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User Association and Power Allocation in Multi-Connectivity Enabled Millimeter-Wave Networks With Limited Backhaul

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ABSTRACT Millimeter-wave (mmWave) communication has been recognized as a key technology to improve the rate performance of the next-generation wireless networks. However, the mmWave signals suffer from severe path loss and penetration attenuation due to the extremely high frequency characteristics. As a result, a massive number of small base stations (SBSs) would be deployed in mmWave networks to provide seamless coverage. To overcome obstacle blockages, the multi-connectivity technology that enables a user to associate with multiple SBSs simultaneously has been proposed by 3GPP, which brings new challenges to resource allocation. This paper investigates the joint user association and power allocation problem in such a multi-connectivity enabled mmWave network aiming at maximizing the system sum rate while considering the backhaul capacity limit and users' individual rate requirements. The optimization problem is highly non-convex and NP-hard to solve. By decoupling it into user association subproblem and power allocation subproblem, we first propose a novel swapping algorithm on top of the classic many-to-many matching scheme to perform user association, and then apply the difference of convex functions (D.C.) programming approach to transform the non-convex power allocation subproblem into a convex one and solve it by an iterative algorithm. Simulation results demonstrate the superior performance of the proposed multi-connectivity user association and power allocation schemes over the existing ones.

INDEX TERMS Multi-connectivity, user association, power allocation, millimeter-wave communications, limited backhaul.

I. INTRODUCTION

THE DEMANDS for frequency resources have been significantly increased recently due to the ever-increasing number of smart terminals and the emerging advanced applications. To confront the serious spectral scarcity problem, the millimeter-wave (mmWave) communication has been introduced to the fifth-generation (5G) and beyond wireless communication systems [1]. However, due to the extremely high frequency characteristics, mmWave signals not only suffer from high path loss but also are vulnerable to obstacles such as buildings, forests, rain, and people, etc. The harsh propagation environment brings new technical challenges in practical mmWave communication networks [2], [3]. One is to overcome the small coverage problem, and another one is to overcome the communication outage caused by the obstacles between mmWave small base-stations (SBSs) and users by maintaining a line-of-sight (LoS) link.

Network densification and multi-connectivity technology have been proposed to overcome the aforementioned challenges. By ultra-densely deploying mmWave SBSs in a certain area, the coverage of each SBS is significantly reduced [4]. For overcoming the blockage effect, the multi-connectivity technology that allows a user to establish and maintain communication links with multiple SBSs simultaneously has been proved to be able to improve the rate performance, enhance the communication reliability, and provide seamless services [5], [6].

Despite the great potentials of the multi-connectivity enabled ultra-dense mmWave network, many new technical challenges naturally arise. For instance, the dense deployment of SBSs brings strong inter-link interference, which could degrade network performance. To fully explore the benefits of densely deployed SBSs, which user should be associated with which SBSs needs to be carefully studied to avoid strong inter-link interference. Such a user association scheme is highly desirable in the ultra-dense multi-connectivity enabled mmWave network. Yet the combinatorial user association problem is generally NP-hard. In addition, properly allocating transmission power can also help reduce the inter-link interference, which, however, is more complicated than that in the traditional single-connectivity based wireless communication networks. Furthermore, the backhaul capacity is usually limited in practice and could be much more stringent in dense networks due to the high deployment cost and geographical limitations, which should also be taken into consideration [7]. Therefore, to reap the full potentials of ultra-dense mmWave networks, it is of paramount importance to investigate the joint multi-connectivity user association and power allocation problem while considering the backhaul limit.

A. RELATED WORK

User association and resource allocation have been studied in various types of wireless networks [8], [9], [10], [11], [12], [13] in the literature. The authors in [8] studied the joint user association and power allocation problem to maximize the energy efficiency of a heterogeneous network under the constraints of quality of service (QoS) requirements and proposed a generalized Dinkelbach method to address the formulated problem. The beam-user association problem was studied in [9] for mmWave communications and a low complexity algorithm was proposed. A study in [10] focused on an ultra-dense mmWave network and investigated the user association and subband allocation problem. To solve the optimization problem, a many-to-one matching based algorithm with externalities considered was designed. In a unmanned aerial vehicle (UAV) assisted cellular network, [11] presented a joint user association and power control framework based on the coalition game theory and the successive convex approximation algorithm to maximize the sum rate while considering load balancing and user fairness. The authors in [12] targeted at the user association and power allocation problem in mmWave-based energy harvesting networks for maximizing the system energy efficiency under cross-tier interference constraints and QoS requirements, and proposed an iterative gradient algorithm to solve the problem. A dynamic mmWave network was further considered in [13] and an offline algorithm based on the multi-agent reinforcement learning framework was devised to realize adaptive user association with the aim of maximizing the long-term total sum rate. However, the capacity limit of practical backhauls was not considered in the above literature.

The limited backhaul capacity was further taken into account in [14], [15], [16], [17] when studying the user association and resource allocation problem. A study in [14] formulated a backhaul-aware user association and resource allocation problem to optimize the network utility in heterogeneous networks and adopted the Lagrangian dual method to solve it. The varying backhaul capacity in satellite-terrestrial integrated networks was considered in [15], [16]. Under such constraints, a dynamic greedy user association scheme was proposed in [15] for load balancing, and a joint user association, bandwidth assignment and power allocation framework was established in [16] to maximize the system utility by employing the alternating optimization approach. The authors in [17] developed an intelligent power control algorithm based on the recurrent neural network to trade off between sum rate and energy consumption under the backhaul constraints.

Though with insightful results obtained in the above works, they all focused on the traditional single-connectivity scenario, where each user is only allowed to associate with one unique SBS for data transmission. Only a few existing works focused on the multi-connectivity based networks [18], [19], [20], [21], [22], [23], [24], [25], [26]. The multi-connectivity enabled user association and power allocation problem has been studied in [18], [19], [20]. Specifically, in [18], a heuristic joint user association and power control algorithm was proposed with the multi-objective of maximizing system energy efficiency and balancing traffic loads among SBSs given users' QoS requirements. In [19], a novel non-dominated sorting genetic algorithm II was proposed to solve the formulated problem, while the equal-weighted Tchebycheff method and the successive convex approximation were applied in [20]. However, [18], [19], [20] ignored the inter-link interference, which could lead to performance loss especially in ultra-dense mmWave networks. A number of other optimization methods have also been attempted to solve the multi-connectivity user association and resource allocation problem. By modeling the network as a graph, [21] adopted a machine learning approach, and a many-to-many matching based method was proposed in [22], [23]. A study in [24] devised a three-stage association scheme to deal with channel dynamics. In a coordinated multi-point (CoMP) scenario, the authors in [25] utilized the classic many-to-many swapping matching theory to solve the user BS association problem. The authors in [26] jointly optimized user association, power control and access point deployment, and proposed a Monte Carlo based method, which was computationally costly in the worst case.

Although some researchers have started to consider the multi-connectivity capability of users recently, the inter-link interference was ignored in [18], [19], [20] and only the user association problem was investigated in [21], [22], [23], [24]. Moreover, all of them ignored the backhaul limit. How to deal with the complicated user association and power allocation problem in a multi-connectivity enabled mmWave network while jointly considering the limited backhaul capacity, severe inter-link interference and users' individual QoS requirements is still largely unknown, which is, however, important for harvesting the performance gains brought by the ultra-dense deployment of mmWave SBSs and the multi-connectivity ability of users. This is the main focus of the paper.

B. CONTRIBUTIONS

In contrast to [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26] that either considered the traditional single-connectivity case or ignored the inter-link interference/the backhaul constraint, this paper makes efforts to maximize the downlink sum rate of a multi-connectivity enabled mmWave network where each user can establish and maintain communication links with multiple mmWave SBSs simultaneously subject to the backhaul capacity constraint and individual user's minimum rate requirement. The main contributions of this paper can be summarized as follows.

