Joint active and passive beamforming optimization for multigroup multicast system aided by intelligent reflecting surface

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Abstract
An intelligent-reflecting-surface aided multigroup multicast communication system is investigated in this paper. We develop energy-efficient designs for both the precoding matrix at the base station and passive reflecting beamforming at intelligent-reflecting-surface, subject to the minimum signal-to-interference-plus-noise ratio constraint of each user and the unit-modulus constraint imposed by passive intelligent-reflecting-surface. This leads to a complex non-convex problem for which to tackle we propose two novel algorithms based on alternating optimization techniques. Specifically, one algorithm employs semi-definite relaxation to obtain the suboptimal reflection coefficient vector and suboptimal precoding vector for each group. In order to reduce the computational complexity, the second algorithm transforms this non-convex problem into two second-order cone programming problems. Numerical results show that intelligent-reflecting-surface can significantly reduce the power consumption of the base station.

1 INTRODUCTION

With the development of artificial intelligence and communication technologies, the global mobile data traffic is expected to reach 77 exabytes per month by 2022 [1–3]. To meet these demands, various technologies have been proposed, such as full duplex (FD), millimetre wave (mmWave) communication, massive multiple-input multiple-output (MIMO), ultra-dense network (UDN), and intelligent reflecting surface (IRS) [4–6]. Due to the flexibility and low-cost, IRS stands out from these technologies and attracts tremendous researchers’ interest.

IRS is a meta-surface consisting of a vast amount of reconfigurable passive reflecting elements which can change the phase and direction of the reflected signal to enhance the received signal or suppress interference without any power amplifier. When each element of IRS is designed properly, it can not only provide array gain but also beamforming gain, which can significantly improve the spectrum efficiency and energy efficiency. At the same time, because of its light-weight, low-cost, and conformal geometry, IRS can be easily attached to the wall or ceiling [7–10].

The maximum sum-rate of an IRS-based multiuser MIMO system was studied in [11], but only the downlink was considered. So a two-way communication system was investigated in [12, 13], where the IRS and full-duplex were combined to improve the spectrum efficiency and energy efficiency of the system. Comparing with [12], the authors of [13] also took the direct link between BS and users into account, and the system sum rate was maximized by jointly optimizing the source precoders and the IRS phase shift matrix. And the secure IRS assisted two-way communication scheme was proposed in [14]. In order to reduce the inter cell interference in multi cell communication system and assist the downlink transmission of cell edge users, the authors of [9] placed an IRS at the cell boundary of multiple cells, and the weighted sum rate of all users was maximized through the joint design of BS precoding matrix and IRS phase shift.

When an IRS is deployed in the vicinity of eavesdropper, the secrecy communication rates can also be improved, that is because the signal reflected by IRS can be tuned to cancel out the signal from BS at the eavesdropper [15]. The authors of [16] maximized the secrecy rate of IRS-aided multi-antenna system by jointly optimizing the source transmit covariance and the IRS’s phase shift matrix. The influence of artificial noise (AN) in physical layer security was discussed in [17], and the author formulated a secrecy rate maximization problem for the...
IRS-assisted system by jointly designing of transmit beamforming with AN and the IRS reflecting beamforming.

An IRS-based downlink multiuser MISO system was studied in [18], and the energy efficiency was maximized by optimizing the transmit power allocation and the phase shifts of reflecting elements. However, only one IRS was considered in [18]. Thus, a multiple IRSs aided downlink wireless communication system was studied in [19], where the energy efficiency of the system was maximized by jointly optimizing the phase shift and on-off status vector of all IRSs and transmit beamforming of the transmitter. In order to better control multiple IRSs, base station should not only know the channel state information (CSI) but also know the on-off state informations of IRSs. However, the on-off state information of each IRS element is multiplexatively modulated onto the reflected signal of reflecting elements. Thus, the authors of [20] proposed a turbo message passing algorithm to distinguish the user signals and the on-off state information of each IRS element, and formulated a sum rate maximization problem by adjusting the on-off state and phase shift of reflecting element in the uplink IRSs-aided-Mu-MIMO system. But in practice, BS is unable to completely known the CSI due to the fading environment, and there will be large state space when IRSs’ ON/OFF state is considered. Therefore, [21] proposed a deep RL framework to make a decision using on-the-fly information in the cellular networks, and maximize the average energy efficiency of the IRSs-assisted multiuser MISO system by jointly optimizing the transmit power allocation, IRS phase shifter, and IRS reflector’s ON/OFF state. Furthermore, a novel random passive beamforming scheme which without CSI acquisition was proposed by [22] to reduce the training costs. The worst-case robust beamforming design for the IRS-aided MU-MISO system was first studied in [23], where the imperfect CSI of reflection channel was considered. In addition, the imperfect cascaded BS-IRS-user channels were considered in [24], where the bounded CSI error model and the statistical CSI error model were both studied to minimize the total transmit power.

