (12), with the condition $V_{RF}^H V_{RF} = \gamma^2 [I_{N_s}\ 0]$. The objective function from (7), aimed at maximizing over V_{RF}, is reformulated to handle all eigenvalues, approximating the function when N_{RF} is approximately N_s. Thus, the RF precoder design problem is effectively represented by (12).

3. SIMULATION

In this section, we showcase the findings from our simulation study, aimed at evaluating the efficiency of our proposed algorithm in a massive MIMO system. We will examine the impact of the SNR (the ratio of signal power to noise power) on spectral efficiency and BER (rate of errors in bit transmission) in hybrid MIMO beamforming systems. Various configurations will be analyzed by varying the number of antennas, the number of RF channels, and the number of data streams. Furthermore, we will conduct comprehensive comparisons with existing hybrid beamforming algorithms and a pure digital beamforming system.

We consider a base station utilizing a massive MIMO system. A linear antenna configuration within a Rayleigh multipath propagation environment is assumed [26], described by the following channel matrix:

$$H_k = \sqrt{\frac{N_t N_r}{L}} \sum_{l=1}^{L} \alpha_k^l a_r \emptyset_{rk}^l a_t \left(\emptyset_{rk}^l\right)^H \tag{22}$$

The complex gain $\alpha_k^l \sim \mathcal{CN}(0,1)$ represents the l-th path's strength between the base station and the k-th user, with hase angles $\emptyset_{rk}^l \in [0, 2\pi]$ and $\emptyset_{tk}^l \in [0, 2\pi]$. Additionally, $a_r(.)$ and $a_t(.)$denote the response vectors of the antenna array on reception and transmission, respectively. The response vectors of the array configuration with N_t uniform linear antenna elements are given as (23):

$$a(\phi) = \frac{1}{\sqrt{N_t}} \left[1, e^{jkdsin(\phi)}, \cdots, e^{jkd(N_t-1)sin(\phi)}\right]^T \tag{23}$$

where $k = \frac{2\pi}{\lambda}$, d represents the distance between antennas and λ denotes the wavelength of the signal.

At the receiving end, we also consider a single user equipped with a massive MIMO system. In our simulation, we model an environment with 15 multipath components between the base station and each user. These components have uniformly distributed arrival and departure angles, with a distance of $\lambda/2$ separating each antenna element. We evaluate the system's performance in terms of spectral efficiency and bit error rate.

3.1. Impact of varying the number of transmit and receive antennas

We study a base station using hybrid MIMO beamforming technique with two RF channels ($N_{RF} = 2$) for both transmission and reception, and two data streams ($N_s = 2$). The optimization of precoders and combiners through the genetic algorithm can be easily accomplished by adjusting the input parameters of the algorithm. The input parameters of the genetic algorithm (after several trials) are listed:
- Population size: 20 individuals
- Number of generations: 20
- Mutation rate: 0.8
- Crossover rate: 0.01
- Bit length: 16

We vary the number of antennas both in transmission and reception to evaluate performance based on spectral efficiency and bit error rate.

a. Spectral efficiency in terms of SNR with variation of N_t and N_r.

Based on the findings depicted in Figure 2, we observe the following points: Spectral efficiency increases as SNR increases. An increase in the number of antennas used for transmission and reception also leads to improved spectral efficiency. For example, in a massive MIMO beamforming system with 512×512 antennas compared to a 16×16 MIMO system, the bandwidth efficiency improves from 10 bits/s/Hz at an SNR of 10 dB.

b. Bit error rate (BER) in terms of SNR variation with N_t and N_r

From the results in Figure 3, the following observations can be made: BER continuously decreases as SNR increases. BER decreases as the number of antennas used for transmission and reception increases.

For example, for a BER of 10^{-2}, the SNR improves by 20 dB when transitioning from a 16×16 MIMO system to a 512×512 MIMO system. Thus, at an SNR of 0 dB, the minimal BER (10^{-4}) is achieved for the 512×512 MIMO system.