- We investigate the complicated user association and power allocation problem in a multi-connectivity enabled mmWave network with limited backhaul. Specifically, we aim to maximize the downlink sum rate of all users while guaranteeing the minimum rate requirement of each user and satisfying the backhaul capacity constraint. Such an optimization problem is a mixed integer non-linear programming (MINLP) problem and thus NP-Hard. By decoupling it into two subproblems, the joint multi-connectivity user association and power allocation problem is solved in two stages.
- For the user association subproblem, different from most existing works that neglected the effect of user association on inter-link interference, in the mmWave network with directional beams, the interference received is highly coupled with the association result between users and SBSs. To this end, we propose a novel swapping algorithm on top of the classic many-to-many matching process to conduct multi-connectivity based user association.
- For the power allocation subproblem, we apply the difference of convex functions (D.C.) programming to convert the non-convex power allocation problem into a sequence of convex optimization problems via two types of Taylor series approximations, and then propose an effective iterative power allocation algorithm.
- Extensive simulation results demonstrate that our proposed multi-connectivity user association scheme and D.C. programming based iterative power allocation algorithm both achieve considerable performance gains compared to the benchmarks.

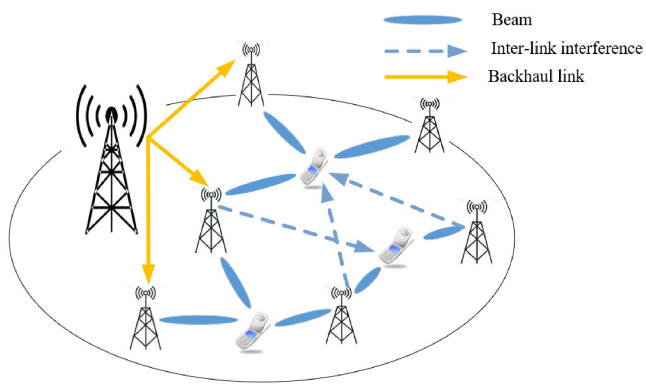

FIGURE 1. Illustration of multi-connectivity enabled mmWave network.

The rest of this paper is organized as follows. Section II introduces the system model and formulates the optimization problem. Section III decouples the original optimization problem into a multi-connectivity user association subproblem and a power allocation subproblem, and propose the solutions. Simulation results are presented in Section IV, and Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

As shown in Fig. 1, we consider the downlink transmission of an ultra-dense network composed of I users in $\mathcal{I} = \{1, 2, \ldots, I\}$, J mmWave SBSs in $\mathcal{J} = \{1, 2, \ldots, J\}$ and one sub-6GHz (operating at frequencies below 6GHz) macro BS (MBS). Both SBSs and users are equipped with large antenna arrays to form highly directional beams. To improve the reliability of mmWave communications, it is assumed that multi-connectivity is enabled at each user to associate with multiple SBSs simultaneously. By assuming that N^u and N^b radio frequency (RF) chains are available at each user and each SBS, respectively, a user can support at most N^u transmission links and an SBS can serve at most N^b users [21]. All the SBSs serve users over the same frequency band.

Assume that each SBS j is connected to the sub-6G MBS through a limited backhaul link with capacity $B_j, \forall j \in \mathcal{J}$. The MBS in the network acts as a central control unit that sends the required control signals. A user's downlink data is first transmitted from the core network to the MBS, then delivered to a mmWave SBS through the backhaul link, and finally transmitted to the user via mmWave communication links. Thus, the sum rate of the communication links associated with a single mmWave SBS should not exceed the capacity limit of the corresponding backhaul link between this SBS and the MBS.

Similar to [27], [28], [29], a sectored antenna model is adopted in this paper to approximate the actual beam gain for analytical tractability. Specifically, for the communication link between SBS j and user i, let θ_j^t and θ_i^r denote the transmission beamwidth of SBS j and the reception beamwidth of user i, respectively. ϕ_{ji}^t and ϕ_{ij}^r denote the corresponding beam alignment error, i.e., the offset angle between the beam steering direction and the boresight direction between SBS j and user i. The transmission beam gain $g_{ji\to ji}^t(\theta_j^t, \phi_{ji}^t)$ and the reception beam gain $g_{ij\to ij}^r(\theta_i^r, \phi_{ij}^r)$ between SBS j and user i can be then expressed as

$$g_{ji\to ji}^t\left(\theta_j^t, \phi_{ji}^t\right) = \begin{cases} \frac{2\pi - \left(2\pi - \phi_{ji}^t\right)z}{\theta_{ji}^t}, & \text{if} \quad |\phi_{ji}^t| \le \frac{\theta_j^t}{2}, \\ z, & \text{otherwise}, \end{cases} \tag{1}$$

and

$$g_{ij\to ij}^r\left(\theta_i^r, \phi_{ij}^r\right) = \begin{cases} \frac{2\pi - \left(2\pi - \phi_{ij}^r\right)z}{\theta_{ij}^r}, & \text{if} \quad |\phi_{ij}^r| \le \frac{\theta_i^r}{2}, \\ z, & \text{otherwise}, \end{cases} \tag{2}$$

respectively, where $0 < z \ll 1$ is the sidelobe gain.

The channel gain between SBS j and user i is modeled as

$$g_{ji}^c = |h_{ji}|^2 L_{ji}, \tag{3}$$

where $|h_{ji}|^2 \sim \text{Gamma}(m, m^{-1})$ denotes the small-scale fading coefficient, which follows the Nakagammi-m distribution. L_{ji} represents the path loss. As mmWave signals are vulnerable to obstacles, the LoS and non-line-of-sight (NLoS) links have different path loss. According to [30], the probability that there exists an LoS link between SBS j and user i, $\Pr_{ji}^{los}$, is given by

$$\Pr_{ji}^{los} = \exp\left(-\sigma d_{ji}\right), \tag{4}$$

where parameter σ captures the effect of the density and the sizes of environmental blockers, and d_{ji} is the distance between SBS j and user i. The path loss L_{ji} is then given by

$$L_{ji} = \Pr_{ji}^{los} L_{ji}^{los} + \left(1 - \Pr_{ji}^{los}\right) L_{ji}^{nlos}, \tag{5}$$

where the LoS path loss L_{ji}^{los} and the NLoS path loss L_{ji}^{nlos} can be obtained from

$$L_{ji}^{(n)los} = 10^{-\frac{\beta}{10}} d_{ij}^{-\alpha_{(n)los}}, \tag{6}$$

with α_{los} and α_{nlos} being the path-loss exponents for the LoS link and NLoS links, respectively. β is the reference path loss in dB at the distance of 1m, which is a frequency-dependent constant.

To indicate which users are associated with which SBSs, we define an $I \times J$ matrix X with the ith row and jth column element $x_{i,j} \in \{0, 1\}$. $x_{i,j} = 1$ if user i is associated with SBS j; otherwise, $x_{i,j} = 0$. Since the frequency band is reused by all users, the communication link between user i and SBS j suffers from interference from the other communication links, denoted by I_{ij}. One can obtain that

$$I_{ij} = \sum_{\substack{k \in \mathcal{I}, m \in \mathcal{J} \\ (k,m) \neq (i,j)}} x_{km} p_{km} g_{mk\to ji}^t\left(\theta_m^t, \phi_{mi}^t\right) g_{mi}^c g_{km\to ij}^r\left(\theta_i^r, \phi_{im}^r\right), \tag{7}$$

where $p_{km} = [\mathbf{P}]_{k,m}$ is the transmission power from SBS m to user k. It can be seen from (7) that the interference received

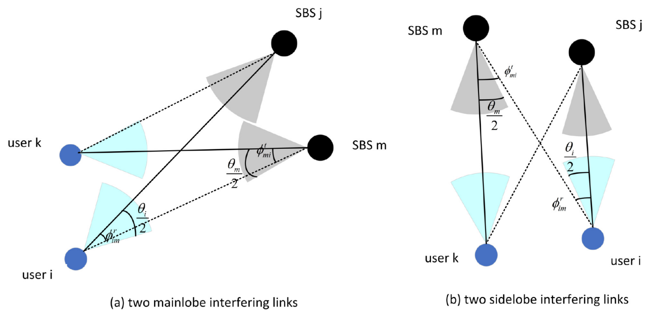

FIGURE 2. **The interference model of mainlobe and sidelobe interference.**

by a communication link is determined by both the transmission beam gain $g_{mk\to ji}^t(\theta_m^t, \phi_{mi}^t)$ and the reception beam gain $g_{km\to ij}^r(\theta_i^r, \phi_{im}^r)$, each of which can either be the mainlobe gain or the sidelobe gain, as shown in Fig. 2, depending on the user association, the beamwidth, and the beam alignment error, etc. This is in sharp contrast to the traditional scenario with omnidirectional antennas, where the inter-link interference is a constant.

