IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received August 29, 2019, accepted September 11, 2019, date of publication September 13, 2019, date of current version September 26, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2941261

Ping-Pong Optimization of User Selection and Beam Allocation for Millimeter Wave Communications

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ABSTRACT Both millimeter wave (mmWave) communication and massive multiple-input multiple-output (MIMO) are important technologies in the 5G era. To reduce the cost of a mmWave massive MIMO system in practice, hybrid beamforming usually adopted, which however inevitability complicates both user selection and analog beam allocation. To this end, in this paper we jointly optimize user selection and beam allocation under a wideband frequency selective mmWave channel. To be practical, both beam collision and inter-user interference have been taken into account. To tackle the non-convexity of the formulated problem, we propose a ping-pong-like optimization method by using hybrid particle swarm optimization and simulated annealing (HPS). Concretely, the joint optimization problem is divided into two sub-problems and the near-optimal solution is approached via ping-pong iteration optimization. The Metropolis acceptance criterion of simulated annealing algorithm is introduced to overcome the drawback of traditional particle swarm optimization, improving global search capability of HPS algorithm. The simulation results verify the effectiveness and flexibility of the proposed method compared with existing methods.

INDEX TERMS Millimeter wave communication, hybrid beamforming, user selection, beam allocation, particle swarm optimization, simulated annealing.

I. INTRODUCTION

Millimeter Wave (mmWave) communication technology, which can provide up to GHz of unauthorized bandwidth, is a key candidate for the explosive growth of data traffic in fifth-generation (5G) mobile communication systems. However, a higher carrier frequency and a shorter wavelength imply that mmWave communication may incur severe path losses and blockages compared to sub-6 GHz frequency signals. Massive multiple-input multiple-output (Massive MIMO) is the main way in which mmWave communication systems address path loss, as it offers a high beamforming gain of massive antenna arrays [1], [2]. Although massive MIMO with full digital beamforming can obtain optimal performance, using the same number of radio frequency (RF) chains as antennas results in high hardware costs and power consumption. Full analog beamforming (ABF) is easy to implement and has low hardware complexity, but it can only support a limited rate of data transmission due to its single RF chain behind the transceivers. Hence, hybrid analog and digital beamforming (HBF), as a crucial combination of massive MIMO and mmWave communication, achieves a trade-off between system performance and hardware complexity and has attracted widespread attention [3]–[5].

User scheduling under HBF architectures is totally different from traditional user scheduling methods under sub-6 GHz architectures [6]. Due to the hybrid architecture for mmWave massive MIMO systems, user scheduling in HBF becomes a joint optimization problem of user selection and beam allocation (referred to as JUSBA in this paper), compared with only user selection in the fourth generation (4G) orthogonal frequency division multiplexing (OFDM) MIMO communication systems, which belong to full digital beamforming (DBF) systems [7]. In other words, we need to choose not only which user to schedule but also which beam to serve the user. JUSBA, which belongs to the user-beam mapping problem, essentially deals with the user selection problem in the beam domain. In addition, the performance of the scheduling method depends not only on user selection and beam allocation algorithms but also on the design of the

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Feng.

digital precoder and power allocation. In summary, the above unfavorable factors pose serious challenges to the scheduling problem under HBF. To the best of our knowledge, multiuser mmWave massive MIMO systems under an HBF architecture have not received much attention.

A. PRIOR WORK

JUSBA is related to the *user-selection-only* problem and the *beam-allocation-only* problem. Based on the criterion of efficiency or fairness, there are different kinds of user scheduling algorithms under sub-6 GHz, such as the Round-Robin (RR) algorithm, the maximum signal to interference plus noise ratio (SINR) based algorithm, the proportional fairness (PF) algorithm and the semi-orthogonal user selection (SUS) algorithm, etc [8], [9]. However, the existing scheduling schemes cannot be applied to mmWave communication systems directly, as they do not fully exploit the features of mmWave propagation. Moreover, as the beam domain does not exist under sub-6 GHz, the prior works in [8], [9] just conducted the user selection without involving the beam assignment problem.

As for the *beam-allocation-only* problem, in most previous studies, the users to be scheduled are predefined [10]–[17], the number of which is the same as the number of RF chains. However, in a practical urban cell, the number of candidate users in one cell is far greater than the number of RF chains in the base station. Thus, some users must be scheduled. Most prior works have focused on beam- allocation-only in mmWave massive MIMO systems [10]–[17] or, more generally, antenna selection in MIMO systems [18]. In the maximum magnitude (MM) beam allocation algorithm [10], several beams with larger received power are selected for each user. However, the MM algorithm has two disadvantages: (i) it only considers the power of the received signal for each user-beam pair without considering the inter-user interference, which leads to performance losses of the achievable sum rates, especially in the case of a high signal-to-noise ratio (SNR); and (ii) because it does not consider beam collision between users, different users may select the same beam so that some RF chains are wasted and do not contribute to performance improvement. In [11], an interference-aware beam allocation algorithm was proposed to deal with inter-user interference by classifying users into interference users and non-interference users. Based on submodular optimization and the matroid theory, the beam allocation problem in [12] was formulated as a combinatorial optimization problem. Reference [13] formulated beam allocation into an assignment problem and then solved the problem with the classical Hungarian algorithm. However, [12] and [13] neglected inter-user interference, thus the beam allocation problem was significantly simplified, leading to non-negligible performance loss. In [14], the beam allocation problem was taken as a travelling salesman problem (TSP), and a bio-inspired ant colony optimization-based algorithm was proposed. A data-driven analog beam selection method for mmWave systems was investigated in [15] by taking the beam selection problem as a multiclass-classification problem and solving it via the support vector machine (SVM) algorithm. Under the beam division multiple access transmission scheme [16], to maximize the sum rates, a greedy-based beam allocation method was presented. In fact, the greedy-based algorithm is an important and effective way to deal with beam allocation problems, and it can be divided into incremental greedy [6], [12], [16], [19] and decremental greedy [17] algorithms.

Although these previous studies [8]–[17] do not take JUSBA into consideration, they are still instructive to the interests of this paper. To the best of our knowledge, only a few studies have jointly considered the allocation of beams and the selection of users [6], [19], [20]. In [19], the joint optimization problem was formulated as a non-convex combinatorial optimization problem, and a DC-based (difference of two convex functions) method and a greedy-based method were proposed. Reference [6] exploited the problem in the Lyapunov-drift optimization framework for lens antenna array beam-based downlinks, and a BCU-based (block coordinated update) algorithm and a greedy-based algorithm were presented. With the help of Lyapunov-drift optimization tool, [20] proposed an algorithm that conducted user scheduling, resource allocation and analog precoder design for broadband mmWave mimo system under hybrid architecture. The above three methods provide an analytical way to solve combinatorial optimization problems that belong to NP-hard problems which have no mature approach to acquire an analytical solution. However, all of them have extremely high complexity, which is even higher than the exhaustive searching (ES) method. Accordingly, [6] and [19] present heuristic greedy methods to reduce complexity after proposing analytical methods.

The aforementioned studies have the following problems: (1) most studies were conducted under a narrowband channel that was assumed to be frequency flat, while in practical mmWave communication systems with large bandwidths, the channel is frequency selective; (2) few studies jointly considered beam collisions and inter-user interference, and even fewer articles jointly considered beam allocation and user selection, which has proven to be an NP-hard problem; and (3) to solve the JUSBA problem, the analytical solutions have a prohibitively high complexity, while heuristic solutions such as greedy-based solutions are unable to achieve satisfactory performance.