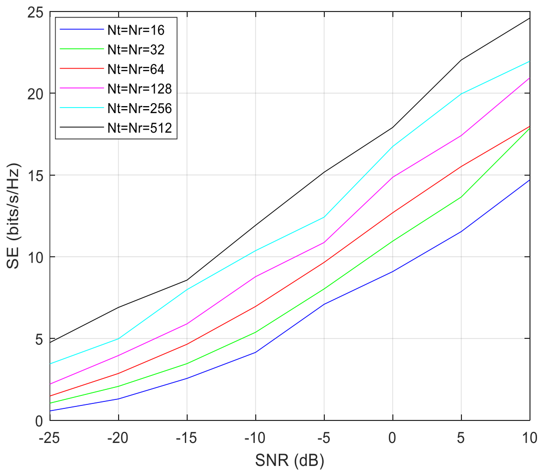

Figure 2. Spectral efficiency as a function of SNR for various values of the number of transmitting and receiving antennas where $N_{RF} = N_s = 2$

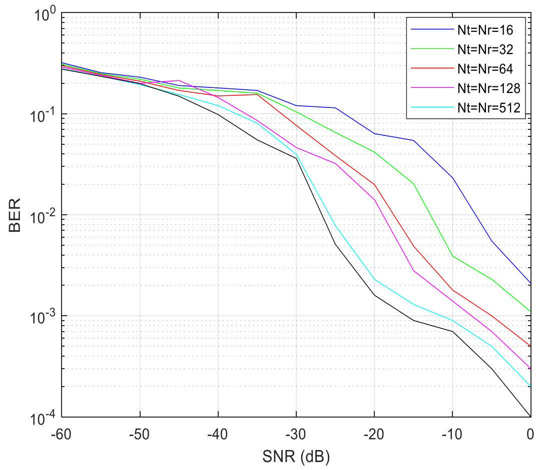

Figure 3. BER as a function of SNR for various values of the number of transmitting and receiving antennas where $N_{RF} = N_s = 2$

3.2. Impact of varying the number of RF chains

In this part of the simulation, we analyze the bandwidth efficiency of hybrid precoding techniques in a MIMO beamforming system (64×64) with two data streams ($N_s = 2$), based on SNR. We vary the number of RF chains for both transmission and reception in each case studied.

a. Spectral efficiency in terms of SNR variation with N_{RF}

Based on the findings depicted in Figure 4, several notable observations can be derived. Spectral efficiency increases as SNR increases. A slight increase in spectral efficiency is observed when the number of RF channels used for both transmission and reception increases from 6 to 10. For example, at an SNR of 0 dB, spectral efficiency experiences an enhancement of 2.5 bits/s/Hz in a hybrid MIMO beamforming system with $N_{RF} = 10$, compared to a system with $N_{RF} = 8$. However, the number of RF channels does not significantly impact spectral efficiency; rather, it helps minimize system implementation costs.

b. Bit error rate (BER) in terms of SNR variation with N_{RF}

From the results in Figure 5, the following observations can be made: BER decreases as SNR increases. Increasing the number of RF channels for both transmission and reception leads to a decrease in BER. For instance, for a BER of 10^{-2}, the SNR improves by 11 dB when increasing the number of RF channels from 6 to 10. However, this improvement is modest, suggesting that the influence of RF channels on system performance is negligible. Hence, reducing the number of RF channels is possible to cut costs.

3.3. Impact of variation in rf chains at transmission and reception with $N_{RF} = N_s$

In this simulation section, we analyze the spectral efficiency of hybrid precoding techniques in a MIMO beamforming system (64×64), based on the SNR. We vary the number of RF chains for both transmission and reception while maintaining $N_{RF} = N_s$.

a. Spectral efficiency in relation to SNR and N_{RF} variation

According to the results presented in Figure 6, a notable trend emerges: Spectral efficiency increases as SNR increases. With an increase in the number of RF chains, bandwidth efficiency also improves. For example, at an SNR of -10 dB, spectral efficiency experiences an enhancement of 100 bits/s/Hz in a hybrid MIMO beamforming system with $N_{RF} = N_s = 10$ compared to a system with $N_{RF} = N_s = 2$.

b. Bit error rate in relation to SNR and N_{RF} variation

The outcomes in Figure 7 highlight the direct correlation between increasing the number of RF channels for both transmission and reception and the reduction in bit error rate (BER). For instance, for a BER of 10^{-2}, an improvement of 8 dB in SNR is achieved by increasing the number of RF chains from 4 to 10.