The corresponding signal-to-interference-plus-noise ratio (SINR) is then

$$SINR_{ij} = \frac{p_{ij} g_{ji\to ji}^t\left(\theta_j^t, \phi_{ji}^t\right) g_{ji}^c g_{ij\to ij}^r\left(\theta_i^r, \phi_{ij}^r\right)}{I_{ij} + WN_0}, \tag{8}$$

where W and N_0 represent the bandwidth and the power spectral density of additive white Gaussian noise (AWGN), respectively. The achievable rate over the communication link from mmWave SBS j to user i, R_{ij}, can be expressed as

$$R_{ij} = W \log_2\left(1 + SINR_{ij}\right). \tag{9}$$

The sum rate of the whole system is then

$$R_{tot} = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} x_{ij} R_{ij}. \tag{10}$$

As mentioned earlier, the amount of data transmitted via a backhaul link is usually limited by its capacity in practice. Given the backhaul capacity between SBS j and the MBS, B_j, the sum rate of the links associated with SBS j should satisfy

$$\sum_{i \in \mathcal{I}} x_{ij} R_{ij} \le B_j, \quad \forall j \in \mathcal{J}. \tag{11}$$

B. PROBLEM FORMULATION

With multi-connectivity enabled at each user, our objective is to maximize the total achievable sum rate of the mmWave communication network by jointly optimizing user association and power allocation while considering the limited backhaul capacity and the individual minimum rate requirement of each user. The optimization problem can be formulated as

$$\mathcal{P}1: \max_{\mathbf{X}, \mathbf{P}} \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} x_{ij} R_{ij}$$

$$\text{s.t.} \quad C_1: \sum_{i \in \mathcal{I}} x_{ij} \le N^b, \quad \forall j \in \mathcal{J},$$

$$C_2: \sum_{j\in\mathcal{J}} x_{ij} \le N^u, \ \forall i \in \mathcal{I},$$
$$C_3: \sum_{i\in\mathcal{I}} x_{ij}p_{ij} \le p_{j,max}, \ \forall j \in \mathcal{J},$$
$$C_4: \sum_{i\in\mathcal{I}} x_{ij}R_{ij} \le B_j, \ \forall j \in \mathcal{J},$$
$$C_5: \sum_{j\in\mathcal{J}} x_{ij}R_{ij} \ge R_i^{min}, \ \forall i \in \mathcal{I},$$
$$C_6: p_{ij} \ge 0, \ \forall i \in \mathcal{I}, \ j \in \mathcal{J},$$
$$C_7: x_{ij} \in \{0,1\}, \ \forall i \in \mathcal{I}, \ j \in \mathcal{J}, \qquad (12)$$

where C_1 follows that each SBS can serve at most N^b users, and C_2 constrains that each user can associate with at most N^u SBSs simultaneously. The power constraint of each SBS j is given by C_3 with $p_{j,max}$ being the maximum transmission power. C_4 follows the backhaul capacity constraint in (11). C_5 guarantees the minimum rate requirement R_i^{min} for each user i.

III. PROPOSED MULTI-CONNECTIVITY USER ASSOCIATION AND POWER ALLOCATION SCHEMES

It can be seen that $\mathcal{P}1$ jointly optimizes the integer indicators of user association and the continuous transmission power allocation, which is a non-convex MINLP problem and has been proved to be NP-Hard [31]. The common practice to handle an MINLP problem is to relax the integer indicators into continuous ones. However, our problem $\mathcal{P}1$ is still non-convex after such relaxation due to the non-convex objective function and constraints C_4 and C_5. Therefore, we propose to decouple the optimization problem $\mathcal{P}1$ into two subproblems: 1) a multi-connectivity user association subproblem and 2) a downlink transmission power allocation subproblem, and solve them in two stages. Specifically, in the first stage, by supposing that the transmission power of each SBS is equally allocated to its associated communication links, the user association subproblem is transformed into a two-side many-to-many matching problem. The classic many-to-many matching scheme is then applied for initialization and a novel swapping algorithm is proposed to modify and improve the user association. In the second stage, given the user association result, an iterative power allocation algorithm is proposed based on D.C. programming by converting the non-convex power allocation subproblem into a sequence of convex ones.

A. MULTI-CONNECTIVITY USER ASSOCIATION SUBPROBLEM

By assuming equal power allocation at each SBS over all communication links as a starting point, we have $p_{ij} = p_{j,max}/N^b, \forall i, \forall j$, with which the multi-connectivity user association subproblem can be formulated as

$$\mathcal{P}2: \max_X \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} x_{ij}R_{ij}(X|P)$$
$$\text{s.t.} \quad C_1, C_2, C_4, C_7. \qquad (13)$$

It can be seen that $\mathcal{P}2$ is still a non-linear integer programming problem and thus NP-hard.

Aiming at devising a low-complexity user association algorithm, we recognize that problem $\mathcal{P}2$ can be modeled as a two-side many-to-many matching problem by deeming users and SBSs as two sets of disjoint players to be matched with each other [32]. Note that in our considered multi-connectivity enabled mmWave networks, all the communication links reuse the same frequency band, and thus suffer from inter-link interference. As one link's interference substantially depends on the other association results, the association between SBSs and different users are closely coupled with each other. Such interdependence is difficult to be handled by the classic many-to-many matching theory and usually brings severe performance degradation [33]. To tackle this difficulty, a novel swapping algorithm will be proposed in this section. Before applying the proposed swapping algorithm to deal with the aforementioned interdependence problem, users are initially associated with SBSs by adopting the classic many-to-many matching algorithm, which is detailed in the following.

1) MANY-TO-MANY MATCHING ALGORITHM

Let us denote μ as a matching, where $\mu(i)$ represents the set of SBSs that are associated with user i, and $\mu(j)$ is the set of users that are associated with SBS j. $\mu(i) = \emptyset$ if user i is not matched to any SBS, and $\mu(j) = \emptyset$ if SBS j is not matched to any user. The definition of a proper many-to-many matching is given below.

Definition 1: Consider two disjoint mmWave SBS set $\mathcal{J}$ and user set $\mathcal{I}$, a many-to-many matching is a function $\mu : \mathcal{I} \to \mathcal{J}$ that satisfies

1) $\mu(i) \subseteq \mathcal{J}$ with $|\mu(i)| \le N^u$;
2) $\mu(j) \subseteq \mathcal{I}$ with $|\mu(j)| \le N^b$;
3) $i \in \mu(j) \Leftrightarrow j \in \mu(i)$.

Before starting the many-to-many matching process, the utility function and preference of users and SBSs should be predetermined such that users and SBSs can choose their preferred partners. With the objective of maximizing the total sum rate, we use the achievable rate R_{ij} as the utility function of the participated SBS j and user i, i.e., $u_i^j = u_j^i = R_{ij}$. Based on the utility function, the corresponding preference $\succeq_i$ and $\succeq_j$ of user i and SBS j, respectively, can be calculated to specify the preferred one between any two options:

$$j_1 \succeq_i j_2 \Leftrightarrow u_i^{j_1} > u_i^{j_2} \qquad (14)$$

indicates that user i prefers to associate with SBS j_1 than SBS j_2. Similarly,

$$i_1 \succeq_j i_2 \Leftrightarrow u_j^{i_1} > u_j^{i_2} \qquad (15)$$

means that SBS j prefers to match with user i_1 than user i_2.