B. CONTRIBUTION

In this paper, we aim to address the JUSBA problem for mmWave massive MIMO communication systems under an HBF architecture. The main contributions are as follows:

- While most previous studies have focused on narrowband mmWave communications, we treat the JUSBA problem in the wideband channel. By adopting OFDM, a wideband frequency selective channel is transformed into several narrowband frequency flat subchannels.

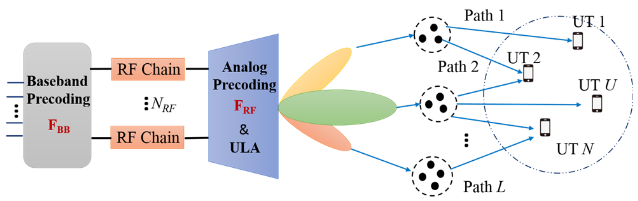


FIGURE 1. System model for hybrid multi-user massive MIMO communication. A baseband precoder and an analog precoder construct the HBF architecture. The millimeter-wave channel is characterized via L paths. In the cell, there are a total of N candidate users and only U users scheduled.

- By jointly considering beam collision and inter-user interference and the practical scenario that transceivers cannot obtain perfect channel state information (CSI), the JUSBA problem is formulated as a non-convex combinatorial optimization problem with constraints.
- To address the combinatorial programming problem, a ping-pong-like algorithm based on HPS is proposed. To overcome the drawback of traditional particle swarm optimization (PSO), the Metropolis acceptance criterion of simulated annealing (SA) algorithm is introduced to improve global search capability of HPS algorithm.

The remainder of this paper is organized as follows. To investigate JUSBA, we present system and channel models in Section II. By introducing the scheduling indicate function and a beam training procedure to acquire equivalent channel information, we formulate the problem into a non-convex combinatorial optimization problem in Section III. In Section IV, the P-HPS algorithm is specified. In Section V, simulation results are presented to prove the effectiveness of the proposed algorithm.

Notation: Bold uppercase $\mathbf{A}$, handwriting uppercase $\mathcal{A}$, bold lowercase $\mathbf{a}$, and non-bold a denote matrix, date set, vector, and scalar value, respectively. The transpose, conjugate transpose, and inverse of matrix $\mathbf{A}$ are denoted as $\mathbf{A}^T$, $\mathbf{A}^H$, and $\mathbf{A}^{-1}$, respectively. $\mathbb{E}(\cdot)$ and $a!$ are the expectation and factorial operations, respectively. $\mathbf{I}_N$ is the identity matrix of order N, and $\|\mathbf{A}\|_F$ denotes the Frobenius norm.

II. SYSTEM MODEL

We consider a downlink multi-user massive MIMO system with M antennas at the base station (BS) and a single antenna at each user terminal (UT), as shown in Figure 1. There is a fully connected hybrid architecture BS equipped with N_{RF} ($N_{RF} < M$) RF chains, each of which connects with a uniform linear array (ULA) via analog phase shifting networks. A baseband precoder $\mathbf{F}_{BB}$ and an analog precoder $\mathbf{F}_{RF}$ construct the HBF architecture. For the wideband mmWave channel, the analog precoder needs to be jointly designed for all OFDM subcarriers, while the digital precoder can be designed individually [21]. For resource limited urban cells, there are N candidate users in the cell among which only U users can be chosen. Note that this model can be easily extended to a more practical case with multiple BSs, by particularly considering the inter-BS interference [22].

In the downlink transmission, the original transmitter signal at subcarrier $k(k = 1, \cdots, K)$ is $\mathbf{s}[k] \in \mathbb{C}^{U\times 1}$, which satisfies normalization $\mathbb{E}\left[\mathbf{s}[k]\mathbf{s}[k]^H\right] = \frac{P}{KU}\mathbf{I}_U$, where P is the total transmit power. $\mathbf{s}[k]$ is first precoded by the baseband precoder $\mathbf{F}_{BB}[k] \in \mathbb{C}^{N_{RF}\times U}$ and then transformed to the time domain using K-point IFFTs and adding a cyclic prefix to symbol blocks. The resulting signal is processed by the time domain analog precoder. It is worth mentioning that the analog precoder remains the same for all the subcarriers, and hence, we can denote it as $\mathbf{F}_{RF} \in \mathbb{C}^{M\times N_{RF}}$, which remains independent with the frequency. For the purpose of power normalization, we set $\|\mathbf{F}_{RF}\mathbf{F}_{BB}[k]\|_F^2 = N_{RF}$. The discrete-time transmitted complex baseband signal at the k-th subcarrier $\mathbf{x}[k]$ from BS can be written as

$$\mathbf{x}[k] = \mathbf{F}_{RF}\mathbf{F}_{BB}[k]\,\mathbf{s}[k]. \tag{1}$$

To embody the frequency selective characteristics of the wideband mmWave channel [23], assuming that the channel has a maximum delay tap N_c and considering the commonly used wideband geometric channel model, the channel between the BS and the u-th UT with d-th ($d = 0, 1, \cdots, N_c$) delay tap can be expressed as

$$\mathbf{h}_u^d = \sqrt{\frac{M}{L\beta_u}}\sum_{l=1}^{L}\alpha_{l,u}p(dT_s - \tau_{l,u})\boldsymbol{\alpha}^H(\varphi_{l,u}, M), \tag{2}$$

where L, β_u, and T_s stand for the total number of paths, path loss, and sampling period, respectively; $\alpha_{l,u}$ denotes the complex gain of the l-th path of the u-th user; $\tau_{l,u}$ is the delay of the l-th path; $p(t)$ is the pulse-shaping filter observed at t; $\varphi_{l,u}$ is the angle of departure (AoD); and $\boldsymbol{\alpha}\left(\varphi_{l,u}, M\right)$ is the transmit normalized array response vector. For a ULA with M elements [19], [23], the array response vector can be given by

$$\boldsymbol{\alpha}_{ULA}(\varphi, M) = (\frac{1}{\sqrt{M}}[1, e^{j\beta d\sin\varphi}, \ldots, e^{j\beta d(M-1)\sin\varphi}])^T, \tag{3}$$

where $\beta = 2\pi/\lambda$, λ is the signal wavelength, and d denotes the antenna array spacing distance. Based on [21], the channel of the u-th UT at subcarrier k can be written as

$$\mathbf{h}_u[k] = \sum_{d=0}^{N_c-1}\mathbf{h}_u^d\, e^{-j\frac{2\pi k}{K}d}. \tag{4}$$

Assuming that synchronization is perfect and that the received signal is transformed to the frequency domain using K-point FFT, the received signal at the u-th ($u = 1, \cdots, U$) UT can be expressed as

$$\mathbf{y}_u[k] = \mathbf{h}_u[k]\,\mathbf{x}[k] + \mathbf{n}[k]. \tag{5}$$

where $\mathbf{n}[k]$ is i.i.d. $\mathbf{n}[k] \in \mathbb{CN}(0, \sigma^2\mathbf{I})$ additive complex Gaussian noise at subcarrier k. For the multi-BS case, an interference item should be added in addition to the noise.

