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Power minimization for GSIC-based uplink cell-free massive MIMO-NOMA systems

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Abstract
Non-orthogonal multiple access (NOMA) and multiple-input multiple-output (MIMO) are considered promising techniques to satisfy the demands for high spectrum efficiency and massive connectivity in future wireless communication. In this paper, a novel framework to realize transmission in cell-free massive MIMO-NOMA system with deep integration between MIMO and NOMA is proposed. A new method is developed to divide users into different groups according to their equivalent path loss, and then "group-level successive interference cancellation" (GSIC) is used to cancel the inter-group interference when demodulating the users. Based on the new framework, a rigorous closed-form expression of the achievable sum rate in uplink cell-free massive MIMO-NOMA system is derived. In addition, a parallel iterative method is used to obtain the best power control scheme. Simulations show that the proposed scheme can effectively reduce the total power consumption and outperforms the orthogonal multiple access (OMA) transmission and traditional SIC-NOMA schemes based on user clustering.

Keywords: Cell-free massive MIMO, Non-orthogonal multiple access, Group-level successive interference cancellation, Power control

1 Introduction

The Internet of things (IoT) is the "Internet of all things connected," which is a huge network formed by combining various sensing devices with the network to interconnect people, machines, and things at any time, any space. However, the numbers of IoT terminals and big data services are rapidly growing, and wireless physical layers are facing new challenges [1]. There are the ever-increasing demands for massive connectivity and high spectrum efficiency for the upcoming IoT using beyond the fifth-generation (B5G) and the sixth-generation (6G) networks; thus, non-orthogonal multiple access (NOMA) and massive multiple-input multiple-output (MIMO) are considered key techniques [2]. NOMA mainly includes two categories: power-domain NOMA and code-domain NOMA. This paper focuses on the former. In the power-domain NOMA, multiple user messages are transmitted on the same resource blocks. At the receiver, the demodulation order of multiple users is determined by the channel state information (CSI), and the successive interference cancellation (SIC) technique is used to remove the inter-user interference [3]; hence, the system capacity can be significantly increased. In [4, 5], NOMA was invoked in industrial IoT (IIoT), which satisfies the demands for large connectivity and high spectrum efficiency. According to the water-filling principle, the maximal power was allocated to the node with the best channel in [5], which determined the demodulation order. However, in the system that combines NOMA with MIMO (MIMO-NOMA), user channels are in the form of matrices, which fails to determine the demodulation order for users during SIC based on CSI. Thus, research on massive MIMO-NOMA becomes more challenging.

In the existing studies for MIMO-NOMA, there are two main categories: user clustering methods and user-specific beamforming methods. In [6], the signal alignment method was used to optimize the MIMO-NOMA system. However, in the user-clustered method based on signal alignment, the angle between equivalent channels after the signal alignment may be very small, for which some useful signals will be lost when the base station equalizer is used to suppress inter-cluster interference, which causes the problem of high power consumption. The user-specific beamforming method was used in [7]. Unlike the user-clustered method, each user in this method had a different beamforming vector, so that the optimization degree of freedom was obviously greater than that of the user-clustered method. However, this method failed to reflect the advantages of space division multiple access (SDMA) in MIMO-NOMA, which implies that SIC must be used among all users that occupy the same resource blocks. Once a user has error decoding, serious error propagation will occur, which greatly influences the performance of the system. Considering the limitations of these works, in [8], a precoding scheme based on the novel grouping was proposed in uplink MIMO-NOMA systems to minimize power consumption. Group-level successive interference cancellation (GSIC) was proposed in a reflecting intelligent surface (RIS)-aided uplink NOMA system for the first time in [9]. Users were divided into different groups according to CSI, and the users in the same group were considered as a whole. The GSIC was used to remove intergroup interference by sequentially demodulating group users, while orthogonal multiple access (OMA)/SDMA was used among intra-group users. Wang et al. [8, 9] showed that the MIMO-NOMA system based on GSIC could reduce the total power consumption.

To the best of our knowledge, no prior literature has studied GSIC in a cell-free massive MIMO-NOMA system. Unlike traditional cellular networks, cell-free massive MIMO cancels the concept of cells, which enables it to avoid inter-cell interference [10]. Many distributed access points (APs) jointly provide uniform service to all users using the same resource blocks [11]. In addition, a central processing unit (CPU) is designed to connect all APs through a backhaul network. Then, simple signal processing is performed in each AP, and the CPU conducts complex processing. The distance between AP and CPU is close, which coincides with the demands for low power consumption and ultra-low latency required by the IoT. In a cell-free massive MIMO-NOMA system, optimization based on SIC was deeply investigated in [12–14]. In [12], the authors took the first attempt to combine NOMA with cell-free massive MIMO and showed that NOMA could serve more users than OMA. In [13], a low complexity suboptimal user-clustered method based on Jaccard coefficients was proposed to improve the sum rates of a cell-free massive MIMO-NOMA system. Nguyen et al. [14] formulated a max–min quality-of-service (QoS) power control problem in a cell-free massive MIMO-NOMA system and proved that NOMA-based cell-free massive MIMO could achieve higher power efficiency than OMA. These works were based on the user-clustered method, and the users in the same cluster followed the principle of NOMA, while the users among different clusters followed the principle of SDMA. Similar to the single-cell MIMO-NOMA system, this clustering-based scheme has the disadvantage of low power efficiency. Since the combination of GSIC and massive MIMO-NOMA is expected to significantly improve the power efficiency, this paper proposes to apply GSIC to uplink cell-free massive MIMO-NOMA systems by dividing users into different groups based on their differences in equivalent path loss. Through the transmission of NOMA among different groups and SDMA within each group, the transmission mechanism with deep integration between MIMO and NOMA is realized.