The famous deferred acceptance algorithm [34] for many-to-many matching simply works as follows in an iterative way. Firstly, each user i calculates its preference list $\mathcal{PL}_i$ over the disjoint set according to the descending order of the utility functions, and similarly, each SBS j calculates its own preference list $\mathcal{PL}_j$. In one iteration, each user proposes to q_u most preferred SBSs on its preference list to request for a matching, where q_u is its current matching quota. After the user proposal, the indices of the selected SBSs are removed from the preference list of the user. For each SBS, it holds the received proposals initially. If there exists enough matching quota, denoted by q_b, and the backhaul capacity constraint is satisfied, the SBS keeps the matching and turns to the next round; otherwise, the SBS sequentially rejects the initially accepted users with the least preference on its preference list until both the matching quota constraint and the backhaul capacity constraint are met. The users rejected by SBSs then continuously propose to other SBSs in the next iteration. By repeating the above process, the matching result, i.e., $\mu(i)$ for each user i and $\mu(j)$ for SBS j, will be updated until no user's proposal is rejected or all the users' preference lists are empty.

2) SWAPPING ALGORITHM

Unfortunately, in contrast to the traditional systems with omnidirectional antennas where the effect of user association on the inter-link interference can be neglected, in this mmWave directional transmission scenario, when a new user-SBS link is established, the interference seen by the other links is substantially influenced. This might make the previously calculated preference lists no longer stand. Such interdependence, which is known as externalities in matching, cannot be handled by the classic many-to-many matching algorithm. In the following, we will propose a novel swapping algorithm to overcome this problem so as to increase the total sum rate.

Based on the intuition that a bad user-SBS association usually leads to weak received power of the desired signal yet high interference from the other links, swapping such a bad user-SBS association to a better one is likely to improve the total sum rate. Motivated by this, we propose to swap the SBS in a bad communication link. The proposed many-to-many swapping algorithm is described as follows.

Firstly, upon the user association matrix X, i.e., matching result μ, obtained by the classic many-to-many matching algorithm, we sort the user-SBS association pairs in ascending order according to their achievable rates. The pair with a smaller sort index is then given a higher priority of seeking for a swap. The swapping operation is defined as

$$\begin{aligned}\left\{\mu_{i_i,j_1}^{i_2,j_2}\right\} = &\{\mu\}\backslash\{\mu(j_1),\mu(j_2)\}\\ &\cup\{\mu(j_1)\backslash\{i_1\}\cup\{i_2\}\}\\ &\cup\{\mu(j_2)\backslash\{i_2\}\cup\{i_1\}\},\end{aligned} \tag{16}$$

for any two users $i_1, i_2 \in \mathcal{I}, i_1 \neq i_2$ and any two SBSs $j_1, j_2 \in \mathcal{J}, j_1 \neq j_2$ with $j_1 \in \mu(i_1), j_2 \in \mu(i_2), j_1 \notin \mu(i_2), j_2 \notin \mu(i_1)$.

For the swapping algorithm, in each iteration, it begins from the user-SBS association pair (i, j) with the highest swapping priority, whose optimal potential user-SBS association pair (i', j') for swapping is obtained by $(i', j') = \arg\max_{(i',j')} U(\mu_{i,j}^{i',j'})$, where $U = \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} x_{ij}R_{ij}$ is the system utility. If the two association pairs (i, j) and (i', j') satisfy the following swapping rule

$$\left\{\mu_{i,j}^{i',j'}\right\} \succ \{\mu\} \Leftrightarrow U(\mu) < U\left(\mu_{i,j}^{i',j'}\right), \tag{17}$$

and the backhaul capacity constraint C_4 still holds for each mmWave SBS after swapping, the matching result μ is then updated to $\mu_{i,j}^{i',j'}$ to improve the system utility. If the swapping condition in (17) is not met or the backhaul constraint is violated, the algorithm moves to the next user-SBS association pair with the second highest swapping priority to perform the above swapping steps sequentially. The iteration ends until there is no user-SBS association pair that can be swapped to improve the system utility under the backhaul capacity constraint.

Thus far, we have presented the classic many-to-many matching process to initialize user association, and proposed a novel swapping algorithm to further modify and improve the user association. The details of the proposed multi-connectivity user association scheme can be found in Algorithm 1.

3) CONVERGENCE ANALYSIS

Note that after initializing the user association by many-to-many matching method, in the second swapping stage, the total sum rate is always increased by each swapping operation. As a result, the sum rate monotonically increases in the swapping stage. Since the number of users and the number of SBSs are finite, there are only a finite number of swapping operations, and hence the total sum rate is upper-bounded. It can be then concluded that the convergence of the proposed multi-connectivity user association scheme is guaranteed by the monotone convergence theory.

4) COMPLEXITY ANALYSIS

Note that Algorithm 1 consists of two stages. In the first initial many-to-many matching stage, as all the I users propose to J SBSs, at most $I-1$ users could be sequentially rejected by one SBS in each iteration. Since there exists J iterations in the worst case, the complexity of the many-to-many matching stage is $O(IJ^2)$. In the second swapping stage, suppose that there are K iterations of swapping. In each iteration, the complexity of sorting the association pairs is $O(I\log I)$ and searching the user-SBS pairs for swapping requires the complexity of $O(I)$. Therefore, the complexity of the second swapping stage is $O(K(I + I\log I))$. The overall computational complexity of Algorithm 1 is then $O(K(I + I\log I) \;+ IJ^2)$.

B. POWER ALLOCATION SUBPROBLEM

Given user association X, in this subsection, our objective is to optimize the downlink transmission power allocation for maximizing the sum rate subject to each SBS's limited backhaul capacity and each user's minimum rate requirement. The corresponding power allocation subproblem can

Algorithm 1: Multi-Connectivity User Association

Input: User set $\mathcal{I}$, SBS set $\mathcal{J}$, user quota $q_{u,i} = N^u$, SBS quota $q_{b,j} = N^b$, backhaul capacity B_j

Output: Association result $\mathbf{X}$ (matching result μ)

Initialize $\mathcal{PL}_i$, $\mathcal{PL}_j$ according to $\succeq_{i,j}$, initialize matching $\mu(i) = \emptyset$, $\mu(j) = \emptyset$, swap flag = true;
Many-to-many matching stage;
while $\exists i \in \mathcal{I} : \mathcal{PL}_i \neq \emptyset$ *and exist rejected proposals* **do**
    for $\forall i \in \mathcal{I}$ **do**
        user i proposes to its most preferred $q_{u,i}$ SBSs for a matching request according to $\mathcal{PL}_i$ and remove these SBSs from $\mathcal{PL}_i$;
    end
    for $\forall j \in \mathcal{J}$ **do**
        if *SBS j has enough $q_{b,j}$ and B_j* **then**
            accept all the received proposals;
        else
            accept all the received proposals initially;
            while $|\mu(j)| \geq N^b$ *or insufficient B_j* **do**
                reject the least preferred user in $\mathcal{PL}_j$
            end
        end
    end
    update $\mu(i)$, $\mu(j)$, $q_{u,i}$, $q_{b,j}$;
end
Swapping stage;
while *the swap flag is true* **do**
    set swap flag to false;
    sort all the matching pairs (i, j) according to their achieved rates in ascending order;
    for *pair (i, j) in ascending sort index* **do**
        search another matching pair (i', j') by $(i', j') = \max_{(i',j')} U\left(\mu_{i,j}^{i',j'}\right)$;
        if *$\{i, j, i', j'\}$ satisfies (17) and backhaul constraint* **then**
            execute the swapping operation $\left\{\mu_{i,j}^{i',j'}\right\}$;
            set swap flag to true and break;
        end
    end
end

be reformulated from $\mathcal{P}1$ as

$$\mathcal{P}3: \max_{P} \quad \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} x_{ij} R_{ij}(P|X) \qquad \text{s.t.} \quad C_3, C_4, C_5, C_6. \tag{18}$$

Unfortunately, due to the coupled power allocation of different SBSs resulting from the interference term, both the objective function and the constraints C_4 and C_5 are non-convex.