IRS is also very promising in simultaneous wireless information and power transfer (SWIPT) aided system, the weighted sum rate (WSR) maximization problem of IRS-assisted SWIPT MIMO systems was first studied in [25], where the IRS can not only compensate the power loss for ERs, but also maximize the WSR of distant IRSs by passive beamforming.

In the above work, only passive IRS is considered, so an active-IRSs-assisted multiuser MISO system was studied in [2], and the network power consumption was minimized by jointly optimizing the beamforming vector at the BS, the allocation and phase-shift matrices of active IRS sets.

In spite of this high research interest, only a small number of papers consider the application of IRS in a multicast system which can effectively alleviate the pressure of tremendous wireless data traffic and play a vital role in the next generation wireless networks [10]. The authors of [10] first explored the performance benefits of deploying an IRS in multigroup multicast communication systems, and proposed SOCP and low-complexity MM algorithm to maximize the sum rate of all multicasting groups. This paper differs from [10] in the following two main aspects. First, the goal of [10] is to maximize the sum rate of all multicasting groups, while this paper is to minimize the BS transmit power. Second, the main constraint of [10] is the maximum transmit power of BS, while the main constraint of this paper is the minimum SINR of each user. As such, the algorithm proposed in [10] is not applicable to this paper.

Against this background, the contributions of this paper can be summarized as follows:

1) We first propose a power consumption minimization problem in an IRS-aided multigroup multicast communication system by jointly optimizing the precoding matrix at BS and the passive reflecting beamforming at IRS. It is difficult to solve this problem due to the non-convex SINR constraint of each user and the unit-modulus constraint imposed by passive IRS.

2) We propose two algorithms based on alternating optimization techniques to solve this non-convex problem, i.e. SDR-alternating algorithm and SOCP-alternating algorithm. In the algorithm 1, we transform the feasible problem about reflection vector into a problem of maximizing the total SINR residual of all users to find the optimal reflection vector more effectively, and apply Gaussian random method to find the rank-1 solution of precoding and reflection vector. In order to reduce the extra variable dimension brought by the SDR and simplify complication. In the algorithm 2, we first vectorize the precoding matrix, and then turn the original non-convex problem into two SOCP problems to find the optimal precoding matrix and reflection vector directly.

3) Finally, we conduct extensive simulations to explore the relationship between the performance of IRS and the distance of IRS-BS, and compare the performance of increasing the transmitting antenna at BS and increasing the reflector at IRS.

The rest of this paper is organized as follows. In Section 2, the IRS-aided multigroup multicast communication system is described, and the BS transmit power minimization problem is formulated. Two novel algorithms are presented in Section 3. An extensive simulation results are provided in Section 4. Finally, conclusions of this paper and future research directions are drawn in Section 5.

Notation: Scalar, column vector, matrix are denoted by italic letter (e.g. a), lowercase boldface letter (e.g. a) and uppercase boldface letter (e.g. A) respectively. $A \in \mathbb{C}^{M \times N}$ means A is a complex matrix with M rows and N columns, whereas $A_{MN}$ denote the (M, N)th element of A. We use $\langle \cdot \rangle^H$, $\langle \cdot \rangle^T$, $\| \cdot \|$ to denote the conjugate transpose, transpose and Frobenius norm respectively. The symbols trace(·), vec(·) denote the trace operation and vectorization operation, respectively. real(·), $\angle(\cdot)$ denote the real part and angle of a complex number, respectively. $A \otimes B$ denote the Kronecker products of A and B. diag(a) is a diagonal matrix whose diagonal elements are the corresponding elements of a. $A \succeq 0$ means that A is a positive semidefinite matrix. Notation $n \sim \mathcal{CN}(0, \delta^2)$ means that n is a circularly symmetric complex Gaussian (CSCG) random vector with zero mean and variance $\delta^2$. 