Green communication is the focal topic of future communication systems. With respect to renewable energy, Liu et al. [15] proposed simultaneous wireless information and power transfer (SWIPT). By using wireless information transfer (WIT) and wireless power transfer (WPT) in different time slots and power streams, SWIPT can simultaneously receive information and harvest energy. With respect to resource allocation, Li et al. [16] adopted a dynamic game model to achieve the best relationship between the inter-cell interference of multibeam satellite systems (MSS) and the power resources of users. In this paper, to optimize the power allocation scheme of a cell-free massive MIMO-NOMA system based on GSIC, a power optimization problem is formulated by jointly designing transmit power coefficients and equalizers, and a parallel iterative method is invoked to solve the optimization problem. Our contributions are listed as follows:

(1) A novel framework of group-level optimization based on GSIC is proposed for the uplink cell-free massive MIMO-NOMA system, where users are divided into different groups based on their equivalent path loss for the first time. In the new framework, the inter-group multiple access follows the principle of NOMA, and GSIC is invoked to reduce the inter-group interference, while the intra-group multiple access follows the principle of SDMA. In addition, an achievable sum rate is derived considering the error propagation and intra-group interference.
(2) A power minimization problem is formulated on the premise of ensuring the QoS and transmit power limit of each user. Using the relationship between the equalizers and the transmit power coefficients, the original joint optimization problem is transformed to a power optimization problem. In addition, the optimal power control scheme is obtained through a parallel iterative method. Simulations show that compared with OMA and SIC-NOMA based on user clustering, the proposed scheme can effectively reduce the total power consumption. The effect is significant when the number of users is large.

1.1 Notations

Throughout this paper, lower-case boldface letters denote vectors and matrices are represented by upper-case boldface letters. $\mathbf{z}^H$, $\mathbf{z}^*$, and $[\mathbf{z}]_k$ denote the conjugate-transpose, conjugate, and the kth element of vector $\mathbf{z}$, respectively. $|\cdot|$ indicates the absolute operator. Finally, $\mathbf{n} \sim \mathcal{CN}(0,1)$ is a complex Gaussian random vector, whose mean is zero and variance is 1.

2 System model

In this paper, the uplink transmission of a cell-free massive MIMO-NOMA system is considered, where K users and L APs equipped with single antenna are randomly and uniformly distributed in a square area. All APs are connected to a CPU through a backhaul network. The users are divided into M groups based on their equivalent path loss to all APs, and the number of users in a group is $\mathrm{U_k}$. For convenience, the kth user in the mth group is defined as $\mathrm{UE_{m,k}}$. The channel gain between $\mathrm{UE_{m,k}}$ and all APs can be modeled as

$$\mathbf{h}_{m,k} = \boldsymbol{\beta}_{m,k}^{1/2} \mathbf{g}_{m,k}, \tag{1}$$

with

$$\boldsymbol{\beta}_{m,k} = \mathrm{diag}\left\{\beta_{1,m,k}, \cdots, \beta_{l,m,k}, \cdots, \beta_{L,m,k}\right\}, \tag{2}$$

where $\boldsymbol{\beta}_{m,k}$ is a diagonal matrix and $\beta_{l,m,k}$ is the large-scale channel gain which changes very slowly. In addition, each element in $\mathbf{g}_{m,k}$ independently follows a complex Gaussian distribution with a zero mean and unit variance.

3 Methods

3.1 New method of user grouping

The so-called GSIC implies that the users are divided into different groups following some principle and the users in a group are considered as a whole, which can also be considered a virtual user. After sorting the groups (virtual users), the virtual users can be sequentially demodulated and the inter-group interference can be removed.

To divide the users into multiple groups, this paper proposes a new method of user grouping based on the equivalent path loss of each user. The users in different groups follow the principle of NOMA, using GSIC to remove the inter-group interference, while the users in the same group follow the principle of SDMA. Therefore, two factors are considered during user grouping:

(i) The number of users in each group: Since the users in the same group follow the principle of SDMA, there should be fewer users in each group than the number of APs, i.e., $\mathrm{U_k} < L$, which ensures that the users in each group can be demodulated in parallel.