1) D.C. PROGRAMMING BASED POWER ALLOCATION

To make it tractable, D.C. programming is employed here to convert the non-convex problem into a sequence of convex optimization problems [35]. Specifically, the link rate R_{ij} can be obtained from (9) as

$$R_{ij} = f_{ij}(\boldsymbol{p}) - g_{ij}(\boldsymbol{p}), \tag{19}$$

where

$$f_{ij}(\boldsymbol{p}) = W \log_2\left(\sum_{k\in\mathcal{I}, m\in\mathcal{J}} p_{km} G_{km\to ij} + WN_0\right), \tag{20}$$

and

$$g_{ij}(\boldsymbol{p}) = W \log_2\left(\sum_{\substack{k\in\mathcal{I}, m\in\mathcal{J} \\ (k,m)\neq(i,j)}} p_{km} G_{km\to ij} + WN_0\right). \tag{21}$$

Here, $G_{km\to ij} = g^t_{mk\to ji}(\theta^t_m, \phi^t_{mi}) g^c_{mi} g^r_{km\to ij}(\theta^r_i, \phi^r_{im})$, and $\boldsymbol{p} = \mathrm{vec}(P)$ is the vectorized form of matrix P. It can be seen that both $f_{ij}(\boldsymbol{p})$ and $g_{ij}(\boldsymbol{p})$ are concave. As a result, the link rate R_{ij} is a D.C. function. Moreover, as both $f_{ij}(\boldsymbol{p})$ and $g_{ij}(\boldsymbol{p})$ can be well approximated by its first-order Taylor expansion in a fairly large neighborhood range of $\boldsymbol{p}^l$ in each iteration l [36], we have

$$f_{ij}(\boldsymbol{p}) \approx f_{ij}\left(\boldsymbol{p}^l\right) + \triangledown f_{ij}^T\left(\boldsymbol{p}^l\right)\left(\boldsymbol{p} - \boldsymbol{p}^l\right), \tag{22}$$

and

$$g_{ij}(\boldsymbol{p}) \approx g_{ij}\left(\boldsymbol{p}^l\right) + \triangledown g_{ij}^T\left(\boldsymbol{p}^l\right)\left(\boldsymbol{p} - \boldsymbol{p}^l\right), \tag{23}$$

where $\triangledown g_{ij}(\boldsymbol{p}^l)$ and $\triangledown f_{ij}(\boldsymbol{p}^l)$ are the gradients of $g_{ij}(\boldsymbol{p}^l)$ and $f_{ij}(\boldsymbol{p}^l)$, respectively. One can easily obtain from (20) and (21) that

$$\triangledown f_{ij}(\boldsymbol{p}) = \frac{1}{\sum_{k\in\mathcal{I}, m\in\mathcal{J}} p_{km} G_{km\to ij} + WN_0} \boldsymbol{e}_{ij}, \tag{24}$$

and

$$\triangledown g_{ij}(\boldsymbol{p}) = \frac{1}{\sum_{k\in\mathcal{I}, m\in\mathcal{J}} p_{km} G_{km\to ij} + WN_0} \boldsymbol{q}_{ij}, \tag{25}$$

where $\boldsymbol{e}_{ij}$ and $\boldsymbol{q}_{ij}$ are both column vectors with

$$\boldsymbol{e}_{ij}(k, m) = \frac{G_{km\to ij}}{\ln 2}, \forall k \in \mathcal{I}, \forall m \in \mathcal{J}, \tag{26}$$

and

$$\boldsymbol{q}_{ij}(k, m) = \begin{cases} \frac{G_{km\to ij}}{\ln 2}, & \text{if } (k, m) \neq (i, j), \\ 0, & \text{if } (k, m) = (i, j), \end{cases} \tag{27}$$

Therefore, the link rate R_{ij} can be approximated by

$$R_{ij}^{lb} = f_{ij}(\boldsymbol{p}) - \left(g_{ij}\left(\boldsymbol{p}^l\right) + \triangledown g_{ij}^T\left(\boldsymbol{p}^l\right)\left(\boldsymbol{p} - \boldsymbol{p}^l\right)\right), \tag{28}$$

and

$$R_{ij}^{ub} = \left(f_{ij}\left(\boldsymbol{p}^l\right) + \triangledown f_{ij}^T\left(\boldsymbol{p}^l\right)\left(\boldsymbol{p} - \boldsymbol{p}^l\right)\right) - g_{ij}(\boldsymbol{p}). \tag{29}$$

Proposition 1: R_{ij}^{lb} and R_{ij}^{ub} are a lower-bound concave approximation and an upper-bound convex approximation of the original non-convex link rate R_{ij}, respectively.

Proof: See the Appendix. ■

Algorithm 2: Power Allocation

Input: Error tolerance variable ϵ, a feasible solution $\boldsymbol{p}^0$, iteration index $l = 0$

Output: Optimal power allocation result $\boldsymbol{p}$

while $\left|R^l - R^{l-1}\right| \geq \epsilon$ **do**

  Using (24) and (25) to calculate $\nabla f_{ij}(\boldsymbol{p}^l)$ and $\nabla g_{ij}(\boldsymbol{p}^l)$ respectively;

  Using (26) and (27) to obtain R_{ij}^{lb} and R_{ij}^{ub} respectively;

  Solve problem $\mathcal{P}4$ to obtain $\boldsymbol{p}^*$;

  Set $l = l + 1$, and let $\boldsymbol{p}^l = \boldsymbol{p}^*$;

  Calculate $R^l = \sum_{i \in I} \sum_{j \in J} R_{ij}^{lb}$;

end

By replacing the original link rate in $\mathcal{P}3$ with either the aforementioned lower-bound approximation or the upper-bound approximation, $\mathcal{P}3$ can be equivalently transformed to the following optimization problem:

$$\begin{aligned} \mathcal{P}4 : \max_{\boldsymbol{p}} \ & \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} x_{ij} R_{ij}^{lb} \\ \text{s.t.} \ & \tilde{C}_3 : \sum_{i \in \mathcal{I}} x_{ij} \boldsymbol{p}_{ij} \leq P_{j,max}, \quad \forall j \in \mathcal{J}, \\ & \tilde{C}_4 : \sum_{i \in \mathcal{I}} x_{ij} R_{ij}^{ub} \leq B_j, \quad \forall j \in \mathcal{J}, \\ & \tilde{C}_5 : \sum_{j \in \mathcal{J}} x_{ij} R_{ij}^{lb} \geq R_i^{min}, \quad \forall i \in \mathcal{I}, \\ & \tilde{C}_6 : p_{ij} \geq 0, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \end{aligned} \tag{30}$$

Thanks to the concave approximation of the objective function and the convex approximation of constraint C_4 and C_5, the optimization problem $\mathcal{P}4$ is now a standard convex optimization problem, which can be solved via a standard convex optimization package [37]. The optimal transmission power allocated to each SBS-user link can be then obtained by iteratively solving problem $\mathcal{P}4$. Specifically, after initializing a feasible solution $\boldsymbol{p}^0$, in the l-th iteration, the solution $\boldsymbol{p}^l$ that increases the sum rate can be obtained by solving problem $\mathcal{P}4$ given the power allocation result $\boldsymbol{p}^{l-1}$ in the last iteration. The iteration terminates until convergence. Details of the D.C. programming based power allocation algorithm is presented in Algorithm 2.

