Sum Rate Maximization for NOMA-Aided Cell-Free System

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Abstract. In this paper, a downlink non-orthogonal multiple access (NOMA)-aided cell-free system is proposed. Multiple access points (APs) are distributed in a wide area and cooperatively serve users using NOMA. A sum rate maximization problem is formulated, where the beamforming coefficients at APs are jointly optimized subject to the minimum rate requirements and decoding order of NOMA users. An iterative algorithm is proposed, where semi-definite programming (SDP) and penalty based methods are employed to address the resultant non-convex problem. Numerical results show that our proposed algorithm converges within 10 iterations, and the sum rate enhancement can be achieved with the aid of our proposed algorithm compared to the orthogonal multiple access (OMA) system. Furthermore, NOMA achieves better user fairness compared with spatial domain multiple access (SDMA), while may suffer a sum rate loss.

Keywords: Beamforming design · Cell-free · Non-orthogonal multiple access

1 Introduction

The envisaged future wireless communications systems are expected to satisfy tens of Gbps peak data rate and massive connectivity demands [1–3]. However, the inefficient usage of radio resources in orthogonal multiple access (OMA) techniques is the main bottleneck of communication performance enhancement [4]. Therefore, non-orthogonal multiple access (NOMA) techniques have been proposed for attaining high spectral efficiency (SE), high connectivity and harmonious integrity [5,6]. Particularly, by serving users via the same radio resource, NOMA has been widely advocated for the improved SE as well as the number of users supported [7]. Furthermore, the cell-free network infrastructure has been proposed as a beneficial technique recently [8]. In this kind of infrastructure, a number of access points (APs) equipped with a small number of antennas are geographically distributed and connected to a central processing unit (CPU) for signal processing [9]. These APs serve users in the same time and within the same frequency bands without cell classification, hence leading to benefits such as low propagation and low inter-cell interference [10].

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Given the distinctive benefits of cell-free and NOMA, several works have employed NOMA in cell-free systems for the their advantages [11,12]. The authors of [13] analyzed the sum rate achieved by the cell-free MIMO-NOMA system with three linear precoders. The authors of [14] proposed a machine learning based user clustering algorithm in the cell-free NOMA system for maximizing the sum-rate. Most of studies focus on the performance analysis of the NOMA assisted cell-free system with each AP equipped with a single antenna. To our best knowledge, there is no existing work on the beamforming coefficients optimization for NOMA-aided cell-free system, which motivates this work.

In this paper, we propose a downlink NOMA aided cell-free system in order to amalgamate their advantages. A sum rate maximization problem for the optimization of the beamforming coefficients at APs is formulated, and an iterative based algorithm is developed by employing the successive convex approximation (SCA) and penalty based methods. We focus on verifying the performance enhancement of our proposed system in terms of the sum rate. Simulation results unveil that aided by our proposed algorithm, the sum rate is significantly enhanced by amalgamating cell-free and NOMA compared with conventional OMA and cell-based counterparts.

Notations: Lower case letters and bold face letters denote scalars and matrices, respectively. $\mathbb{C}^{M\times N}$ denotes the space of $M \times N$ complex valued matrices, $(\cdot)^T$ and $(\cdot)^\dagger$ denote the transpose and conjugate transpose operations, respectively, $\text{Rank}(\cdot)$ and $\text{Tr}(\cdot)$ denote the rank and the trace of the matrix, respectively, $\mathbf{A} \succeq 0$ indicates that $\mathbf{A}$ is a positive semi-definite matrix.

2 System Model and Problem Formulation

We consider a a downlink NOMA-aided cell-free system as illustrated in Fig. 1. In this setup, M distributed N_t-antenna APs cooperatively serve N single-antenna users over the same radio resources. A central processing unit (CPU) is deployed for control and planning, to which APs are connected by optical cables [15]. The NOMA is employed at APs in the cell-free system, where each user is served with a beamformer at each AP. Let $\mathcal{N} = \{1, ..., N\}$ and $\mathcal{M} = \{1, .., M\}$ denote the index set of users and APs, respectively.