(ii) The equivalent pass loss of per user: In a single-cell massive MIMO-NOMA system, users can be divided into different groups according to their path loss to the base station. Motivated by this, we propose a new method of user grouping in a cell-free massive MIMO-NOMA system. Since users are served by all APs, user grouping can be implemented considering the equivalent path loss to all APs of each user. In other words, users with identical equivalent path loss are divided into a group. The equivalent path loss of $\mathrm{UE_{m,k}}$ to all APs is defined as follows:

$$\lambda_{m,k} = \frac{1}{\sum_{l=1}^{L} \beta_{l,m,k}} (m = 1, 2, \cdots, M, k = 1, 2, \cdots, K), \tag{3}$$

where $\beta_{l,m,k}$ is the large-scale channel gain of $\mathrm{UE_{m,k}}$. The equivalent path loss of users in different groups should satisfy the following equation:

$$\lambda_{m,k} < \lambda_{m',k'} \left(m < m'\right). \tag{4}$$

We present an example of equivalent path loss contours for five APs in Fig. 1, where users with equal equivalent pass loss are in the same contour.

3.2 Uplink data transmission

In the uplink transmission, user messages are simultaneously transmitted to all APs. The received signal at the lth AP can be expressed as

$$\mathbf{f} = \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U}_k} \mathbf{h}_{m,k} w_{m,k} x_{m,k} + \mathbf{v}, \tag{5}$$

where $\mathbf{h}_{m,k}$ is the channel gain vector between $\mathrm{UE_{m,k}}$ and the lth AP, $w_{m,k}$ and $x_{m,k}$ are the transmit power coefficient and transmit signal of $\mathrm{UE_{m,k}}$, respectively. In addition, $\mathbf{v}$ is the noise vector with each element following $\mathcal{CN}(0, \sigma_{m,k}^2)$. To derive the uplink achievable sum rate formula, we rewrite the received signal at the lth AP in the form of a matrix:

$$\mathbf{f} = \sum_{m=1}^{M} \mathbf{H}_m \mathbf{W}_m \mathbf{X}_m + \mathbf{v}, \tag{6}$$

with

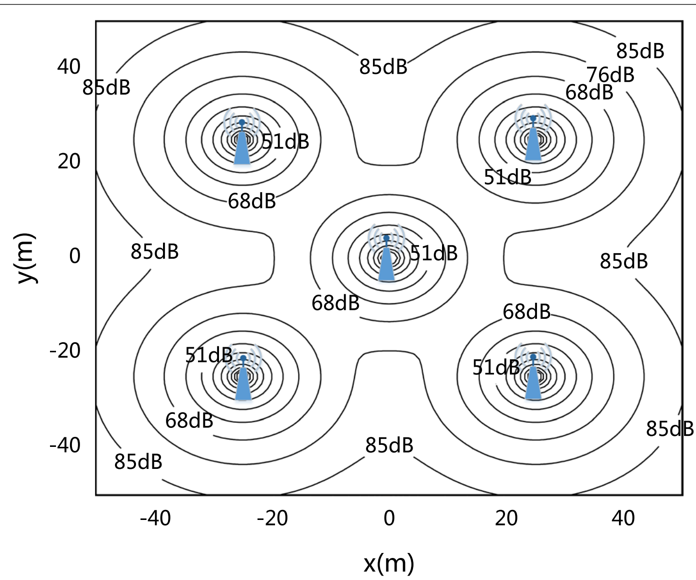

Fig. 1 Illustration of equivalent path loss contour for a cell-free system with five APs

$$\mathbf{H}_m = \left[\mathbf{h}_{m,1}, \cdots, \mathbf{h}_{m,\mathrm{U_k}}\right], \tag{7}$$

$$\mathbf{W}_m = \mathrm{diag}\left\{w_{m,1}, \cdots, w_{m,\mathrm{U_k}}\right\}, \tag{8}$$

$$\mathbf{X}_m = \left[x_{m,1}, \cdots, x_{m,\mathrm{U}_k}\right]^T, \tag{9}$$

where $\mathbf{H}_m$ and $\mathbf{W}_m$ are the channel gain matrix and transmit power coefficient matrix of the mth group, respectively. $\mathbf{X}_m$ is the transmit signal of users in the mth group.

3.3 Analysis of achievable sum rate

Considering the power-domain NOMA, the order of demodulation is determined by the signal strength, and the users with higher power are prioritized. Therefore, in the cell-free massive MIMO-NOMA system based on GSIC, since the equivalent path loss in the first group is the smallest, we first detect the user signals in the first group. Before the user signals in the second group are decoded, all user signals in the first group will be removed, and so on, until the user signals in all groups are demodulated. The comparison between the new framework of GSIC-NOMA and the tradition SIC-NOMA based on user clustering is shown in Fig. 2.