2) CONVERGENCE ANALYSIS

According to Proposition 1, we have $R_{ij}^{ub}(\boldsymbol{p}) = (f_{ij}(\boldsymbol{p}^l) + \nabla f_{ij}^T(\boldsymbol{p}^l)(\boldsymbol{p} - \boldsymbol{p}^l)) - g_{ij}(\boldsymbol{p}) \geq R_{ij}(\boldsymbol{p}) \geq R_{ij}^{lb}(\boldsymbol{p}) = f_{ij}(\boldsymbol{p}) - (g_{ij}(\boldsymbol{p}^l) + \nabla g_{ij}^T(\boldsymbol{p}^l)(\boldsymbol{p} - \boldsymbol{p}^l))$. Therefore, if constraints $\tilde{C}_4$ and $\tilde{C}_5$ are satisfied, i.e., $\sum_{i \in I} x_{ij} R_{ij}^{ub}(\boldsymbol{p}) \leq B_j$ and $\sum_{j \in J} x_{ij} R_{ij}^{lb} \geq R_i^{min}$, we can always obtain $\sum_{i \in I} x_{ij} R_{ij}(\boldsymbol{p}) \leq B_j$ and $\sum_{j \in J} x_{ij} R_{ij} \geq R_i^{min}$. This guarantees that the optimal solution of $\mathcal{P}4$ in each iteration is strictly located in the feasible region of $\mathcal{P}3$. Since $R_{ij}(\boldsymbol{p}) \geq R_{ij}^{lb}(\boldsymbol{p})$ holds, one can obtain the following inequality

$$\begin{aligned} R_{ij}\left(\boldsymbol{p}^{l+1}\right) &= f_{ij}\left(\boldsymbol{p}^{l+1}\right) - g_{ij}\left(\boldsymbol{p}^{l+1}\right) \\ &\geq f_{ij}\left(\boldsymbol{p}^{l+1}\right) - g_{ij}\left(\boldsymbol{p}^{l}\right) - \nabla g_{ij}^T\left(\boldsymbol{p}^{l}\right)\left(\boldsymbol{p}^{l+1} - \boldsymbol{p}^{l}\right) \\ &\geq f_{ij}\left(\boldsymbol{p}^{l}\right) - g_{ij}\left(\boldsymbol{p}^{l}\right) - \nabla g_{ij}^T\left(\boldsymbol{p}^{l}\right)\left(\boldsymbol{p}^{l} - \boldsymbol{p}^{l}\right) \\ &= f_{ij}\left(\boldsymbol{p}^{l}\right) - g_{ij}\left(\boldsymbol{p}^{l}\right) \\ &= R_{ij}\left(\boldsymbol{p}^{l}\right). \end{aligned} \tag{31}$$

It can be observed from (31) that the objective function is either increased or maintained in each iteration and thus the objective function is bounded due to the limited communication resources. As the solution of $\mathcal{P}4$ in each iteration is strictly located in the feasible region of $\mathcal{P}3$, Algorithm 2 converges to a locally optimal solution to the original power allocation problem $\mathcal{P}3$ finally.

3) COMPLEXITY ANALYSIS

The key of Algorithm 2 is to solve the standard convex optimization problem $\mathcal{P}4$. The interior point method can be adopted to solve $\mathcal{P}4$, which has the computational complexity of $O(\gamma^{0.5}(\gamma + \theta)\theta^2)$ where θ is the number of variables and γ is the number of inequality constraints [38]. In our case, we have IJ variables and $(2J + IJ + I)$ inequality constraints. By supposing that Algorithm 2 terminates after T iterations, the complexity of Algorithm 2 can be obtained as $O(T(2J + IJ + I)^{0.5}(2IJ + I + 2J)I^2J^2)$.

IV. SIMULATION RESULTS

In this section, extensive simulations are conducted to demonstrate the performance of the proposed multi-connectivity user association and power allocation algorithms. In the simulations, we consider a mmWave communication hot region ranged in a square area of $100m \times 100m$. The mmWave SBSs and users are uniformly and randomly distributed in this region. For the ease of simulation tractability, we assume perfect beam alignment, that is, the directions of the transmission and reception beams of an associated user-SBS pair are coincided with the geographical boresight direction between the user and the SBS, i.e., $\phi_{ji}^t = 0$ and $\phi_{ij}^r = 0$ if $x_{ij} = 1$ [21]. The main simulation parameters are shown in Table 1 unless otherwise stated [39], [40]. The simulations are performed in a MATLAB environment and each simulation result is obtained by averaging over 500 independent replications.

To validate the performance of our proposed algorithms, we adopt the following user association and power allocation schemes for the sake of comparison.

- *UA-PA:* The user association is obtained by the proposed Algorithm 1 and the transmission power of each SBS is allocated to its associated links according to the proposed Algorithm 2.
- *UA-EP:* The user association is obtained by Algorithm 1, and the transmission power of each SBS is equally allocated to its associated users.

TABLE 1. Simulation parameters.

Parameter	Value
Carrier frequency/bandwidth	28GHz/1GHz
Maximum mmWave SBS transmission power $p_{j,max}$	37dBm
N^u, N^b (unless otherwise stated)	2, 4
Path-loss exponent $\alpha_{los}, \alpha_{nlos}$	2.0, 3.0
LoS probability parameter σ	0.01
Reference path loss at 1m β	61.3dB
Small-scale fading parameter m_{los}, m_{nlos}	2, 3
Noise spectral density N_0	-134dBm/HZ
Transmission/Reception beamwidth (unless otherwise stated)	20^o
Backhaul capacity of SBS B_j	15Gbps
Minimum rate requirement R_i^{min}	500Mbps
Sidelobe gain z	0.1
Maximum tolerance ϵ	0.001

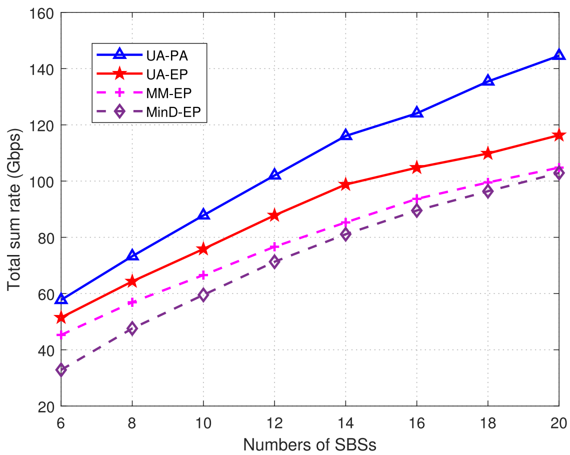

FIGURE 3. Total sum rate as the number of SBSs increases. $I = 20$.

- *MM-EP:* The user association is performed by the classic many-to-many matching algorithm and the transmission power of each SBS is equally allocated to its associated users.
- *MinD-EP:* The user association is performed according to the min-distance criterion and the transmission power of each SBS is equally allocated to its associated users.

Fig. 3 shows the total sum rate achieved with the proposed user association and power allocation scheme, UA-PA, and the benchmarks versus the number of SBSs. It is shown that as the number of SBSs increases, the sum rate increases monotonically. This is because that with more SBSs deployed in a finite region, the access distance from a user to an SBS becomes smaller on average, which greatly reduces the path loss and hence enhances the received signal strength. In addition, users are provided with more association choices when there are more SBSs, which benefits the swapping process that swaps the associated SBSs for users to avoid severe inter-link interference. More importantly, it can be seen from Fig. 3 that our proposed UA-PA scheme achieves higher sum rate than the UA-EP scheme, which validates the effectiveness of the proposed power allocation algorithm.