The received signal of the n-th user is the superposition of the signals transmitted by M APs, which can be expressed as:

$$y_n = \sum_{m=1}^{M} \mathbf{h}_{m,n}^\dagger \mathbf{w}_{m,n} s_n + \sum_{m=1}^{M} \sum_{n' \neq n} \mathbf{h}_{m,n}^\dagger \mathbf{w}_{m,n'} s_{n'} + n_n, \tag{1}$$

where $\mathbf{w}_{m,n} \in \mathbb{C}^{M\times 1}$ denotes the beamforming coefficients at the m-th AP, to the n-th user, s_n denotes the signal of the n-th user, $\mathbf{h}_{m,n} \in \mathbb{C}^{M\times 1}$ is the channel between the m-th AP and the n-th user, n_n is the additive white Gaussian noise (AWGN) at the n-th user with variance δ_n^2.

Based on the NOMA principle, the successive interference cancellation (SIC) is employed at users for signal detection, the users with high decoding order

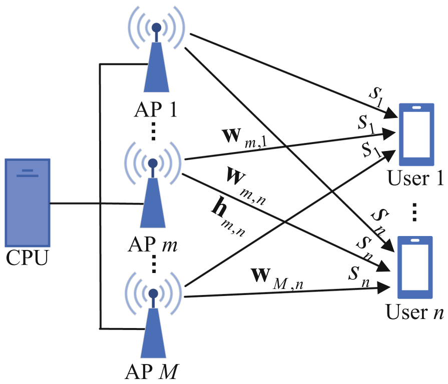

Fig. 1. Illustration of NOMA-aided cell-free system.

decode the signals of the users with low order before detecting their own signals. To be specific, define $\pi(n)$ as the decoding order of the user n, for any two users n' and n with $\pi(n') > \pi(n)$, the user n' will detect its own signal after detecting the signals of the user n. An important observation is the decoding order is a essential problem to be considered, and an efficient NOMA user ordering design is proposed in Sect. 3.3.

For ease of exposition, we assume that the decoding order is $\pi(n) = n$, $\forall n \in \mathcal{N}$ in the following, the achievable rate at the user n after SIC operation is given by

$$R_{n\to n} = \log_2\left(1 + \frac{\left|\sum\limits_{m=1}^{M} \mathbf{h}_{m,n}^{\dagger}\mathbf{w}_{m,n}\right|^2}{\sum\limits_{\tilde{n}=n+1}^{N}\left|\sum\limits_{m=1}^{M} \mathbf{h}_{m,n}^{\dagger}\mathbf{w}_{m,\tilde{n}}\right|^2 + \delta_n^2}\right). \tag{2}$$

In addition, for any user n' with $\pi(n') > \pi(n)$, they need to decode user n's signal and perform SIC before detecting their own signals, the rate for the user n' to decode the message of user n is

$$R_{n'\to n} = \log_2\left(1 + \frac{\left|\sum\limits_{m=1}^{M} \mathbf{h}_{m,n'}^{\dagger}\mathbf{w}_{m,n}\right|^2}{\sum\limits_{\tilde{n}=n+1}^{N}\left|\sum\limits_{m=1}^{M} \mathbf{h}_{m,n'}^{\dagger}\mathbf{w}_{m,\tilde{n}}\right|^2 + \delta_{n'}^2}\right), \tag{3}$$

Once the condition $R_{n'\to n} \geq R_{n\to n}, \forall n \in \mathcal{N}, \pi(n') > \pi(n)$ is satisfied, user n' is able to perform SIC, then detect their own signals. Therefore, both the rates of *desired messages* ($R_{n\to n}$) and *other users' messages* ($R_{n'\to n}$) decide the rate of user n, which can be expressed as

$$R_n = \min\left(R_{n\to n}, R_{(n+1)\to n}.., R_{N\to n}\right),\ n = 1, ..., N-1. \tag{4}$$

Note that for the user N with the highest decoding order, its achievable rate can be expressed as

$$R_{N \to N} = \log_2(1 + \frac{\left| \sum_{m=1}^{M} \mathbf{h}_{m,N}^{\dagger} \mathbf{w}_{m,N} \right|^2}{\delta_N^2}), \tag{5}$$

and since no user n' need to detect the signal of user N, we have $R_N = R_{N \to N}$.