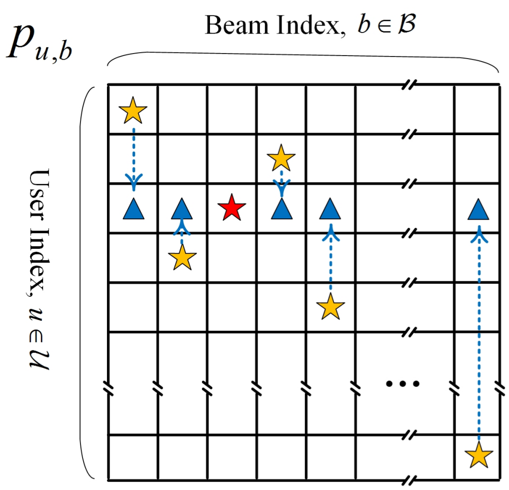


FIGURE 2. **Graphical representation of inter-user interference in the JUSBA problem. The star denote users to be scheduled, while the triangles represent interference to the scheduled users.**

III. PROBLEM FORMULATION

In this section, we discuss how to formulate the JUSBA problem in mathematical language. To solve for user selection in the beam domain, we should re-examine the process of calculating the achievable sum rates from the perspective of a user-beam pair. Note that $\mathbf{F}_{BB}[k] = \left[\mathbf{f}_{BB}^{1}[k], \ldots, \mathbf{f}_{BB}^{u}[k], \ldots, \mathbf{f}_{BB}^{U}[k]\right]$ denotes the digital precoder, while $\mathbf{F}_{RF} = \left[\mathbf{f}_{RF}^{1}, \ldots, \mathbf{f}_{RF}^{u}, \ldots, \mathbf{f}_{RF}^{U}\right]$ stands for the analog precoder. Assuming that all users have equal power transmission for simplicity, we can define the equivalent channel gain $p_{u,b}[k]$ between the u-th user and the b-th beam at subcarrier k as

$$p_{u,b}[k] = \frac{P}{U\sigma^2}\left|\mathbf{h}_u[k]\mathbf{f}_{RF}^{u,b}\mathbf{f}_{BB}^{u,b}[k]\right|^2, \tag{6}$$

where $P/(U\sigma^2)$ denotes the transmitted SNR. Moreover, we introduce an indicator function $I_{u,b}[k]$ to indicate if the beam and user pair have been chosen, i.e., $I_{u,b}[k] = 1$ means the u-th user is scheduled by the BS with beam b, and otherwise, $I_{u,b}[k] = 0$. The SINR of the u-th user and the b-th beam can be defined as

$$SINR_{u,b}[k] = \frac{I_{u,b}[k]p_{u,b}[k]}{1 + \sum\limits_{u' \in \mathcal{U}\backslash u}\sum\limits_{b' \in \mathcal{B}\backslash b} I_{u',b'}[k]p_{u',b'}[k]}, \tag{7}$$

where $\mathcal{U} = [1, 2, \ldots, U, \ldots, N]$ is the alternative user set and $\mathcal{B} = \left[\mathbf{f}_{RF}^{1}, \ldots, \mathbf{f}_{RF}^{U}, \ldots, \mathbf{f}_{RF}^{B}\right]$ is the alternative beam set in which B is the total number of beams in the codebook.

For easy understanding, in Figure 2, we use an $N \times B$ matrix of equivalent channel gain where the rows stand for the user index and the columns denote the beam index. All we need to do is carefully select at most N_{RF} elements in the matrix to maximize the sum rate, and each row and column only have at most one element to be selected (Once selected, we mark them as stars).

When coming to the inter-user interference, without a loss of generality, we take the *red star* in Figure 2 as an example. The other *yellow stars* are also the users to be scheduled. Once a user has been assigned to a beam, the side lobes of this beam will inevitably interfere with other users. The *blue triangles* denote inter-user interference to the *red star*.

According to [21], [24], [25], the achievable rate of the u-th user is written as

$$R_u = \frac{1}{K}\sum_{k=1}^{K}\sum_{u=1}^{U}\sum_{b=1}^{B}\log_2\left(1 + SINR_{u,b}[k]\right). \tag{8}$$

Then, based on the criterion of sum-rate maximization, we can formulate the JUSBA problem into the following programming as

$$\begin{aligned}
&\max_{\mathbf{I}} \ \frac{1}{K}\sum_{k=1}^{K}\sum_{u=1}^{U}\sum_{b=1}^{B}\log_2\left(1 + SINR_{u,b}[k]\right)\\
&s.t.\ \mathrm{C1}: \quad I_{u,b}[k] \in \{0,1\}, \quad \forall u \in \mathcal{U},\ b \in \mathcal{B}\\
&\quad\ \ \mathrm{C2}: \quad \sum_{b=1}^{B} I_{u,b}[k] \le 1, \quad \forall u \in \mathcal{U}\\
&\quad\ \ \mathrm{C3}: \quad \sum_{u=1}^{U} I_{u,b}[k] \le 1, \quad \forall b \in \mathcal{B}\\
&\quad\ \ \mathrm{C4}: \quad \sum_{u=1}^{U}\sum_{b=1}^{B} I_{u,b}[k] = N_{RF}, \quad \forall u \in \mathcal{U},\ b \in \mathcal{B}
\end{aligned} \tag{9}$$

where $\mathbf{I}$ is the set of $I_{u,b}[k]$. Constraint (C1) means that the binary link variable I can only take a value of 0 or 1. Constraint (C2) and (C3) guarantee that each beam can only be allocated to at most one user and each user can only be assigned to at most one beam, respectively. As a result, there is no beam collision between selected users. In the HBF architecture, the simultaneous transmission of data streams depends on the number of RF chains, and hence, the total number of users to be scheduled must satisfy the constraint (C4), which means the user number to be scheduled $U = N_{RF}$.

IV. PROPOSED ALGORITHMS

From the above discussion, programming (9) involves non-linear objective coupled discrete constraints in user selection or beam allocation and a binary constraint of the indicator function. We can confirm that (9) is a non-convex combinatorial optimization problem. Obviously, it is an NP-hard problem, and no mature solution can be adopted directly. An exhaustive searching (ES) method over all possible subsets of user-beam pairs is the optimal user scheduling method, but its extraordinary complexity and time requirements make it infeasible, especially when the number of beams and users increases. The ES method stands for the upper bound of the sum rate in our later simulation. In this section, we first give a brief introduction of the codebook-based beam training, which is widely used in mmWave massive MIMO systems to acquire equivalent CSI. Later, a ping-pong optimization method based on the HPS method to solve the JUSBA problem is proposed. Finally, the details of the HPS method are presented.

A. CODEBOOK-BASED BEAM TRAINING

Because we consider the scheduling scenario in which the BS does not acquire perfect or statistical CSI, beam training based on a predefined codebook between the BS and the users is necessary to obtain the equivalent CSI. It is challenging to acquire perfect CSI in massive MIMO systems, and hence, a reasonable beam training scheme with a well-designed codebook is a practical way to solve the analog precoder $\mathbf{F}_{RF}$ and the digital precoder $\mathbf{F}_{BB}$. From (7) we can see that both power intensity and multiuser orthogonality could affect the SINR and further affect the achievable sum rate. Under HBF architecture, the analog precoder $\mathbf{F}_{RF}$ is responsible for improving the received SNR and reducing inter-user interference, while the digital precoder $\mathbf{F}_{BB}$ is responsible for further eliminating residual inter-user interference. If in the analog precoding stage, inter-user interference is greatly suppressed or even eliminated, that is, if programming (9) is perfectly resolved, then we can temporarily ignore the digital precoder $\mathbf{F}_{BB}$, leading to an equivalent channel gain between the u-th user and the b-th beam at subcarrier k as

$$p_{u,b}^{IE}[k] = \frac{P}{U\sigma^2}\left|\mathbf{h}_u[k]\mathbf{f}_{RF}^{u,b}\right|^2, \quad (10)$$

where IE is short for interference eliminated. Temporarily ignoring the digital precoding stage is not without a basis. In mmWave massive MIMO communication systems, candidate beams are far beyond the scheduled users, so we could select the user-beam pairs that remain orthogonal to each other. Once the analog precoder $\mathbf{F}_{RF}$ is determined, channel estimation and digital precoding could be conducted based on an equivalent channel matrix. Details will be given at the end of this section.