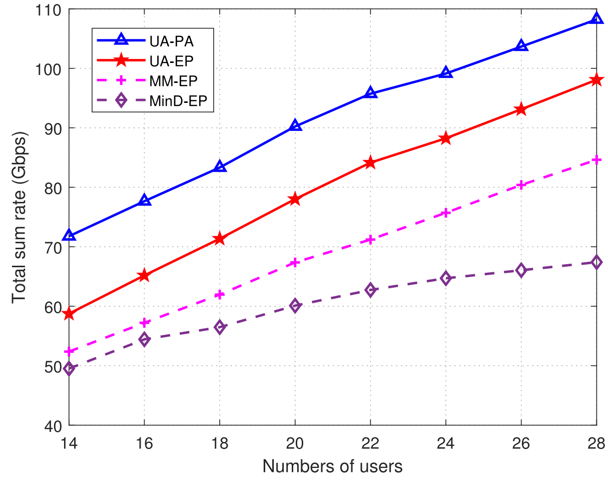

FIGURE 4. Total sum rate as the number of users varies. $J = 10$.

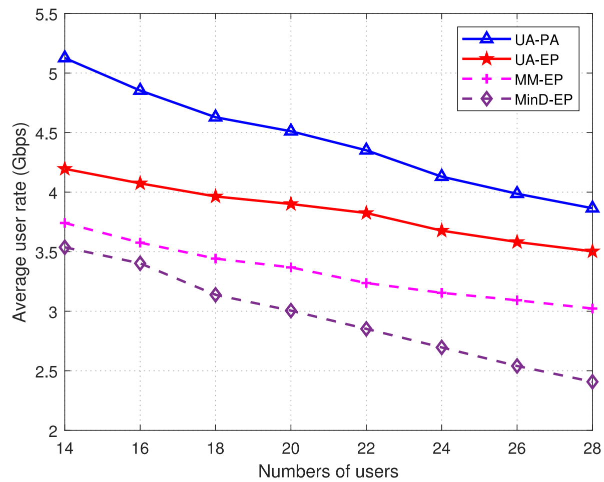

FIGURE 5. Average user rate as the number of users varies. $J = 10$.

Specifically, compared to UA-EP, our UA-PA can reach up to 19.3% performance gain when the number of SBSs is 15. With equal power allocation, it can be found that the UA-EP scheme achieves 15.9% and 20.5% higher sum rate than MM-EP and MinD-EP, respectively, which explicitly shows the superior performance of the proposed multi-connectivity user association algorithm. This is because that our proposed swapping algorithm can swap the associated SBSs for users to avoid bad associations and thus reduce severe mainlobe interference, which is, however, not considered in the two baselines.

Fig. 4 and Fig. 5 present the total sum rate and the average user rate versus the number of users. It is shown in Fig. 4 that the total sum rate increases as the number of users increases, as more users leads to more communication links transmitting over the same frequency resource and higher diversity for user-SBS association, both of which improve the total sum rate. However, from the prospective of users, more users means more existing competitors accessing the

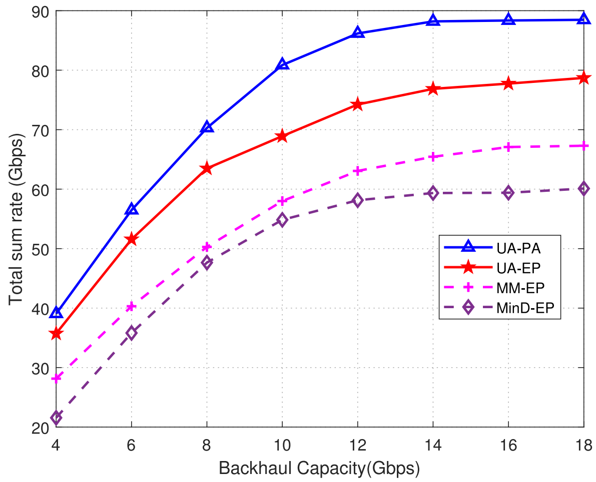

FIGURE 6. Total sum rate as the SBS's backhaul capacity varies. $J = 10$, $I = 20$.

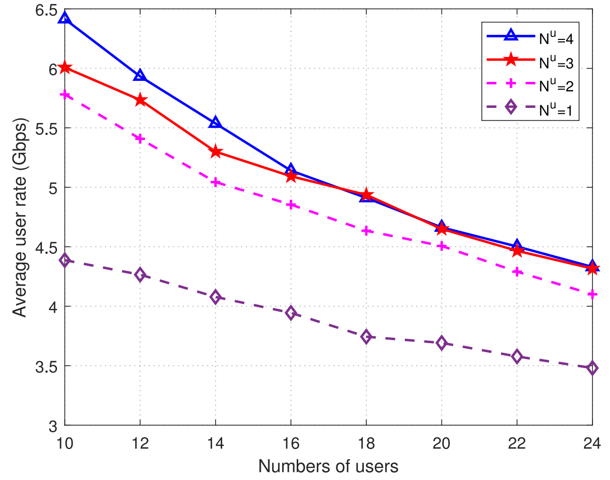

FIGURE 7. Average user rate with different user connection quota N^u. $J = 10$.

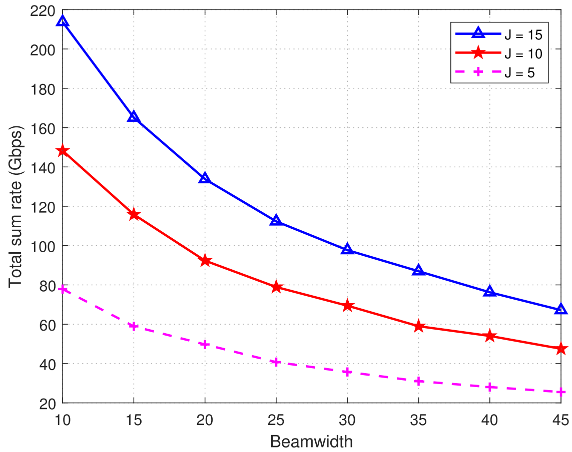

FIGURE 8. Total sum rate with different beamwidth. $I = 20$.

available communication resources, and more communication links brings more severe inter-link interference. As a result, the average per-user rate decreases when increasing the number of users as can be seen in Fig. 5. Moreover, it is shown in Fig. 4 that when the number of users is 10, the performance gap between UA-EP and MM-EP is 9.6%, and the gap between UA-EP and MinD-EP is 16.3%. By increasing the number of users to 28, the gap reaches up to 16.7% and 49.9%, respectively. This indicates that the proposed multi-connectivity user association algorithm can effectively avoid the strong interference in the cases with a large number of users, and thus is suitable for future dense scenarios where massive users are expected.

Fig. 6 depicts the impact of the backhaul capacity limit on the total sum rate with different user association and power allocation schemes when there are 10 SBSs and 20 users. It is shown that the total sum rate first grows as the backhaul capacity increases and then converges to some constant. In fact, a larger backhaul capacity allows an SBS to serve more users and/or transmit higher power to attain higher achievable rate. When the backhaul capacity is sufficiently large, the finite communication resources become the performance bottleneck, and thus the sum rate remains as a constant. The results indicate that the backhauls in practice need to be carefully designed according to the application scenario and service requirements.

Fig. 7 presents the average user rate with different user association quota, i.e, the maximum number of SBSs a user can associate with. It is shown that the average user rate decreases as the number of users increases for the reason that more users share the finite access resources and backhaul capacity. Furthermore, we can observe that multi-connectivity brings average user rate gain. Compared to the single-connectivity case, setting the association quota N^u as two, three and four achieves up to 26.7%, 34.3% and 39.0% average user rate gain, respectively, when the number of users is 12. Moreover, the rate gain brought by dual-connectivity over single-connectivity is prominent, while the gain further achieved by increasing the number of associated SBSs for each user, N^u, decreases due to the limited communication resources at SBSs. It can be seen that dual-connectivity would be a suitable choice to balance the rate performance and the extra signalling overhead in most practical scenarios.