Then, we formulate the sum rate maximization problem by optimizing the beamformer at each AP as:

$$\max_{\mathbf{w}_{m,n}} \sum_{n=1}^{N} R_n \tag{6a}$$

$$\text{s.t.} \quad R_n \geq R_n^{\min}, \ \forall n \in \mathcal{N}, \tag{6b}$$

$$\sum_{n=1}^{N} \|\mathbf{w}_{m,n}\|^2 \leq P_s, \ \forall m \in \mathcal{M}, \tag{6c}$$

where P_s denotes the maximal transmit power of each AP, (6b) is the quality of service (QoS) requirements of each user, and (6c) is the transmit power constraint of each AP.

3 Proposed Beamforming and User Ordering Design

3.1 Beamforming Coefficients Design

To address the non-convex problem 6, we first introduce a slack vector $\mathbf{r} \in \mathbb{R}_+^N$, and problem (6) can be equivalently written as

$$\max_{\mathbf{w}_{m,n}, \mathbf{r}} \sum_{n=1}^{N} r_n \tag{7a}$$

$$\text{s.t.} \quad \sum_{n=1}^{N} \|\mathbf{w}_{m,n}\|^2 \leq P_s, \ \forall m \in \mathcal{M}, \tag{7b}$$

$$R_n \geq r_n, \ n \in \mathcal{N}, \tag{7c}$$

$$r_n \geq R_n^{\min}, \ n \in \mathcal{N}, \tag{7d}$$

$$(6c). \tag{7e}$$

Here, the overall problem still remains intractable, and we further develop an iterative algorithm as follows. Define $\mathbf{h}_n = [\mathbf{h}_{1,n}^T, ..., \mathbf{h}_{M,n}^T]^T$ as the channel between all APs to the n-th user, and $\mathbf{w}_n = [\mathbf{w}_{1,n}^T, ..., \mathbf{w}_{M,n}^T]^T \in \mathbb{C}^{MN_t \times 1}$ as the beamformer of all APs to the n-th user, which can be generated by the CPU. Then, by denoting $\mathbf{W}_n = \mathbf{w}_n \mathbf{w}_n^{\dagger}$, which satisfies $\mathbf{W}_n \succeq 0$ and $\text{Rank}(\mathbf{W}_n) = 1$, $R_{n \to n}$ in (2) can be reformulated as

$$R_{n\rightarrow n} = \log_2\left(1 + \frac{\mathrm{Tr}\left(\mathbf{H}_n\mathbf{W}_n\right)}{\sum\limits_{\tilde{n}=n+1}^{N}\mathrm{Tr}\left(\mathbf{H}_n\mathbf{W}_{\tilde{n}}\right) + \delta_n^2}\right), \tag{8}$$

similarly, $R_{n'\rightarrow n}$ can be reformulated by

$$R_{n'\rightarrow n} = \log_2\left(1 + \frac{\mathrm{Tr}\left(\mathbf{H}_{n'}\mathbf{W}_n\right)}{\sum\limits_{\tilde{n}=n+1}^{N}\mathrm{Tr}\left(\mathbf{H}_{n'}\mathbf{W}_{\tilde{n}}\right) + \delta_n'^2}\right), \tag{9}$$

where $\mathbf{H}_n = \mathbf{h}_n\mathbf{h}_n^\dagger$. The optimization problem in ((7)) can be equivalently expressed as

$$\max_{\mathbf{W}_n,\mathbf{r}} \ \sum_{n=1}^{N} r_n \tag{10a}$$

$$\text{s.t.} \quad r_n \geq R_n^{\min}, \tag{10b}$$

$$R_{n\rightarrow n} \geq r_n, \ n \in \mathcal{N}, \tag{10c}$$

$$R_{n'\rightarrow n} \geq r_n, \ \pi(n') > \pi(n), \ n = 1, ..., N-1, \tag{10d}$$

$$\sum_{n=1}^{N}\mathrm{Tr}\left([\mathbf{W}_n]_{(m-1)N_t+1:mN_t,(m-1)N_t+1:mN_t}\right) \leq P_s, \ \forall m \in \mathcal{M}, \tag{10e}$$

$$\mathbf{W}_n \succeq 0, \ \forall n \in \mathcal{N}, \tag{10f}$$

$$\mathrm{Rank}\left(\mathbf{W}_n\right) = 1, \ \forall n \in \mathcal{N}, \tag{10g}$$

where $[\mathbf{W}_n]_{(m-1)N_t+1:mN_t,(m-1)N_t+1:mN_t}$ denotes the elements between the index $((m-1)N_t+1, (m-1)N_t+1)$ and (mN_t, mN_t) of matrix $\mathbf{W}_n$, which implies the transmit power of the m-th AP to the n-th user. However, the problem (10) is still non-convex due to the non-convex constraints.