Regarding different groups, in the new framework, most of the inter-group interference can be removed using GSIC. However, because of error propagation and the interference from undemodulated groups, some inter-group interference remains for the current demodulated group. Therefore, at the CPU, all user signals in the mth group can be expressed as

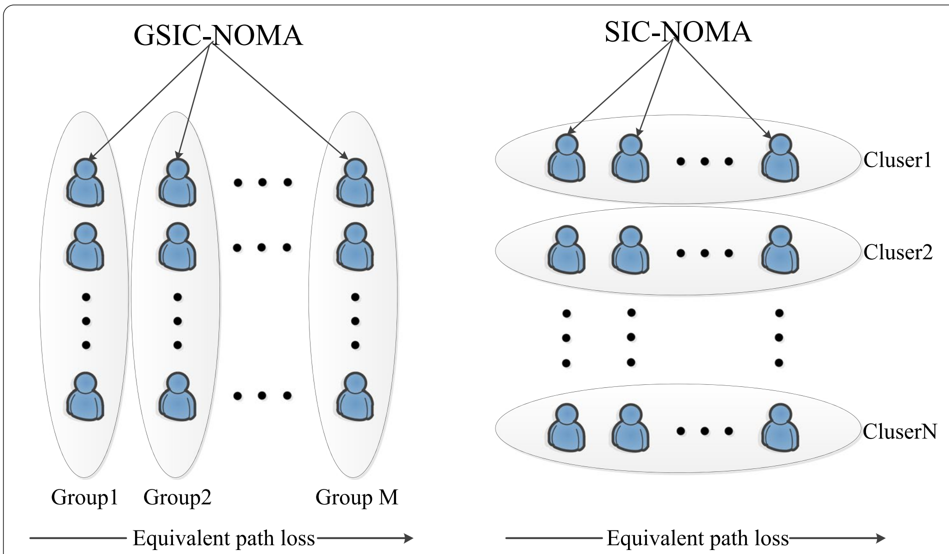

Fig. 2 Comparison between GSIC-NOMA and SIC-NOMA

$$\begin{aligned}\hat{\mathbf{x}}_m =& \underbrace{\mathbf{E}_{\mathrm{m}}^H \mathbf{H}_m \mathbf{W}_m \mathbf{x}_m}_{\text{[Desired Signal]}} + \underbrace{\mathbf{E}_{\mathrm{m}}^H \sum\nolimits_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{x}_i}_{\substack{\text{[Inter-group} \\ \text{Interference after GSIC]}}} \\ &+ \underbrace{\mathbf{E}_{\mathrm{m}}^H \sum\nolimits_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \boldsymbol{\Sigma}_j \mathbf{x}_j}_{\substack{\text{[Error Propagation} \\ \text{caused by Imperfect GSIC]}}} + \underbrace{\mathbf{E}_{\mathrm{m}}^H \mathbf{v}}_{\text{[Noise]}},\end{aligned} \tag{10}$$

where $\mathbf{E}_m$ is the equalizer at the CPU for the users in the mth group. $\boldsymbol{\Sigma}_j$ is a diagonal matrix and represents the interference of the jth group due to error propagation, which can be written as

$$\boldsymbol{\Sigma}_j = \mathrm{diag}\left\{\sqrt{\varepsilon_{j,1}}, \cdots, \sqrt{\varepsilon_{j,\mathrm{U}_j}}\right\}, \tag{11}$$

In the new framework, different users in each group are distinguished by their respective equalizer $\mathbf{E}_m$. In addition to the inter-group interference, interference among different users within a group remains, so the signal of $\mathrm{UE}_{\mathrm{m,k}}$ can be expressed as

$$\begin{aligned}\hat{x}_{m,k} =& \underbrace{[\mathbf{E}_m]_{:,k}^H [\mathbf{H}_m]_{:,k} w_{m,k} x_{m,k}}_{\text{Desired Signal}} + \underbrace{[\mathbf{E}_m]_{:,k}^H \sum\nolimits_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{x}_i}_{\substack{\text{[Inter - group} \\ \text{Interference after GSIC]}}} \\ &+ \underbrace{[\mathbf{E}_m]_{:,k}^H \mathbf{v}}_{\text{Noise}} + \underbrace{[\mathbf{E}_m]_{:,k}^H \sum\nolimits_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \Sigma_j \mathbf{x}_j}_{\substack{\text{[Error Propagation} \\ \text{caused by Imperfect GSIC]}}} + \underbrace{[\mathbf{E}_m]_{:,k}^H \sum\nolimits_{k' \neq k}^{\mathrm{U_k}} [\mathbf{H}_m]_{:,k'} w_{m,k'} x_{m,k'}}_{\text{Intra - group Interference}},\end{aligned} \tag{12}$$

where $[\mathbf{E}_m]_{:,k}$ is the kth column of matrix $\mathbf{E}_m$, which is the equalizer of $\mathrm{UE}_{\mathrm{m,k}}$.