Fig. 8 illustrates the relationship between the total sum rate and the transmission/reception beamwidth ranging from 10° to 45°. The total sum rate decreases as the beamwidth increases. The reason behind is two-fold. On one hand, according to (1) and (2), the transmission and reception beam gain reduces when the beamwidth is enlarged. On the other hand, with a larger beamwidth, the inter-link interference becomes stronger due to the higher probability of mainlobe interference among links. It can be also seen from the figure that the total sum rate gain achieved by deploying more SBSs becomes smaller with a larger beamwidth, as the strong mainlobe interference in this case is the limiting factor that restrains the system performance.

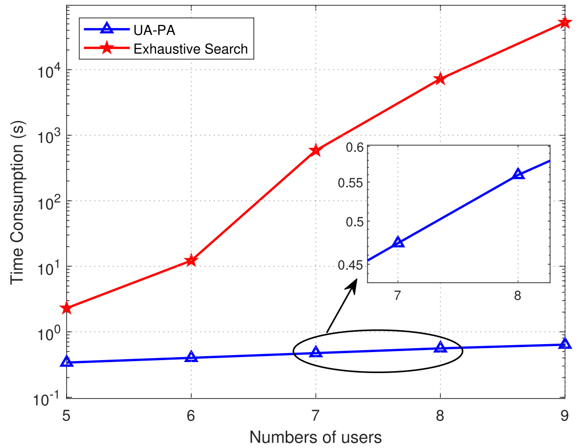

FIGURE 9. Time consumption of different algorithms as the number of users varies. $J = 5$.

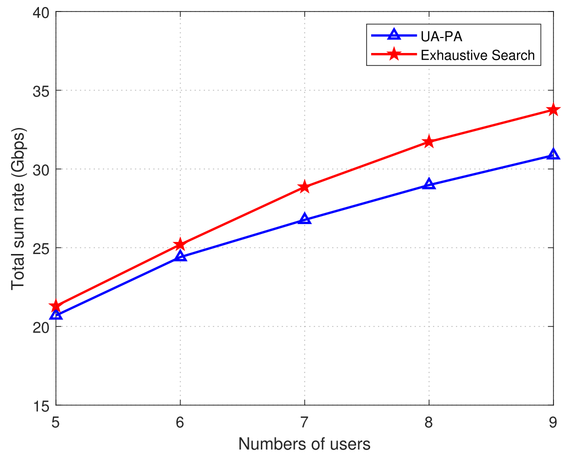

FIGURE 10. Total sum rate as the number of users varies. $J = 5$.

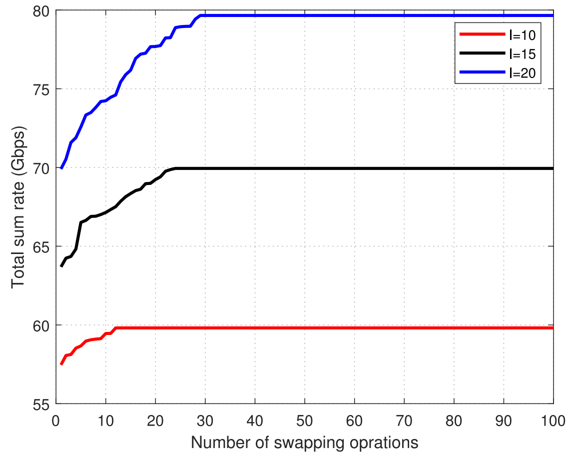

FIGURE 11. Total sum rate versus the number of swapping numbers.

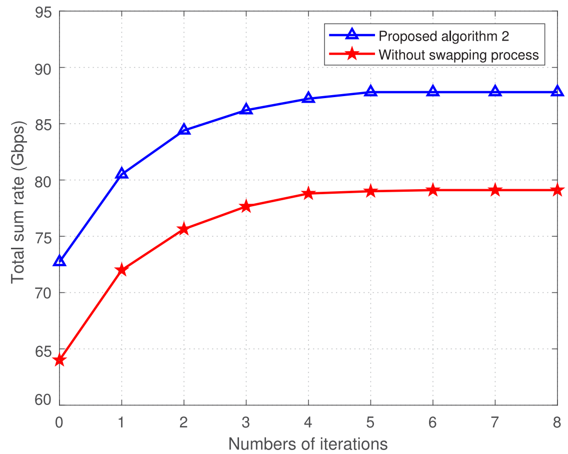

FIGURE 12. Convergence of the proposed power allocation algorithm.

To evaluate the performance gap between the proposed algorithm and the optimal solution, we adopt the exhaustive search method to traverse all possible user association results and perform power allocation according to Algorithm 2 that is near-optimal. Fig. 9 and 10 show the time complexity and performance of our proposed UA-PA scheme and exhaustive search. It can be seen that compared to the exhaustive search, our proposed algorithm can dramatically reduce time complexity at the cost of slightly reduced sum rate. In addition, as the number of users increases, the time consumption of our proposed algorithm increases linearly while the time consumption of exhaustive search increases exponentially.

Fig. 11 shows the convergence of total sum rate versus the number of swapping operations in our proposed multi-connectivity user association algorithm, i.e., Algorithm 1. It can be seen that the total sum rate increases after each swapping operation and then converges after a finite number of swaps, which is consistent with the analysis presented in Section III-A. Moreover, more users accounts for more swapping operations. The convergence of the proposed power allocation algorithm, i.e., Algorithm 2, is plotted in Fig. 12. As can be seen in the figure, the proposed D.C. programming based power allocation algorithm converges after only 5 iterations.

V. CONCLUSION

This paper focused on a multi-connectivity enabled mmWave network with limited backhaul and studied the joint user association and power allocation problem for maximizing the total sum rate of the network under users' minimum rate requirements. The formulated optimization problem is an MINLP and thus difficult to solve. Therefore, we decoupled the original problem into a multi-connectivity user association subproblem and a power allocation subproblem, and solved them in two stages. Firstly, an effective multi-connectivity user association algorithm was developed by proposing a novel swapping algorithm. With the user association result, the non-convex power allocation subproblem was transformed into a convex one by adopting Taylor approximations, and a D.C. programming based iterative power allocation algorithm was proposed. Simulation results verified the superiority of our proposed algorithms over the benchmarks. Note that in this paper we only maximized the total sum rate. In the future work, we will move forward to other interesting and important performance metrics such as energy efficiency, user fairness, transmission reliability and other optimization methods such as the reinforcement learning that has been adopted to address integer optimization problems to further study the joint user association and power allocation problem in such a multi-connectivity enabled mmWave network.

APPENDIX

PROOF OF PROPOSITION 1

Since $f_{ij}(\boldsymbol{p})$ and $g_{ij}(\boldsymbol{p})$ are both concave functions, according to the first order condition of concave function, the first order approximation of the original function is a global overestimator [37], [41]. Then we have

$$f_{ij}(\boldsymbol{p}) \leq f_{ij}\left(\boldsymbol{p}^{l}\right) + \nabla f_{ij}^{T}\left(\boldsymbol{p}^{l}\right)\left(\boldsymbol{p} - \boldsymbol{p}^{l}\right), \tag{32}$$

and

$$g_{ij}(\boldsymbol{p}) \leq g_{ij}\left(\boldsymbol{p}^{l}\right) + \nabla g_{ij}^{T}\left(\boldsymbol{p}^{l}\right)\left(\boldsymbol{p} - \boldsymbol{p}^{l}\right). \tag{33}$$

By combining (19), (28)–(29) and (32)–(33), it can be seen that R_{ij}^{lb} and R_{ij}^{ub} are the global lower-bound and upper-bound approximations of R_{ij} with

$$R_{ij}^{lb} \leq R_{ij} \leq R_{ij}^{ub}. \tag{34}$$

Moreover, the right-hand sides of (32) and (33) are both affine functions, both of which keep the convexity of the original function. Therefore, R_{ij}^{lb} is a concave function and R_{ij}^{ub} is a convex function. It can be then concluded that R_{ij}^{lb} is a lower-bound concave approximation of the original non-convex link rate R_{ij} in (9), and R_{ij}^{ub} is the upper-bound convex approximation of R_{ij}.

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