We first tackle the non-convex rank one constraint by replacing (10g) as

$$\mathrm{Tr}\left(\mathbf{W}_n\right) - \max\left[\mathrm{eig}(\mathbf{W}_n)\right] \leq 0, \ \forall n \in \mathcal{N}, \tag{11}$$

where $\max[\mathrm{eig}(\mathbf{W}_n)]$ denotes the maximum eigenvalue of $\mathbf{W}_n$. An important note is that $\mathrm{Tr}\left(\mathbf{W}_n\right) - \max\left[\mathrm{eig}(\mathbf{W}_n)\right] \geq 0$ holds for any $\mathbf{W}_n$, thus the equality of (11) holds if and only if $\mathbf{W}_n$ is a rank one matrix with one non-zero eigenvalue. Therefore, the rank one constraint can be guaranteed by making $\mathrm{Tr}\left(\mathbf{W}_n\right) - \max\left[\mathrm{eig}(\mathbf{W}_n)\right]$ as small as possible. We introduce a penalty based method, by substituting the penalty function into the (10a), we obtain the new objective function as

$$f \triangleq \sum_{n=1}^{N} r_n - \eta_n\left(\mathrm{Tr}\left(\mathbf{W}_n\right) - \max[\mathrm{eig}(\mathbf{W}_n)]\right), \tag{12}$$

where η_n is the paucity factor. Due to the non-differentiable expression $\max[\text{eig}(\mathbf{W}_n)]$, we further employ its approximation as

$$\max[\text{eig}(\mathbf{W}_n)] = \tilde{\mathbf{w}}_n^\dagger \mathbf{W}_n \tilde{\mathbf{w}}_n, \tag{13}$$

where $\tilde{\mathbf{w}}_n$ is the eigenvector corresponding to the maximum eigenvalue of $\mathbf{W}^{(\tau)}$ in the τ-th iteration. Finally, the rank one constraint can be released by reformulating the objective function as

$$f \triangleq \sum_{n=1}^{N} r_n - \eta_n \left(\text{Tr}\left(\mathbf{W}_n\right) - \text{Tr}\left(\left(\tilde{\mathbf{w}}_n \tilde{\mathbf{w}}_n^\dagger\right)^\dagger \mathbf{W}_n\right)\right). \tag{14}$$

Then, to tackle the non-convex constraint (10c), we introduce slack variables $\{x_n\}$ and $\{y_n\}$ as

$$x_n = \frac{1}{\text{Tr}\left(\mathbf{H}_n \mathbf{W}_n\right)}, \tag{15}$$

$$y_n = \sum_{\tilde{n}=n+1}^{N} \text{Tr}\left(\mathbf{H}_n \mathbf{W}_{\tilde{n}}\right) + \delta_n^2, \tag{16}$$

therefore, $R_{n\to n}$ in (2) can be rewritten as $R_{n\to n} = \log_2\left(1 + \frac{1}{x_n y_n}\right)$. The optimization problem can be reformulated as

$$\max_{\mathbf{W}_n, \mathbf{r}, \{x_n\}, \{y_n\}} \; f \tag{17a}$$

$$\text{s.t.} \quad r_n \geq R_n^{\min}, \tag{17b}$$

$$r_n \leq \log_2\left(1 + \frac{1}{x_n y_n}\right), \; \forall n \in \mathcal{N}, \tag{17c}$$

$$\frac{1}{x_n} \leq \text{Tr}\left(\mathbf{H}_n \mathbf{W}_n\right), \; \forall n \in \mathcal{N}, \tag{17d}$$

$$y_n \geq \sum_{\pi(\tilde{n}) > \pi(n)} \text{Tr}\left(\mathbf{H}_n \mathbf{W}_{\tilde{n}}\right) + \delta_n^2, \; \forall n \in \mathcal{N}, \tag{17e}$$

$$(10\text{d}) - (10\text{f}). \tag{17f}$$

Since the function $f(x, y) \triangleq \log(\frac{1}{xy})$ is a joint convex function with respect to x and y, the lower bound of the right-hand-side of (17c) can be given by