To facilitate the power control constraints in the next subsection, using (12), an achievable sum rate for $\mathrm{UE}_{\mathrm{m,k}}$ can be expressed as follows [10]:

$$R_{m,k} = \log\left(1 + \mathrm{SINR}_{m,k}\right) \tag{13}$$

$$= \log\left(1 + P_d / \left(\sum_{i=1}^{3} P_{I_i} + \sigma_{m,k}^2\right)\right), \tag{14}$$

where $\mathrm{SINR}_{m,k}$ is the signal to interference-plus-noise ratio (SINR) of $\mathrm{UE}_{\mathrm{m,k}}$, which reflects the performance of users. P_d and $P_{I_i}(\mathrm{i} = 1, 2, 3)$ are the powers of the desired signal and interference signals, respectively, which can be expressed as follows:

$$P_d = \left|[\mathbf{E}_m]_{:,k}^H [\mathbf{H}_m]_{:,k} w_{m,k}\right|^2, \tag{15a}$$

$$P_{I_1} = [\mathbf{E}_m]_{:,k}^H \sum_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H [\mathbf{E}_m]_{:,k}, \tag{15b}$$

$$P_{I_2} = [\mathbf{E}_m]_{:,k}^H \sum_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \boldsymbol{\Sigma}_j \boldsymbol{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H [\mathbf{E}_m]_{:,k}, \tag{15c}$$

$$P_{I_3} = \sum_{k'=1,k'\neq k}^{\mathrm{U_k}} \left| [\mathbf{E}_m]_{:,k}^H [\mathbf{H}_m]_{:,k'} w_{m,k'} \right|^2, \tag{15d}$$

By calculating the achievable sum rate of each user, the achievable sum rate of the uplink cell-free massive MIMO-NOMA system based on GSIC can be written as

$$R = \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} R_{m,k} = \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} \log\left(1 + \mathrm{SINR}_{m,k}\right), \tag{16}$$

3.4 Power control scheme

Much attention has been given to energy-efficient communication in future wireless communication, so the total power consumption of the system is worth studying. In this paper, we optimize the power control scheme, which is subject to the QoS per user and maximum transmission power limit. Therefore, in the cell-free massive MIMO-NOMA system, the optimization formula of the total power consumption is

$$\mathbf{P1}: \min_{\{w_{m,k}\},\{\mathbf{E}_m\}} : \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} w_{m,k}^2 \tag{17}$$

$$\text{s.t.} \quad \log_2\left(1 + \mathrm{SINR}_{m,k}\right) \geq R_{m,k}, \tag{18}$$

$$w_{m,k}^2 \leq P_{\max}, \tag{19}$$

where $R_{m,k}$ and $P_{\max}$ are the minimum transmission rate and maximum transmission power of $\mathrm{UE_{m,k}}$, respectively. Since the first constraint in the optimization is non-convex, problem (**P1**) is non-convex.

To simplify the non-convex optimization problem (**P1**), we use the relationship between the equalizer and the transmit power. To maximize the SINR per user, in [8], the best linear equalizer is the minimum mean square error (MMSE) equalizer. Therefore, we use the MMSE equalizer to demodulate the user signals in the *m*th group, which can be expressed as

$$\begin{aligned} \mathbf{E}_m = \Bigg(& \mathbf{H}_m \mathbf{W}_m \mathbf{W}_m^H \mathbf{H}_m^H + \sum\nolimits_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H \\ & + \sum\nolimits_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \boldsymbol{\Sigma}_j \boldsymbol{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H + \sigma_{m,k}^2 \mathbf{I} \Bigg)^{-1} \mathbf{H}_m \mathbf{W}_m \end{aligned} \tag{20}$$

By substituting (20) into $\mathrm{SINR}_{m,k}$ in (13), we can rewrite $\mathrm{SINR}_{m,k}$ as

$$\begin{aligned} \mathrm{SINR}_{m,k} = [\mathbf{H}_m]_{:,k}^H \Bigg(\sum_{k'=1,k'\neq k}^{U_k} [\mathbf{H}_m]_{:,k'}^H [\mathbf{H}_m]_{:,k'} w_{m,k'}^2 + \sum_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H \\ + \sum_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \boldsymbol{\Sigma}_j \boldsymbol{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H + \sigma_v^2 \mathbf{I} \Bigg)^{-1} [\mathbf{H}_m]_{:,k} w_{m,k}^2 \end{aligned} \tag{21}$$

Therefore, the original non-convex optimization problem (**P1**) is transformed into

$$\mathbf{P2}: \min_{\{w_{m,k}\}} : \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} w_{m,k}^2 \tag{22}$$

$$\text{s.t.} \quad \log_2 \left(1 + \mathrm{SINR}_{m,k}\right) \geq R_{m,k}, \tag{23}$$

$$w_{m,k}^2 \leq P_{\max}, \tag{24}$$

After the transformation, the original joint power control and equalizer optimization problem is transformed to a pure power control problem. To obtain the optimal power control scheme, by invoking the contradiction in *Remark 1*, the best transmit power per user can be expressed as (25).