In this paper, the widely used beamsteering codebook [21], [24] is adopted, and the weight matrix of the m-th element in the n-th codebook vector can be defined as

$$\begin{aligned} W(m,n) = \exp&\left(j\pi m \sin(\frac{2\pi n}{2^{N_{bit}}})\right) \\ &m = 0, 1, \ldots, M-1; \\ &n = 0, 1, \ldots, 2^{N_{bit}}-1, \end{aligned} \quad (11)$$

where M is the antenna number, and the total number of beams $B = 2^{N_{bit}}$. In this paper, we set $B = M$. It can be seen from the above formula that the beamsteering codebook uses N_{bit} to quantify the AoDs in the angle domain $[0, 2\pi]$.

In general, the beam training scheme contains a link establishment, sector level searching and beam level searching [26]–[28]. Here, we assume that the first two steps have been completed. In the third beam level searching step, our proposed scheme includes two stages as follows. (1) *BS beam sweeping stage*. Note that each column of $\mathbf{F}_{RF}$ stands for one beam based on the predefined codebook. The BS sequentially sweeps all the codebook in $\mathbf{F}_{RF}$ and transmits one codebook at a time with a single RF chain. In this stage,

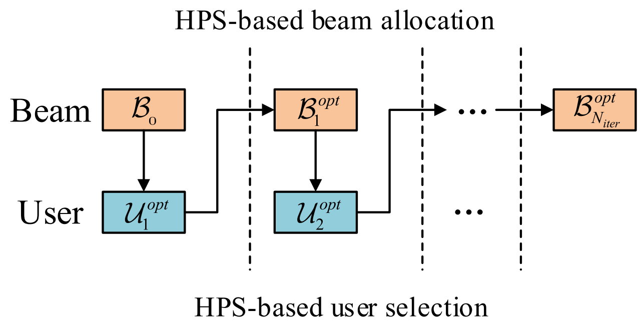


FIGURE 3. Proposed ping-pong optimization scheme based on HPS algorithm for JUSBA.

all the users continue receiving an omnidirectional pattern. (2) *User feedback stage*. Each user feeds back equivalent CSI to the BS, which includes the received signal intensity and the corresponding codebook index, while the signal intensity stands for the equivalent channel gain $p_{u,b}^{IE}$, and the codebook index indicates the location information of users.

Once the beamsteering codebook has been determined and the beam training process is finished, we can easily obtain the equivalent channel matrix of $p_{u,b}^{IE}[k]$, as shown in Figure 2. In this paper, we propose a ping-pong optimization algorithm to reduce the calculational complexity of the JUSBA problem. The algorithm has two key components: the ping-pong optimization problem will be described in section IV-B, and the HPS method will be described in section IV-C.

B. PING-PONG OPTIMIZATION OF JUSBA

From the above discussion, it is difficult to analytically and directly resolve the JUSBA problem. The DCA method in [19] and the Lyapunov-drift optimization method in [6] yield analytical solutions with a higher complexity and a worse performance than those of the ES method. Notably, it is not worth the candle, which is why a heuristic greedy method with a much lower complexity is proposed. In this paper, we propose a method with a similar analytical solution performance but a lower complexity compared with the methods in [6] and [19]. Inspired by [29] and [30], we propose an iteration scheme called ping-pong-like optimization, which divides the JUSBA problem into two sub-problems: a user selection problem when the beam is determined and a beam allocation problem when the user is selected. Moreover, for these sub-problems, much research has been completed and can be used for reference.

The proposed ping-pong optimization scheme based on HPS algorithm (P-HPS) is shown in Figure 3. Denote $\mathcal{B}_i^{opt}(\mathcal{U}_i^{opt})$ as the local optimum beam (user) set in the i-th iteration, which is chosen from candidate set $\mathcal{B} = [\mathbf{f}_{RF}^1, \ldots, \mathbf{f}_{RF}^U, \ldots, \mathbf{f}_{RF}^B]$ ($\mathcal{U} = [1, 2, \ldots, U, \ldots, N]$). The number of elements in $\mathcal{B}_j^{opt}(\mathcal{U}_j^{opt})$ is U, while $j = 1, 2, \cdots, N_{iter}$, and N_{iter} is the predefined maximum iteration time. Our ping-pong optimization scheme begins with selecting the initial beam set $\mathcal{B}_0 = \left[\mathbf{f}_{RF}^1, \mathbf{f}_{RF}^2, \ldots, \mathbf{f}_{RF}^U\right]$, which can be an arbitrary combination of elements in candidate beam set $\mathcal{B}$. Then, for the fixed beam set $\mathcal{B}_0$, the optimal user set $\mathcal{U}_1^{opt}$ that pairs with $\mathcal{B}_0$ can be found based on the achievable sum rate maximization. Similarly, with user set $\mathcal{U}_1^{opt}$ fixed, we seek to find the optimal beam set $\mathcal{B}_1^{opt}$. We repeat such iterations for N_{iter} times in a similar way as ping-pong games. During each iteration, the HPS method is adopted to acquire the optimum solution, which will be presented in detail in section IV-C. In the end, outputs $\mathcal{B}_{N_{iter}}^{opt}$ and $\mathcal{U}_{N_{iter}}^{opt}$ are the final results. The details of the P-HPS method are described as Algorithm 1, which conducts user selection optimization and beam allocation optimization until the iteration time comes to the upper limit.

Algorithm 1 P-HPS Method for JUSBA

Initialization

1 Set initial beam $\mathcal{B}_t^{opt} = \mathcal{B}_0$, iteration time $t = 0$

While $t < N_{iter}$ **do**

User selection stage

2 For given $\mathcal{B}_t^{opt}$, use the HPS algorithm to obtain $\mathcal{U}_t^{opt}$

Beam allocation stage

3 For above $\mathcal{U}_t^{opt}$, use the HPS algorithm again to obtain $\mathcal{B}_t^{opt}$ in turn

4 $t = t + 1$.

End while

Output : $\mathcal{B}_{N_{iter}}^{opt}, \mathcal{U}_{N_{iter}}^{opt}, I_{u,b}$.

C. HPS-BASED ALGORITHM

The PSO algorithm was invented by Kennedy [31] via simulating the collective intelligence and social behavior that exists among fishes and birds and combining it with evolutionary computational methods. When solving a problem with PSO, initial swarms iteratively explore the search space to find solutions. By considering velocity and location in the search space, each particle moves under both the best local solution found by each individual particle and the best overall solution of the swarm. When the algorithm just begins the iteration, a large difference exists in the particle population, and hence, the global searching ability of the PSO algorithm is strong. After multiple iterations, the particles in the population gradually approach the optimal value. At this moment, the searching adjustment is small, and the searching result cannot be guaranteed to be a global optimum, resulting in the *premature* problem in the algorithm [32]. In conclusion, PSO has several advantages including quick convergence and easy implementation, however it often suffers from being trapped into local optima in its search process.