$$\begin{aligned} \log_2\left(1 + \frac{1}{x_n y_n}\right) \geq & \log_2\left(1 + \frac{1}{\tilde{x}_n \tilde{y}_n}\right) - \frac{\log_2 e \left(\tilde{x}_n - x_n\right)}{\tilde{x}_n \left(1 + \tilde{x}_n \tilde{y}_n\right)} \\ & - \frac{\log_2 e \left(\tilde{y}_n - y_n\right)}{\tilde{y}_n \left(1 + \tilde{x}_n \tilde{y}_n\right)} \triangleq \tilde{R}_{n\to n}, \; \forall n \in \mathcal{N}, \end{aligned} \tag{18}$$

where $(\tilde{x}_n, \tilde{y}_n)$ is the feasible point of the first order Taylor expansion. Then the problem (17) can be rewritten as

$$\max_{\substack{\mathbf{W}_n, r_n, \\ \{x_n\},\{y_n\}}} \quad f \tag{19a}$$

$$r_n \leq \tilde{R}_{n\to n}, \ \forall n \in \mathcal{N}, \tag{19b}$$

$$(10\text{d}) - (10\text{f}), (17\text{d}) - (17\text{e}). \tag{19c}$$

Similarly, to address the non-convex constraint (10d), we introduce slack variables $x_{n,n'}$ and $y_{n,n'}$ such that

$$\frac{1}{x_{n,n'}} \leq \text{Tr}\left(\mathbf{H}_{n'}\mathbf{W}_n\right), \ \pi(n') > \pi(n), \tag{20}$$

$$y_{n,n'} \geq \sum_{\tilde{n}=n+1}^{N} \text{Tr}\left(\mathbf{H}_{n'}\mathbf{W}_{\tilde{n}}\right) + \delta_{n'}^2, \ \pi(n') > \pi(n), \tag{21}$$

we can readily obtain that

$$\begin{aligned} r_n \leq &\log_2\left(1 + \frac{1}{\tilde{x}_{n,,n'}\tilde{y}_{n,n'}}\right) - \frac{\log_2 e\left(\tilde{x}_{n,n'} - x_{n,n'}\right)}{\tilde{x}_{n'}\left(1 + \tilde{x}_{n,n'}\tilde{y}_{n,n'}\right)} \\ &- \frac{\log_2 e\left(\tilde{y}_{n,n'} - y_{n,n'}\right)}{\tilde{y}_{n,n'}\left(1 + \tilde{x}_{n,n'}\tilde{y}_{n,n'}\right)}, \ \pi(n') > \pi(n), \end{aligned} \tag{22}$$

where $(x_{n,n'}, y_{n,n'})$ denotes the feasible point of the first-order Taylor expansion. Finally, the considered problem becomes a convex SDP problem, which is given as

$$\max_{\substack{\mathbf{W}_n, \mathbf{r}, \{x_n\},\{y_n\} \\ \{x_{n,n'}\},\{y_{n,n'}\}}} \quad f \tag{23a}$$

$$\text{s.t.} \quad r_n \geq R_n^{\min}, \ \forall n \in \mathcal{N}, \tag{23b}$$

$$(10\text{b}) - (10\text{f}), (17\text{d}), (17\text{e}), (19\text{b}), (20) - (22). \tag{23c}$$

The problem (23) is now convex and can be efficiently solved by CVX. Furthermore, due to the replacement of lower bound in (18) and (22), problem (23) is a lower bound approximation of the origin problem, and its solution ia guaranteed to converge to a locally optimal solution.

3.2 Complexity Analysis

The complexity of solving the SDP problem (23) is $\mathcal{O}[\tau \max(MN_t, 2N + 1)^4 \sqrt{MN_t} \log_2 \frac{1}{\epsilon}]$, where τ is the number of iterations for obtaining convergent solutions of (23), and ϵ is the solution accuracy, The complexity of the proposed ordering design is $\mathcal{O}\left(1\right)$.