$$\begin{aligned} w_{m,k}^2 = \left(2^{R_{m,k}} - 1\right) \Bigg/ \Bigg([\mathbf{H}_m]_{:,k}^H \Bigg(\sum_{k'=1,k'\neq k}^{U_k} [\mathbf{H}_m]_{:,k'}^H [\mathbf{H}_m]_{:,k'} w_{m,k'}^2 \\ + \sum_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H + \sum_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \boldsymbol{\Sigma}_j \boldsymbol{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H + \sigma_v^2 \mathbf{I} \Bigg)^{-1} [\mathbf{H}_m]_{:,k} \Bigg) \end{aligned} \tag{25}$$

Equation (25) shows that the optimal transmit powers of different users interact. Therefore, we use a parallel iteration method to achieve the best power control scheme. The so-called parallel iteration refers to obtaining the minimum power consumption of the system through multiple internal iterations and external iterations. Internal iteration refers to user iteration within a group. In the case of fixed inter-group interference, the internal user power within a group is updated according to (25). External iteration is the user iteration between all groups. After all groups complete an internal iteration, an external iteration is performed to determine whether the total power consumption of the system has converged. If it converges, the total power consumption of the system is considered the lowest at this time. The detailed procedure is summarized in *Algorithm* 1.

Algorithm 1 A Parallel Iteration Method for Power Control

Set the external iteration times p=0, the internal iteration times q=0, the transmit power $P_{m,k} = w_{m,k}^2 = P_{\max}$;
repeat
  $p = p + 1$;
  For $m = 1 : M$
  Fix the interference covariance matrix for the m-th group $\sum_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H + \sum_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \mathbf{\Sigma}_j \mathbf{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H$;
  repeat
    $q = q + 1$;
    Update the transmit power of each group in parallel by (25);
  until $\sum_{k=1}^{\mathrm{U_k}} P_{m,k}^{(p)[q-1]} - \sum_{k=1}^{\mathrm{U_k}} P_{m,k}^{(p)[q]} < \pi_1$
  Set the optimal value of the p-th external iteration as $P_{m,k}^{(p)^*} = P_{m,k}^{(p)[q]}$;
  End
until $\sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} P_{m,k}^{(p-1)*} - \sum_{m=1}^{M} \sum_{k=1}^{\mathrm{U_k}} P_{m,k}^{(p)*} < \pi_2$

As long as the initial transmit power is feasible, the transmit power per user decreases when the number of iterations increases, which implies that the total power consumption of the system will converge to a stationary point [9]. The total computational complexity for *Algorithm* 1 is $\sum_{m=1}^{M}(3M + 2m - 4)\mathcal{O}(L^3)$.

Remark 1 First, a new function $\mathfrak{R}_{n,l}\left(w_{n,l}^2\right)$ is defined to indicate the effect of current user's transmit power $w_{n,l}^2$ on $\mathrm{SINR}_{m,k}$. As the user's transmit power $w_{n,l}^2$ increases, the value of function $\mathfrak{R}_{n,l}\left(w_{n,l}^2\right)$ decreases.

$$\mathfrak{R}_{n,l}\left(w_{n,l}^2\right) = \mathrm{SINR}_{m,k}(m,k) \neq (n,l) \tag{26}$$

Suppose $\left\{\tilde{w}_{m,k}^2\right\}$ is the optimal solution of (**P2**), then any element $\left\{\tilde{w}_{m,e}^2\right\}$in the set satisfies the following inequality:

$$\mathrm{SINR}_{m,e}\left(\tilde{w}_{m,e}^2\right) > 2^{R_{m,e}} - 1 \tag{27}$$

Introducing a new user's transmit power $\widehat{w}_{m,e}^2$ satisfies:

$$\begin{aligned}\widehat{w}_{m,e}^2 = \left(2^{R_{m,e}} - 1\right) / & \left([\mathbf{H}_m]_{:,e}^H \left(\sum_{k'=1,k'\neq k}^{U_k} [\mathbf{H}_m]_{:,k'}^H [\mathbf{H}_m]_{:,k'} \tilde{w}_{m,k'}^2 \right.\right. \\ & \left.\left. + \sum_{i=m+1}^{M} \mathbf{H}_i \mathbf{W}_i \mathbf{W}_i^H \mathbf{H}_i^H + \sum_{j=1}^{m-1} \mathbf{H}_j \mathbf{W}_j \mathbf{\Sigma}_j \mathbf{\Sigma}_j^H \mathbf{W}_j^H \mathbf{H}_j^H + \sigma_v^2 \mathbf{I} \right)^{-1} [\mathbf{H}_m]_{:,e} \right) < \tilde{w}_{m,e}^2\end{aligned} \tag{28}$$

We can verify that $\widehat{w}_{m,k}^2$ also satisfies the constraints in (**P2**):

$$\mathrm{SINR}_{m,e}\left(\widehat{w}_{m,e}^2\right) \geq 2^{R_{m,e}} - 1 \tag{29}$$

$$\widehat{w}_{m,k}^2 < \tilde{w}_{m,k}^2 \leq P_{\max} \tag{30}$$

In addition, as $\mathfrak{R}_{n,l}\left(w_{n,l}^2\right)$ is a monotonically decreasing function, $\widehat{w}_{m,k}^2$ also satisfies the QoS:

$$\mathrm{SINR}_{n,l} = \mathfrak{R}_{n,l}\left(\widehat{w}_{m,k}^2\right) > \mathfrak{R}_{n,l}\left(\tilde{w}_{m,k}^2\right) \geq 2^{R_{n,l}} - 1, (m,k) \neq (n,l) \tag{31}$$

The above explanation contradicts with the fact that $\left\{\tilde{w}_{m,k}^2\right\}$ is the optimal solution of (**P2**). Therefore, (25) is proved.