In physics and metallurgy, annealing is a process in which a material first is heated to a sufficiently high temperature and then its temperature is gradually decreased to allow its molecules to rearrange to an improved crystalline structure with reduced energy. The basic idea of SA [33] algorithm is that the current state generates a new state through the state generation function and accepts the new state through the Metropolis acceptance criterion [34]. The SA algorithm consists of the search space S, the utility function $U(S, R)$, the temperature T, and the cooling rate $\emptyset$. The algorithm is a robust and versatile random search algorithm that converging to global optimal solution with probability 1. However, the disadvantage is that its convergence speed is relatively slow especially when dealing with large search space.

Therefore, in order to combine the advantages of PSO and SA, in this paper we adopt a hybrid heuristic optimization called HPS algorithm. Assume the total number of particles is N_p, and each particle represents a scheduling solution, i.e., the combination of users or beams. The location of the i-th particle is the U-dimensional vector $\boldsymbol{x}_i = [x_{i,1}, \cdots, x_{i,U}]$, in which each element $x_{i,q}(i = 1, 2, \cdots, N_p, q = 1, 2, \cdots, U)$ can take any integer value in the range of [1,N] (for beam particles, the range is [1,B]). For each particle $\boldsymbol{x}_i$, there is a corresponding velocity vector $\boldsymbol{v}_i = [v_{i,1}, \cdots, v_{i,U}]$ where $\left|v_{i,q}^u\right| \leq V_{max}^u$ and $\left|v_{i,q}^b\right| \leq V_{max}^b$ (in what follows, we set $V_{max}^u = N$, $V_{max}^b = B$ [35]). The velocity should not be an arbitrary value because higher velocities would overshoot the optimal solution and lower values might cause the particle to get trapped in local optima. In the n-th iteration, the local optimal solution for i-th particle is expressed as $\mathbf{p}_i(n)$, while the global optimal solution that all N_p particles found is denoted as $\mathbf{p}_g(n)$. Then, the velocity of the next iteration is updated as

$$\begin{aligned}\mathbf{v}_i(n+1) = \omega \cdot \mathbf{v}_i(n) + c_1\varphi_1 \cdot (\mathbf{p}_i(n) - \mathbf{x}_i(n)) \\ + c_2\varphi_2 \cdot \left(\mathbf{p}_g(n) - \mathbf{x}_i(n)\right), \quad (12)\end{aligned}$$

where c_1 and c_2 are constants that influence the random movement of particles around the solution region. φ_1 and φ_2 are two random vectors, the elements of which are uniformly distributed in the range (0, 1), and each represents the acceleration of the particle towards $\mathbf{p}_i(n)$ and $\mathbf{p}_g(n)$, respectively. The inertia weight ω in this paper is defined as

$$\omega(n) = \omega_m - n \times \frac{\omega_m - \omega_s}{n_{\max}}, \quad (13)$$

where ω_m and ω_s ($\omega_m > \omega_s$) are the starting and ending value for $\omega(n)$, respectively. And n_{max} is the maximum iterations of PSO algorithm. When the iteration begins, n close to 0 and $\omega(n)$ is approaching ω_m. And when n close to n_{max}, $\omega(n)$ tends to ω_s. In general, a bigger $\omega(n)$ helps PSO algorithm searching for larger area while a smaller one enables faster convergence to local optima. After obtaining the updated velocity value, the temporary position for i-th particle in ($n + 1$)-th iteration is defined as

$$\mathbf{x}_i(n+1) = \mathbf{x}_i(n) + \mathbf{v}_i(n+1). \quad (14)$$

$\mathbf{x}_i(n+1)$ may be out of the range [1,N] (for beam particles, the range is [1,B]), determining how to adjust the particles when they reach the border of the valid search region is a problem. We take the *reflective borders* as our solution to deal with data that are out of range [35]. With reflective borders, the particles reflect or bounce off the borders of the search region, much light bounces off a mirror or a ball bounces off a wall, i.e., the borders reflect the particle back into the search region. Here we introduce Metropolis acceptance criterion of SA algorithm to update local optimal solution $\mathbf{p}_i(n)$ as following.

$$\mathbf{p}_i(n+1) = \begin{cases} \mathbf{x}_i(n+1), & \exp(\frac{\Delta R}{T_n}) > r \\ \mathbf{p}_i(n), & else, \end{cases} \tag{15}$$

where $\Delta R = R(\mathbf{x}_i(n+1)) - R(\mathbf{p}_i(n))$ denotes the difference of sum rate between two solutions, r is a random value in the interval [0,1). If $\Delta R > 0$, $\mathbf{x}_i(n+1)$ was accepted directly as new local optimal solution, otherwise $\mathbf{x}_i(n+1)$ was accepted when $\exp(\Delta R/T_n) > r$. It means that better particles are directly accepted while worse ones are also possibly accepted with a certain probability. When the temperature is high, the algorithm accepts the deterioration solution with a large probability, which can enhance the global exploration ability of the algorithm. As the temperature T decreases, the probability that the algorithm accepts the deterioration solution gradually decreases, facilitating the algorithm to perform a local fine search. Metropolis acceptance criterion enable the HPS algorithm to jump away from the local optima and finally find the global optimal solution.

The pseudo-code of the HPS-based algorithm is summarized in detail as Algorithm 2. Initialize inertia weight ω_m and ω_s, constant c_1 and c_2, velocity upper bound V_{max}, total particles N_p, maximum iteration times n_{max}, initial temperature T_0, cooling rate Ø. $\mathbf{x}_i(1)$ and $\mathbf{v}_i(1)$ denote initial location and velocity which are randomly selected from the searching area. Then we can calculate achievable sum rate and update local optimum and global optimum. Let ϑ denotes the maximum percentage of particles whose sum rate values are the same in the current swarm. The while loop ends when the iteration time n comes to n_{max} or 90% particles have the same sum rate value. Lines 3-5 calculate inertia weight and velocity to update particle location. Every particle whose velocity is out of bound should be restricted to $[-V_{max}, V_{max}]$. Lines 6-7 update local optimum for i-th particle $\mathbf{p}_i(n+1)$ and global optimal solution under current iterations $\mathbf{p}_g(n+1)$ using the Metropolis acceptance criterion of SA. Lines 8-9 decrease the temperature T by cooling rate Ø and go on operation until the while loop comes to the end.

D. CONVERGENCE OF HPS

In this subsection, we prove the convergence of the algorithm. First we introduce a theorem.