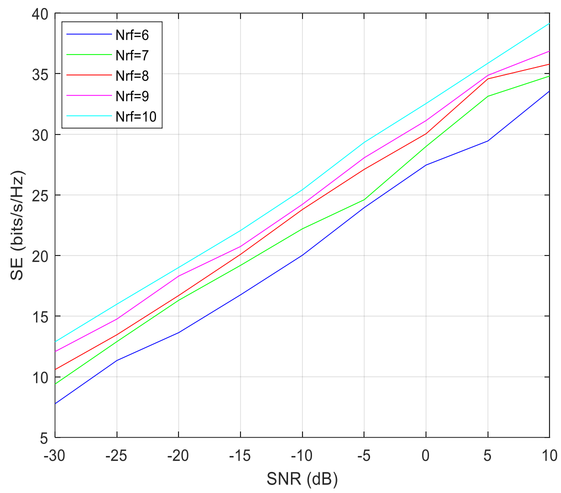

Figure 4. Bandwidth efficiency as a function of SNR for various values of the number of RF chains in a 64×64 MIMO system where $N_s = 2$

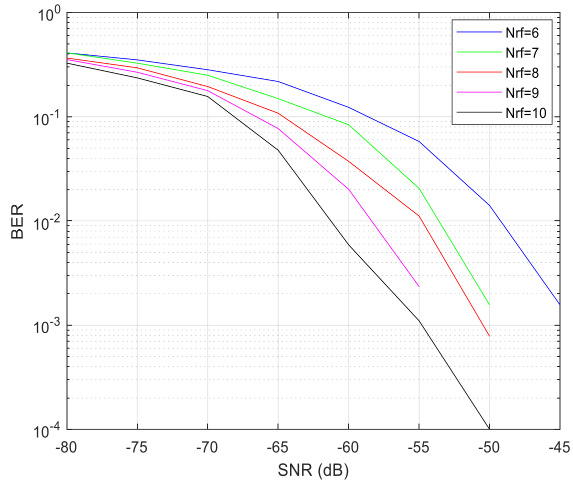

Figure 5. BER as a function of SNR for various values of the number of RF chains in a 64×64 MIMO system where $N_s = 2$

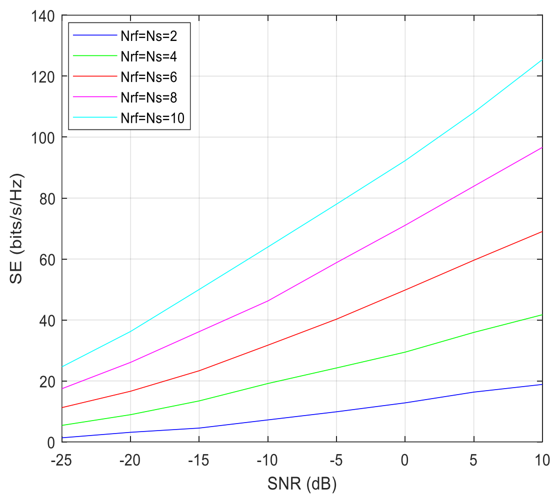

Figure 6. Spectral efficiencies as a function of SNR for various values of the number of RF chains in a 64×64 MIMO system where $N_{RF} = N_s$

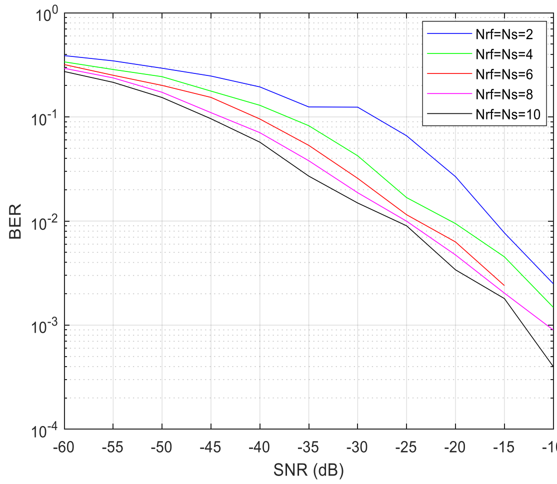

Figure 7. BER as a function of SNR for various values of the number of RF chains in a 64×64 MIMO system where $N_{RF} = N_s$