3.3 Proposed NOMA User Ordering Design

In Sect. 3.1, the optimization problem is solved for a given decoding order. Normally, in the two user case, the optimal decoding order can be found by exhaustively searching all possible candidates. However, the complexity of exhaustive search is unacceptable with the increasing of users. Therefore, we propose an efficient user ordering scheme based on the geometry mean of the distances between users and APs. To be specific, a user can be simultaneously served by all distributed APs in our proposed system, and the decoding order can be determined by

$$\pi\left(\tilde{n}\right) > \pi\left(n\right), \text{ if } \left(\prod_{m=1}^{M} d_{m,n}\right)^{\frac{1}{M}} > \left(\prod_{m=1}^{M} d_{m,\tilde{n}}\right)^{\frac{1}{M}}, \ \forall n \in \mathcal{N}, \tag{24}$$

where $d_{m,n}$ denotes the distance between the n-th user and the m-th AP, Eq. (24) means that the user with small geometry-mean distance to all APs has higher decoding order.

4 Numerical Results

In this part, numerical results are provided to evaluate the effectiveness of our proposed design. We consider a scenario that all APs and users are randomly deployed within the circle whose radius is $R = 100\,\text{m}$, the noise power is set to $\delta_n^2 = -80\,\text{dBm}$. Furthermore, the channel between APs and users can be modeled as the Rayleigh fading, and the large scale path loss can be expressed as

$$L_{m,n} = 10^{\frac{PL_{m,n}+\sigma_{sh}}{10}}, \tag{25}$$

where σ_{sh} is the shadow fading parameter follows the logarithmic normal distribution, $PL_{m,n}$ denotes the path-loss between the m-th AP and the n-th user, which can be expressed as

$$PL_{m,n} = -140.7 - 35\lg d_{m,n} + 20c_0 \lg\frac{d_{m,n}}{d_0} + 15c_1 \lg\frac{d_{m,n}}{d_1}, \tag{26}$$

where $d_{m,n}$ is the distance between the m-th AP and the n-th user, $c_i = \max\{0, \frac{d_i - d_{m,n}}{|d_i - d_{m,n}|}\}$, d_i is the reference distance, $i \in \{0, 1\}$. In simulation, the reference distance d_0 and d_1 are set to $d_0 = 10\,\text{m}$ and $d_1 = 50\,\text{m}$, the mean and the standard deviation of σ_{sh} are set to 1 and $10^{1.6}$, respectively.

Figure 2 illustrates the convergence of the proposed algorithm. Both the performance of the fixed decoding order and of the proposed ordering design is studied. The transmit power of each AP is set to 40 dBm. Observe that the proposed algorithm converges in less than 10 iterations, and our proposed ordering scheme outperforms the fixed order design.

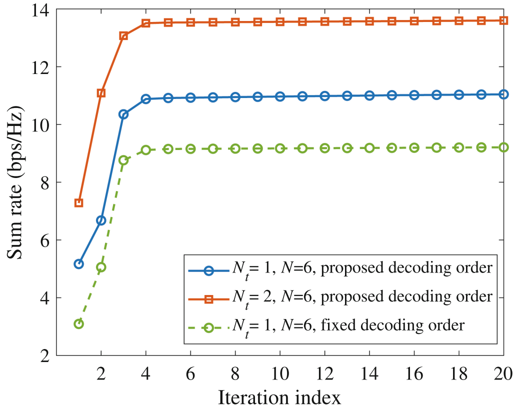

Fig. 2. Convergence of the proposed algorithm.

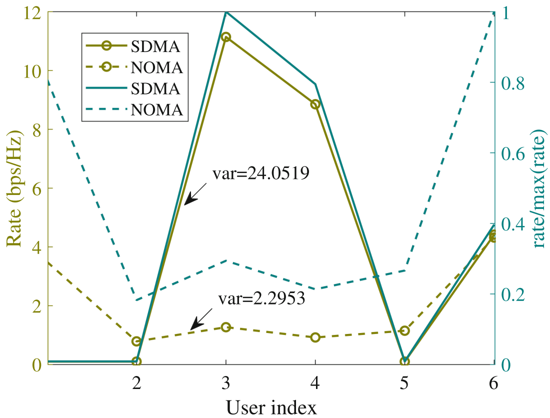

Fig. 3. Rate performance at each user.