Theorem 1 [36]: Assume that $U(S, R)$ denotes the utility function of optimization problem, S_i is the neighborhood of state i. The state generation probability G and the reception probability A of SA algorithm are respectively defined as

$$G_{ij}(T_n) = \begin{cases} 1/|S_i|, & j \in S_i \\ 0, & else, \end{cases} \tag{16}$$

$$\forall i, j \in S : A_{ij}(T_n) = \min\left(1, \exp\left(\frac{R(j) - R(i)}{T_n}\right)\right). \tag{17}$$

Algorithm 2 HPS-Based Algorithm

Initialization

1 Let ω_m, ω_s, c_1, c_2, V_{max}, n_{max}, N_p, T_0, and Ø
  $\mathbf{x}_i(1)$, $\boldsymbol{v}_i(1)$: initial location and velocity selected from the searching area randomly
  Calculate sum rate $R_{\mathbf{x}_i(1)}$
  Update $\mathbf{p}_i(1)$, $\mathbf{p}_g(1)$
2 **While** $n \le n_{max}$ or $\vartheta \le 90\%$ **do**
    For $i = 1$ toN_p **do**
3   Compute ω via (13) and $\mathbf{v}_i(n+1)$ by (12)
4   Repair out of bound particles
5   Compute $\mathbf{x}_i(n+1)$ via (14)
6   Calculate sum rate $R_{\mathbf{x}_i(n+1)}$
7   Update $\mathbf{p}_i(n+1)$ and $\mathbf{p}_g(n+1)$ using (15)
    End For
8   Decrease the temperature by Ø
9   $n \leftarrow n + 1$
  End while

Output : $\mathbf{p}_g$

The Markov chain accompanying the SA algorithm is strong ergodicity and the SA algorithm converges to the global optimal solution with probability 1 when the following condition is satisfied.

$$T_n \ge (1 + \lambda) \cdot \Delta / \ln(n + n_0), \quad n = 0, 1, \cdots, \tag{18}$$

where constant $n_0 \ge 2$, $\lambda = \min_{i \in S/S_{max}} \{\max_{j \in S}\{d_{ij}\}\}$, S_{max} is the set of local optimum, d_{ij} is the minimum transform number from state i to state j, and $\Delta = \max_{i \in S, j \in S_i} \{|R(i) - R(j)|\}$.

Based on Theorem 1, the convergence of HPS algorithm is proven as following.

Proof: Theorem 1 states that when the temperature control parameter satisfies the condition (18), the SA algorithm will converge to global optimal solution with probability 1 as long as the state generation function obeys the uniform distribution in the neighborhood of the current state, and the acceptance of the new state is the Metropolis criterion.

According to (12), (14), φ_1 and φ_2 are two independent random variables obeying uniform distribution U(0,1), hence new state $\mathbf{x_i}(n+1)$ belongs to the neighborhood of $\mathbf{p}_i(n)$

$$\begin{aligned} S_{\mathbf{p}_i(n)} = &(\mathbf{x}_i(n) + \omega \mathbf{v}_i(n), \\ &\times \mathbf{x}_i(n) + \omega \mathbf{v}_i(n) + c_1(\mathbf{p}_i(n) - \mathbf{x}_i(n)) \\ &+ c_2(\mathbf{p}_g(n) - \mathbf{x}_i(n))) \end{aligned} \tag{19}$$

$\mathbf{x_i}(n+1)$ was generated by uniform distribution in $S_{\mathbf{p}_i(n)}$, therefore (16) is satisfied. And new state accepted via (15) by Metropolis criterion meets the requirement of (17). Hence, as long as (18) is satisfied in HPS algorithm, the algorithm converges to the global optimal solution with probability 1.

E. HYBRID PRECODING

After obtaining the optimal analog precoder matrix $\tilde{\mathbf{F}}_{RF} = \mathcal{B}^{opt}_{N_{iter}}$ for the scheduled user set $\mathcal{U}^{opt}_{N_{iter}}$ at subcarrier k, the equivalent channel matrix can be denoted as $\mathbf{H}_{eq}[k] = \mathbf{h}_u[k]\tilde{\mathbf{F}}_{RF}$, which in essence, is the product of the channel matrix and the analog precoder. Note that $p_{u,b}^{IE}[k]$ does not contain detailed information of channel $\mathbf{H}_{eq}[k]$, which is necessary in the digital precoding stage. To estimate $\mathbf{H}_{eq}[k]$, the typical method of pilot-assisted channel estimation is used [37]. Assume that the estimation of $\mathbf{H}_{eq}[k]$ is $\tilde{\mathbf{H}}_{eq}[k]$. The baseband digital precoder based on commonly adopted methods such as the minimum mean square error (MMSE) or the zero-forcing (ZF) criterion can be easily determined by

$$\mathbf{F}_{BB}^{MMSE}[k] = \widetilde{\mathbf{H}}_{eq}^{H}[k]\left(\widetilde{\mathbf{H}}_{eq}[k]\widetilde{\mathbf{H}}_{eq}^{H}[k] + \frac{KU\sigma^2}{P}\mathbf{I}_U\right)^{-1}$$
$$\mathbf{F}_{BB}^{ZF}[k] = \widetilde{\mathbf{H}}_{eq}^{H}[k]\left(\widetilde{\mathbf{H}}_{eq}[k]\widetilde{\mathbf{H}}_{eq}^{H}[k]\right)^{-1}. \tag{20}$$

F. COMPLEXITY ANALYSIS

Next, we provide the complexity analysis of the P-HPS method. The comparisons include the DCA method and the greedy algorithm in [19], the Hungarian algorithm in [13], the MM algorithm in [10] and the ES method. The proposed scheme has N_{iter} iterations, in which each iteration contains $n_{max}N_p^u$ operations in the user selection stage and $n_{max}N_p^b$ operations in the beam allocation stage. Hence, the complexity of the P-HPS method is $\mathcal{O}\{N_{iter}n_{max}(N_p^b + N_p^u)\}$.

The DCA method transforms the non-convex combinatorial problem of (9) into the difference of two convex problems through a series of approximations. Then successive convex approximation and the interior point method are adopted to solve the classical convex optimization problem. During the DCA operation, there are a total of $3NB$optimization variables, $\Omega = 4NB + N + B + 1$ linear constraints and $\mathcal{K}$ operation times. Thus, the computational complexity of the DCA method is $\mathcal{O}\left(\mathcal{K}(NB)^3\Omega\right)$ [19], [38]. In the worst case, the Hungarian algorithm has a complexity of $\mathcal{O}\left(B^3\right)$ [39]. Through some improvements, such as removing the zero columns or rows from the cost matrix, the Hungarian algorithm can be sped up. However, the computational complexity remains on the order of $\mathcal{O}\left(B^3\right)$.

The essence of the greedy algorithm is to acquire an incremental gain of the target metric in each round of selection. To begin, the user-beam pair that maximizes $p_{u,b}^{IE}[k]$ is chosen, and the selected sets and alternative sets are updated. Then, the algorithm selects beam $\bar{b}$ that causes the minimum inter-user interference to the selected user set. Next, the user $\bar{u}$ from the alternative set that pairs with beam $\bar{b}$ and results in the maximum SINR is selected. If the user-beam pair $(\bar{u}, \bar{b})$ bring in sum rate increasing, then they are added to the selected sets. Otherwise, the user-beam pair $(\bar{u}, \bar{b})$ is added to the alternative sets, and iterations are repeated until N_{RF} user-beam pairs are selected or any alternative set is empty (see Algorithm 2 in [19] for details). The computational complexity of the greedy-based method is $\mathcal{O}\left\{NB + \sum_{i=1}^{U-1}(N + B - 2i)\right\}$.

The MM algorithm in [10] selects the user-beam pair that has the maximum magnitude to be scheduled. In this paper, we adopt a simple way to avoid beam collision based on the original algorithm. Once the maximum element in the equivalent channel matrix is chosen, we delete the row and column in which the element is located. Then, we can choose the second largest element in the deleted matrix. This operation is repeated until all U user-beam pairs are selected. The computational complexity of the MM algorithm is $\mathcal{O}\left\{\sum_{i=0}^{U-1}(N - i)(B - i)\right\}$. The ES method searches brutely over all possible user-beam combinations, so it could achieve optimal performance, which is regarded as the upper bound in this paper. The computation complexity of the ES method is $\mathcal{O}(C_N^U C_B^U A_U^U)$, where $C_a^b = \frac{a!}{b!(a-b)!}$ Stands for the combination number, and $A_a^b = \frac{a!}{(a-b)!}$ Denotes the permutation number.