4 Results and discussion

In this section, we provide simulation results to assess the performance of cell-free massive MIMO-NOMA based on GSIC and compare it with OMA and SIC-NOMA based on user clustering. We consider that L APs and M users with single-antenna are uniformly and randomly distributed in a square of $\mathrm{D} \times \mathrm{Dm}^2$. In this paper, the calculation method of large-scale channel gain $\beta_{l,m,k}$ is found in [13]. Other simulation parameters are presented in Table 1.

First, the effect of the minimum rate requirement for the users in a group on the total transmit power consumption is investigated in this paper. Figure 3 numerically depicts the user rate requirement versus the total transmit power consumption in the cell-free massive MIMO-NOMA system for L=50, M=2, and M=3. The total power consumption increases when the user rate requirement increases. Compared with OMA and the traditional SIC-NOMA based on user clustering, the proposed scheme has obvious advantages in total power consumption. The traditional SIC-NOMA has the worst performance because the user-clustered method will make the equivalent channel gain between some users and AP quite small after beamforming, therefore, the system has high transmit power consumption. In the same time slot, compared with OMA, the proposed scheme in this paper can separate twice as many users as OMA. In addition, it removes the inter-group interference through GSIC, which effectively reduces the inter-user interference and improves the SINR of the target user; therefore, the total power consumption of the system is reduced.

Next, the impact of the number of APs on the total transmit power consumption is evaluated. If both number of users and number of APs increase in proportion, Fig. 4

Table 1 Simulation parameters

Parameters	Value
The noise power	− 99 dBm
The length of square D	500 m
The number of groups M	2
The error propagation factor $\varepsilon_{m,k}$	0.01
The number of users in a group $\mathrm{U_k}$	50
The termination thresholds π_1, π_2	10^{-4}
The maximum transmit power $P_{\max}$	20 dBm
The minimum rate requirement $R_{m,k}$	0.1~0.5