Figure 3 shows the rate and the normalized rate of each user in NOMA and spatial domain multiple access (SDMA) scheme, where $P_s = 40$ dBm, the QoS requirements of users is set to $R^{\min} = 0.1$ bps/Hz. It can be found that SDMA can achieve the higher sum rate performance compared with NOMA system with poor fairness among users, i.e., the 1^{st}, 2^{nd} and 5^{th} users only served with the minimal data rates 0.1 bps/Hz. We use the variance of users' rates to describe the fairness, the higher variance implies the poorer fairness. It can be observe that the variance of SDMA is about $var = 24$, much higher than that in NOMA-aided system, which demonstrates the effectiveness of NOMA.

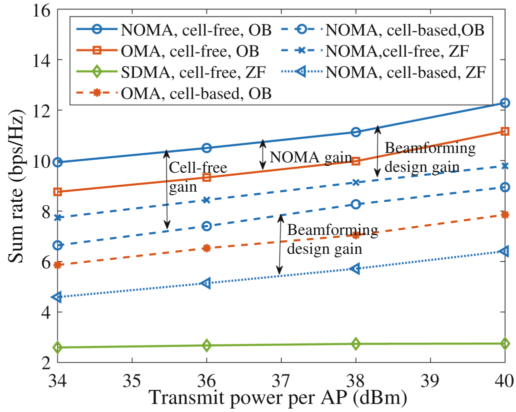

Fig. 4. Sum rate performance versus the transmit power per AP.

Figure 4 plots the sum rate performance versus the total transmit power of all APs, where $N_t = 1$. The results indicate that the sum rate performance increases linearly with the total transmit power. Note that for the cell-central system, users are served by a single AP equipped with 4 antennas and MP_s transmit power. The following insights can be observed: 1) both NOMA and OMA aided cell-free systems outperforms the cell-based system, that is because the cell-free system is capable of deploying antennas closer to users, hence decrease the propagation fading; 2) NOMA-aided cell-free system achieves better performance compared to OMA-aided system with the aid of our proposed optimized beamforming (OB) algorithm; 3) our proposed algorithm out performs the zero forcing (ZF) beamforming benchmark in both OMA and NOMA-aided system, which illustrates the effectiveness of our proposed beamforming coefficient design.

In Fig. 5, the transmit power at each AP for NOMA and OMA schemes is plotted in a 2 user case. The maximal transmit power at each AP is set to 40 dBm, and the number of APs is set to $M = 8$, the minimal required rate of users is set to $R_n^{\min} = R^{\min} = 1$ bps/Hz. The results indicate that the APs allocate average transmit power to NOMA users while allocate almost all power to a user in frequency division multiple access (FDMA). To be specific, AP prefers to provide service to its nearest user in OMA scheme. This can be explained: assume any two NOMA users n' and n with $\pi(n') > \pi(n)$, the user n' has to recover user n's signal after detecting its own signal according to the SIC principle, and the rate for the user n' to detect user n has a great impact on the achievable sum rate. Therefore, the optimized beamforming not only guarantees the achievable rate at user n and n', but also the decoding rate of user n at user n'. However, there is no need for OMA users to decode each other's signals, hence the APs only serve their closest user can achieve higher sum rate performance.

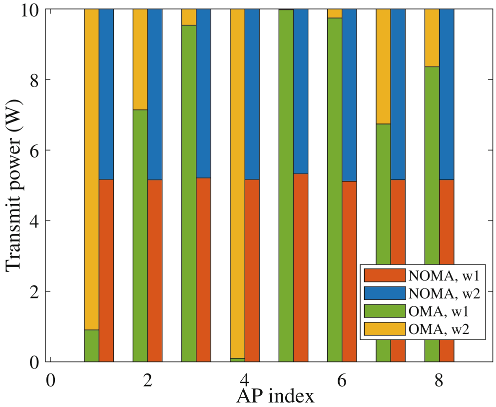

Fig. 5. Transmit power at each AP in NOMA and OMA scheme.

5 Conclusion

In this letter, we proposed a downlink NOMA assisted cell-free system, where each AP served multiple users via NOMA downlink, and users received the superposition of all APs' transmitted signals. To enhance the communication performance, a sum rate optimization problem was formulated for optimizing the beamforming coefficients at each AP. Due to the non-convex objective function as well as constraints, IPF and SDP methods were employed to make the problem tractable. Simulation results confirmed the sum rate improvement of the interplay between cell-free and NOMA compared with the OMA assisted networks. Furthermore, results revealed that NOMA and OMA prefer different resource allocation strategies at APs. Additionally, the better fairness among users' rates can be achieved by employing NOMA.

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