TABLE 1. Parameters of simulation.

Parameters	Values
Central frequency	28 GHz
Antenna structure	ULA
Antenna spacing	Half the wavelength ($d = \frac{\lambda}{2}$)
OFDM subcarriers K	U
Delay tap N_c	4
Path number	4
Path loss	0.25
Sampling period T_S	1/1760 μs
Range of AoDs	Uniformly distributed in $[-\pi, \pi]$
Complex gain $\alpha_{l,u}$	$\alpha_{1,u} \sim \mathbb{C}\mathcal{N}(0,1)$ $\alpha_{i,u} \sim \mathbb{C}\mathcal{N}(0,0.1)$, i=2,3,4
Delay $\tau_{l,u}$	Uniformly distributed in $[0, (N_c - 1)T_S]$
Codebook	Beamsteering codebook($N_{bit} = log_2 M$)

V. SIMULATION RESULTS

In this section, we demonstrate the simulation analysis results of the proposed P-HPS optimization method. The detailed parameters of the wideband mmWave channel in the simulation are shown in Table 1. To obtain the average sum rate under specific SNR values, we perform 100 simulations for each packet, in which a frame containing 1000 bits of data is transmitted, i.e. we take the mean spectral efficiency of 100 times simulation as our average sum rates.

As for proposed P-HPS method, we set $\omega_m = 0.9$, $\omega_s = 0.4$, $c_1 = c_2 = 2$, $V_{max}^u = N$, $V_{max}^b = B$. For temperature control parameter T we have $T = T_0\emptyset^n$. T_0 is initial temperature and is defined by simulation such that the HPS algorithm initially has at least a 90% probability of accepting suboptimal solutions. $\emptyset$ denotes cooling rate that is acceptable with a parameter value in the interval $0.85 \le \emptyset \le 0.99$ [40]. In this paper, we set $\emptyset = 0.95$. n is iteration times which gradually reduces the temperature.

First, we investigate the achievable sum rate of the P-HPS method. We consider the scenario that the BS is equipped with 16 ULA antennas and 4 RF chains, while there are 10 candidate users in the cell, among which only 4 users can be scheduled. We introduce the ES method and DCA method for comparison, as ES method has proven to be global

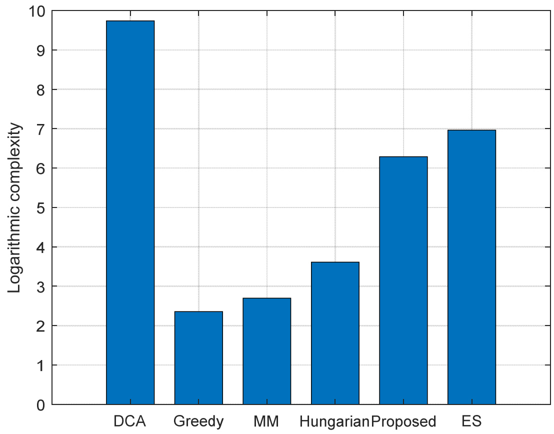


FIGURE 4. Complexity comparison ($M = 16$, $N = 10$, $U = 4$).

optimal solution that will be regarded as upper bound in our simulation, while DCA method shows a good performance in solving the JUSBA problem. As expected, the greater the particle population N_p and the larger maximum iteration times n_{max}, the better the performance of the achievable sum rate. And through simulation, we discover that the particle population N_p has a more sensitive influence to the scheduling results compared with maximum iteration times n_{max}. For fixed ping-pong and PSO iterations ($N_{iter} = 4$, $n_{max} = 50$), in Figure 5(a), we compare the performance versus particle population N_p in 5%, 10%, and 20% of the total candidate particles β. It can be seen that as the particle population increases, the performance improvement is obvious. Figure 5(b) compares the performance versus iteration number for 10, 20, and 50 ping-pong iterations N_{iter} and when the particle number is fixed ($N_{iter} = 4$, $N_p = 0.2\ \beta$). Similarly, the performance improves when the number of iterations increases. Figure 5(c) demonstrates the performance of the proposed algorithm versus the number of ping-pong iterations N_{iter}. Assume that SNR = 10 dB, for fixed populations and iterations of the PSO algorithm ($N_p = 0.2\beta$, $n_{max} = 50$), the proposed algorithm converges to a stable value after only 4 ping-pong iterations, which is very close to