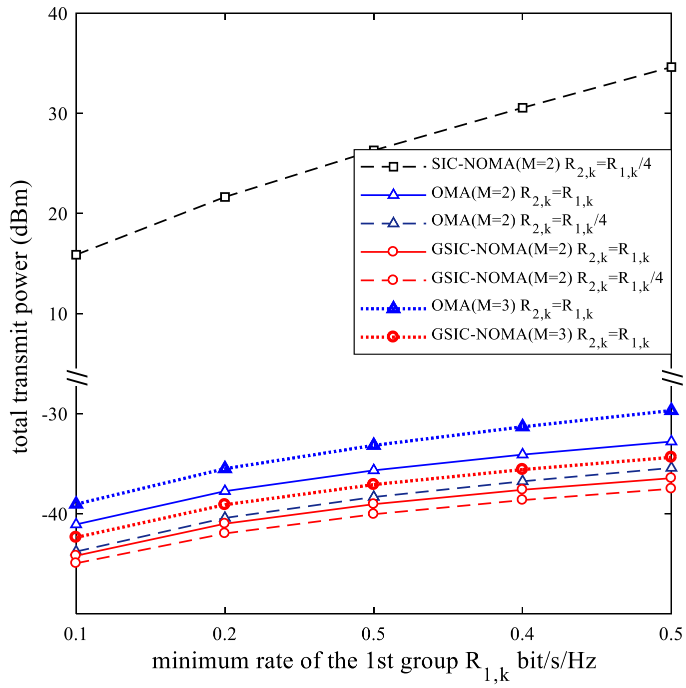

Fig. 3 Total transmit power versus the minimum rate

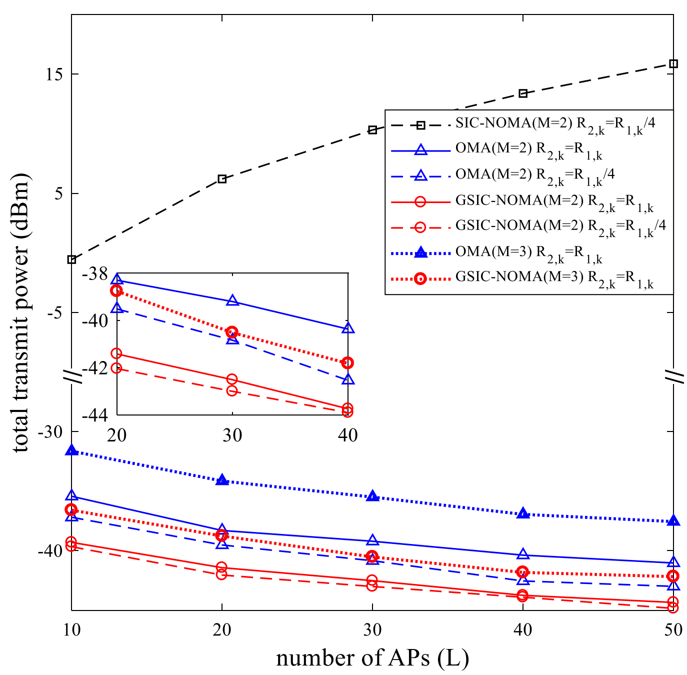

Fig. 4 Total transmit power versus the number of APs

shows the total transmit power for different numbers of APs, with $R_{1,k}$=0.1 bit/s/Hz, M=2, and M=3. Figure 4 shows that when the GSIC-NOMA scheme and OMA scheme are used for transmission, when the number of APs increases, the total transmit power consumption of the system decreases. The reason is that when the number of APs increases, multiple users can be better distinguished during the demodulation period because the interference between users is effectively reduced. Therefore, the total transmit power consumption of the system is reduced. However, for the traditional SIC-NOMA based on user clustering, this benefit diminishes, and the interference between users sharply increases when the number of users increases, which drastically increases the total transmit power consumption of the system.

Figure 5 shows the total transmit power of the GSIC-NOMA and OMA schemes against the number of groups in the cell-free massive MIMO-NOMA system with L=50 and U_k=50. When the number of groups increases, the total transmit power increases. In addition, compared with OMA, more users are served by GSIC-NOMA and the proposed GSIC-NOMA scheme can significantly improve the power efficiency.

5 Conclusion

In this paper, the performance of an uplink cell-free massive MIMO-NOMA system based on GSIC is investigated. A new method of user grouping according to the equivalent path loss of each user is proposed to combine with GSIC. The inter-group users are distinguished based on the principle of NOMA, while the principle of SDMA is invoked during the intra-group transmission. This scheme realizes transmission with deep integration between MIMO and NOMA. Moreover, we use the relationship between the equalizer and the transmit power coefficient to transform the power optimization problem, and a parallel iterative method is used to optimize the power control of the system. The simulation results show that considering error propagation, compared with OMA and traditional SIC-NOMA based on user clustering, the proposed scheme can

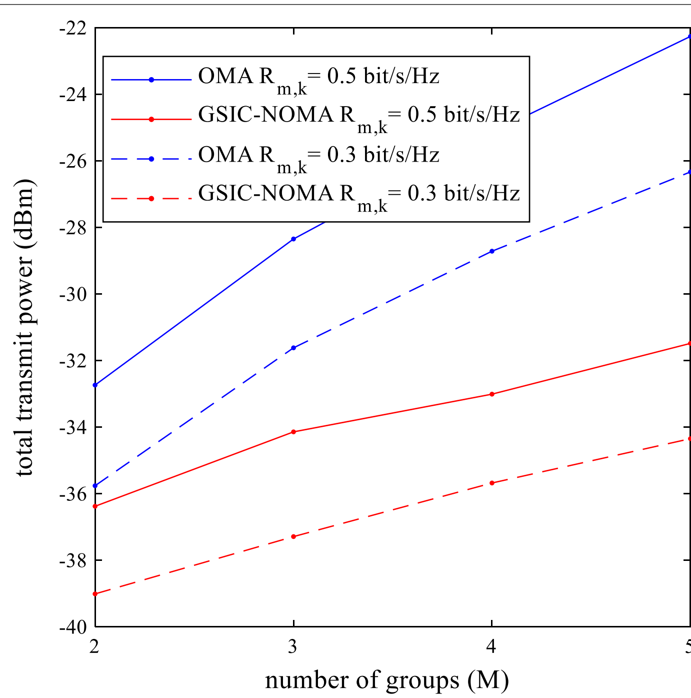

Fig. 5 Total transmit power versus the number of groups

effectively reduce the total transmit power consumption of the system. The effect of GSIC-NOMA is more remarkable when the number of users is large.

Abbreviations
NOMA: Non-orthogonal multiple access; MIMO: Multiple-input multiple-output; GSIC: Group-level successive interference cancellation; OMA: Orthogonal multiple access; IoT: Internet of things; CSI: Channel state information; SIC: Successive interference cancellation; SDMA: Space division multiple access; RIS: Reflecting intelligent surface; AP: Access point; SINR: Signal to interference-plus-noise ratio; MMSE: Minimum mean square error; WIT: Wireless information transfer; WPT: Wireless power transfer; SWIPT: Simultaneous wireless information and power transfer; MSS: Multibeam satellite systems.

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Authors contributions
All authors have contributed equally. All authors read and approved the final manuscript.

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Declarations

Ethics approval and consent to participate
Ethical approval.

Competing interests
The authors declare that they have no competing interests.

Consent for publication
Not applicable

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