3.4. Impact of varying the number of data streams

In this section, we examine how spectral efficiency and bit error rate vary with SNR in a hybrid MIMO beamforming system (64×64) with $N_{RF} = 10$. We also change the number of input data streams (N_s) each time.

a. Spectral efficiency in terms of SNR variation with N_s

From the results in Figure 8, we observe the following: Increasing the number of input data streams leads to improved spectral efficiency. For example, at an SNR of 10 dB, the spectral efficiency improves by 80 bits/s/Hz when transitioning from 2 input data streams ($N_s = 2$) to 10 input data streams ($N_s = 10$) in a hybrid MIMO beamforming system.

b. Bit error rate (BER) in terms of SNR variation with N_s

From the results in Figure 9, we observe the following: i) BER decreases as SNR increases and ii) BER decreases as the number of input data streams (N_s) decreases. Now, we analyze a massive MIMO system with 64 transmitting antennas and 16 receiving antennas, supporting $N_s = 6$ data streams. For the hybrid beamforming MIMO system, we utilize $N_{RF} = N_s = 6$ RF chains for both transmission and reception.

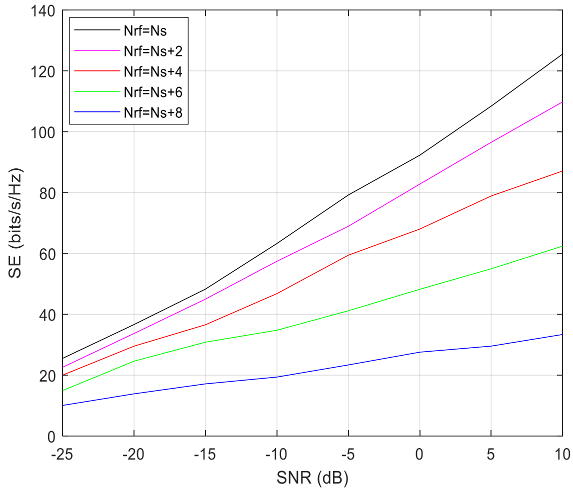

Figure 8. Spectral efficiencies as a function of SNR for various values of the number of data streams in a 64×64 MIMO system where $N_{RF} = 10$

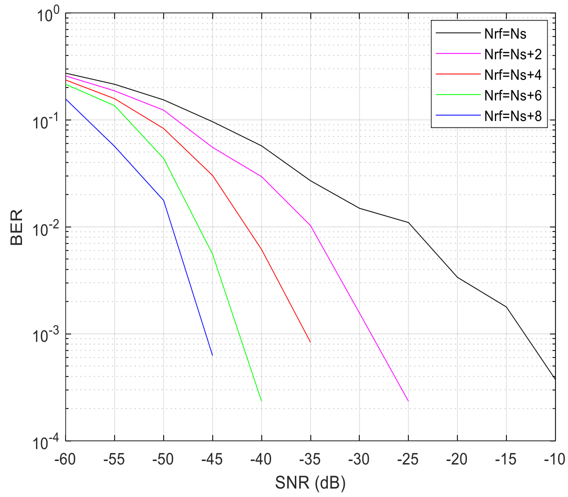

Figure 9. BER as a function of SNR with varying numbers of data streams in a 64×64 MIMO system where $N_{RF} = 2$

As illustrated in Figure 10, the genetic algorithm exhibits commendable spectral efficiency performance compared to the heuristic algorithm presented in study [20]. As well as the hybrid beamforming algorithms introduced in studies [24] and [27]. The efficiency gains are 2 bits/s/Hz compared to the heuristic algorithm and 4 bits/s/Hz compared to the algorithms outlined in studies [24] and [27] at an SNR of 0 dB.