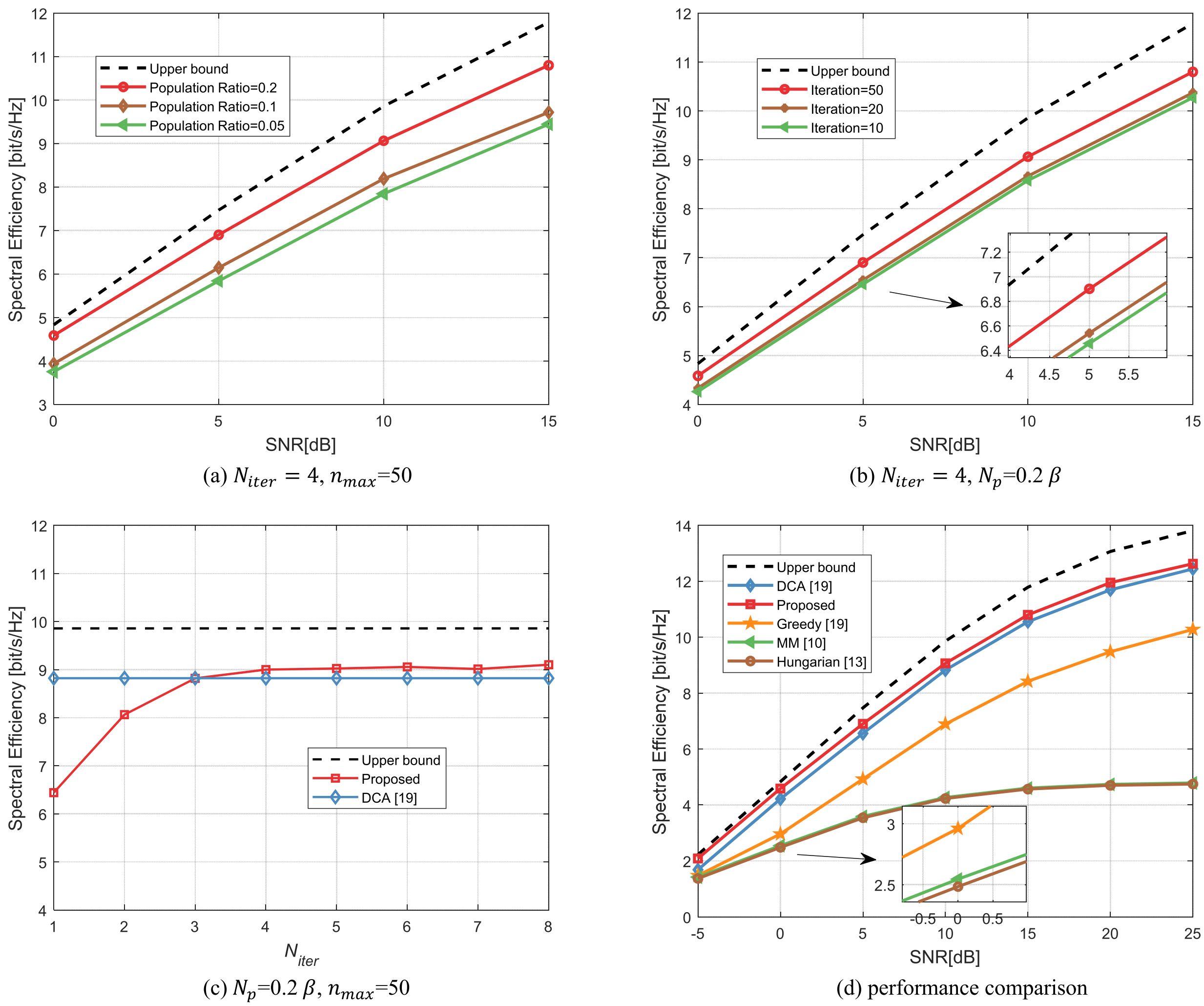
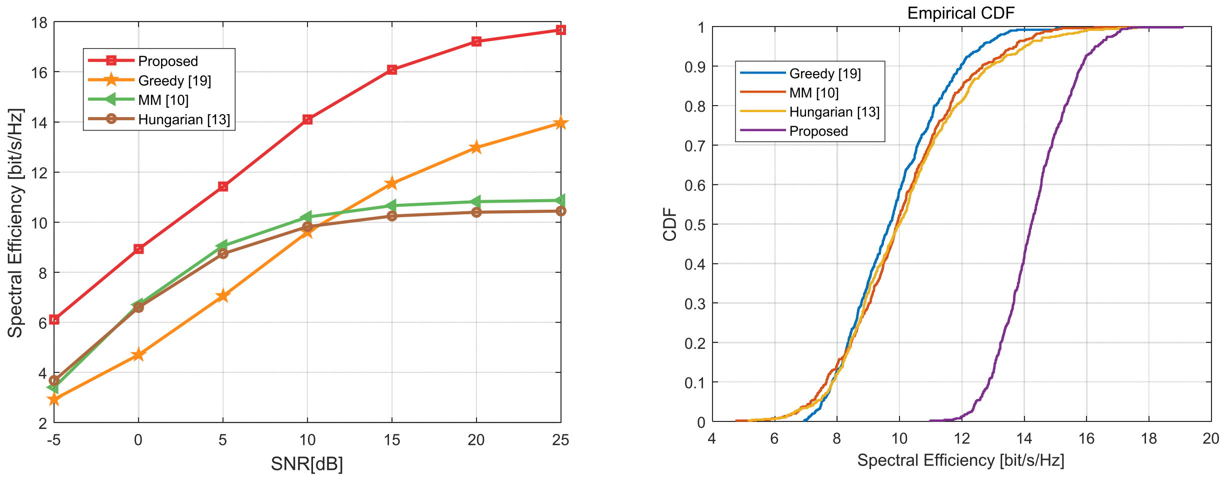


FIGURE 5. The performance of the proposed algorithm with system parameters ($M = 16$, $N = 10$, $U = 4$).



(a) sum rate comparison

(b) CDF comparison

FIGURE 6. The performance of the proposed algorithm with system parameters ($M = 64$, $N = 20$, $U = 10$).

the performance of the ES method. When expanding the SNR operating regions, we can obtain the performance comparison for different scheduling schemes in details with parameters (system parameters: $M = 16$, $N = 10$, $U = 4$; P-HPS parameters:$N_{iter} = 4$, $n_{max} = 50$, $N_p = 0.2\beta$), as shown in Figure 5(d). No doubt that the ES method performs the best in all the considered SNR operating regions. The performance of the proposed P-HPS method can achieve a considerable performance close to the upper limit ES method but requires substantially fewer computing resources, which is 21.25% of the ES method, as shown in Figure 4. In addition, the proposed P-HPS method performs better than the DCA method with much lower complex. The DCA method introduces too many optimization variables, which leads to a prohibitively high complexity. The greedy method has a better performance than the Hungarian algorithms and MM method in all SNR operating regions, while the latter two methods have similar performance but the MM method achieves a relatively good performance.

Next, we expand the simulation to the scenario with parameters (system parameters: $M = 64$, $N = 20$, $U = 10$; P-HPS parameters: $N_{iter} = 20$, $n_{max} = 100$, $N_p = 0.1\beta$) in Figure 6. With the increasing of antennas and candidate users, the complexity of the ES method and DCA method reach a horrible level that system cannot afford. Hence in this scenario we just conduct performance comparison with the greedy method, the Hungarian algorithms and the MM method. From Figure 5(d) and Figure 6(a), we can conclude that the proposed P-HPS algorithm performs better than the other three methods in both simulation scenarios. The main idea of the greedy method is to optimize two metrics (i.e., the received signal energy and user orthogonality) one by one instead of jointly optimizing the two metrics, which will inevitably cause a performance loss. The P-HPS method conducts an exhaustive search of the population number in each iteration and updates the particles by Metropolis acceptance criterion. Further, the search results optimize via ping-pong iterations. Hence, the performance of the P-HPS method is better than that of the greedy one. The MM method and the Hungarian algorithm have a similar performance; however, the MM algorithm has a much lower complexity. In essence, the ideas of the MM and Hungarian algorithms are similar. They both select the user-beam pair with the maximum receive signal power. At the same time, they both consider beam collision in this simulation. Moreover, P-HPS method has more flexibility due to its adjustable parameters, which can achieve good trade-off between computational complexity and system performance.

The stability and effectiveness of the proposed methods when SNR $=$ 10 dB is verified in Figure 6(b), which shows the cumulative distribution function (CDF) for 1000 iterations. The proposed method performs better than the other three methods, the conclusion in Figure 6(a) are confirmed from the perspective of CDF simulation. The proposed scheme and greedy method have a higher stability and precision compared with the MM and Hungarian methods.

Interestingly, in the in the scenario that the BS equips with 16 antennas, the greedy method has a better performance in all the SNR simulation region. While in the scenario with 64 antennas of the BS, the greedy method is worse than the MM and Hungarian methods in the low SNR region; however, the greedy method performs better than the other two methods in the high SNR region. Due to the sparsity of the mmWave channel and because the candidate beams are far beyond the candidate users in massive MIMO systems, the methods that only consider the received signal energy, e.g., the MM and Hungarian methods, could achieve a good performance because energy plays a leading role in low SNR. As the SNR increases, the impact of inter-user interference on performance is more pronounced, hence the achievable sum rate of the MM and Hungarian methods, which ignore inter-user interference, hardly grow, while the greedy method comes up in the high SNR region.

VI. CONCLUSION

In this paper, the JUSBA problem was investigated for mmWave massive MIMO communication systems with an HBF architecture. A practical scenario with a wideband mmWave channel was adopted, and both beam collision and inter-user interference were considered. After the joint optimization problem was modeled as a non-convex combination program, a P-HPS method was proposed to address the problem. The simulation results indicate good performance and evaluate the effectiveness of the proposed algorithm. Future work can take fairness as the optimization goal and extend to multi-cell multi-user hybrid massive MIMO communication systems.

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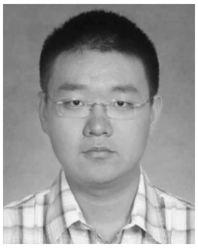

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