Next, we analyze the performance of our algorithm in terms of spectral efficiency. We consider a hybrid beamforming massive MIMO system with 10 antennas for both transmission and reception, and a corresponding number of RF chains in relation to the data streams: $N_{RF} = N_s = 2$. The relatively limited antenna count is chosen to facilitate a comparison with the exhaustive search method. Figure 11 reveals that our algorithm surpasses the heuristic algorithm and the exhaustive search method by 1 bit/s/Hz and outperforms the quantized hybrid beamforming algorithms in [24] and [27] by 3 bits/s/Hz, thereby establishing its superior performance.

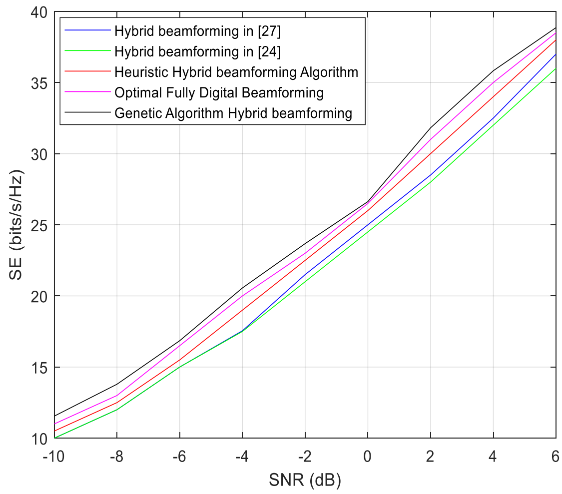

Figure 10. Spectral efficiencies attained through various methods in a 64×16 MIMO system with N_RF=N_s=6

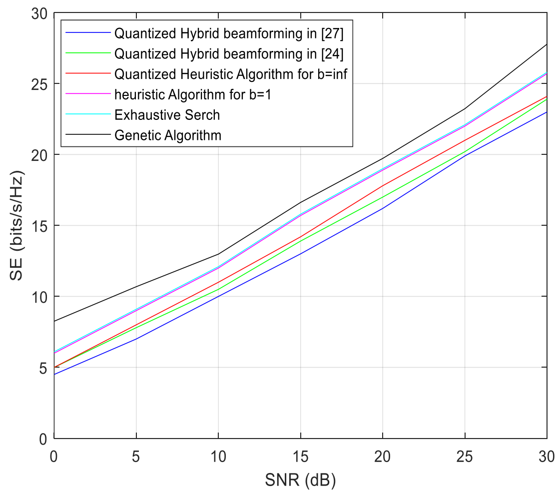

Figure 11. Spectral efficiencies as a function of SNR for various methods in a 10×10 MIMO system where $N_{RF} = N_s = 2$

4. CONCLUSION

In this article, we have examined the concept of hybrid beamforming in massive MIMO systems. This approach employs two sets of weighting vectors for transmission and two sets for reception, with the aim of simplifying and reducing implementation costs by decreasing the required number of RF channels without compromising the performance that can be comparable with digital beamforming systems. The necessary number of RF chains must be no more than double the number of data streams. Furthermore, when the number of RF chains is identical to the number of data streams, this article presents a solution through a meta-heuristic algorithm (genetic algorithm) to maximize overall spectral efficiency in the context of MIMO transmission over a downlink system.

Firstly, we analyzed the effect of varying antenna numbers for both transmission and reception on system performance. Next, we investigated how varying the number of RF channels, for both transmission and reception, affects the bandwidth efficiency and BER of the system. Finally, we examined the influence of the number of data streams on these performance metrics. The numerical results demonstrate that the proposed meta-heuristic method achieves better performance than the heuristic methods and entirely digital beamforming schemes. Through our observations, we noticed that increasing the number of antennas for transmission and reception significantly impacts the quality and capacity of the massive MIMO hybrid beamforming system. Our observations have also shown that reducing the number of RF channels has a negligible effect on the quality and capacity of the massive MIMO system employing hybrid beamforming. This finding confirms that employing this approach simplifies design and reduces costs without compromising system performance.

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