[643]
2 SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we first describe the signal model for the multi-group multicast system assisted by a passive IRS. Then, under the constraints of each users’ SINR and the unit-modulus of IRS, we propose an optimization problem to minimize the total transmit power of BS by jointly optimizing the reflecting beamforming at IRS and the precoding matrix at BS.

2.1 System model

As shown in Figure 1, we consider an IRS-aided multigroup multicast communication system where the BS is equipped with $N$ transmitting antennas to serve $G$ groups of users, and each group contains multiple single-antenna users. The total number of users is $K (K \geq G)$. We use $\kappa_g$ to denote the users of group $g$ and each user can only belong to one group, i.e. $\kappa_i \cap \kappa_j = \emptyset$, if $i \neq j$. The number of reflecting elements at the IRS is denoted by $M$. In this paper we assumed that there are no obstacles between the BS and users, thus the direct link between them can not be ignored. Specifically, the users can not only receive the signal by reflecting channel through the passive IRS, but also by the direct channel between BS and users.

Since the information data transmitted to different groups are precoded as independent and different, users in the same group share the same data while interfered by the data sent to other groups. Therefore, the discrete-time signal received at the user $k$ can be expressed as

$$y_k = (h_{rk} + h_{rk}R_{r})x + n_k,$$

where we use

$$x = \sum_{g=1}^{G} w_{g,k}$$

(2)

to denote the transmitted signal of BS. $s_k$ and $w_g \in \mathbb{C}^{N \times 1}$ represent the desired unit-power complex valued data of group $g$ and the corresponding precoding vector, respectively. And the collection of all precoding vectors are denoted as $W = [w_1, \ldots, w_G] \in \mathbb{C}^{N \times G}$. We use $h_{rk} \in \mathbb{C}^{N \times 1}$, $h_{rk} \in \mathbb{C}^{M \times 1}$ to denote the channel vector from BS to user $k$, and from IRS to user $k$, respectively. $H_{gg} \in \mathbb{C}^{M \times N}$ is the channel matrix between BS and IRS. The diagonal matrix $R = \text{diag}[e^{\theta_1}, \ldots, e^{\theta_M}] \in \mathbb{C}^{M \times M}$ denotes the reflection coefficient matrix of IRS, where $0 \leq \theta_m \leq 2\pi$, $\forall m \in 1, \ldots, M$. And the additive white Gaussian noise (AWGN) power at user $k$ are modelled as $n_k \sim \mathcal{CN}(0, \sigma^2_k)$.

Accordingly, the SINR of user $k$ can be written as

$$\text{SINR}_k = \frac{\| (h_{rk} + h_{rk}R_{r})w \|^2}{\sum_{g \neq k} \| (h_{rk} + h_{rk}R_{r})w_g \|^2 + \sigma^2_k}$$

(3)

In this paper, we assume that the CSI is perfectly known at the BS based on existing channel estimation techniques for IRS assisted channels, such as in [26–28]. And the BS is also responsible for designing the reflection coefficients of the IRS, and sends them to the IRS controller through a dedicated feedback channel [25].

2.2 Problem formulation

In this paper, we are focused on minimizing the total transmit power of BS by jointly optimizing the IRS reflecting beamforming and precoding matrix, under the SINR constraint of each user, i.e. solving the power minimization problem as below

$$\min_{W, R} \sum_{g=1}^{G} \| w_g \|^2,$$

s.t. C1: \( \| (h_{rk} + h_{rk}R_{r})w \|^2 \geq r_k, \)

$$\sum_{g \neq k} \| (h_{rk} + h_{rk}R_{r})w_g \|^2 + \sigma^2_k \quad \forall k \in \kappa_g, \ g \in 1, \ldots, G$$

C2: $0 \leq \theta_m \leq 2\pi, \ m \in 1, \ldots, M$ (4)

where $r_k > 0$ is the minimum SINR constraint for user $k$. It is difficult to solve (4) due to the K non-convex constraints C1, where each precoding vector and phase shifts are coupled. In the next section, we proposed two efficient algorithms based on alternating optimization techniques to solve problem (4) approximately.

3 TOTAL POWER MINIMIZATION

In this section, we will solve the power minimization problem of the IRS aided multigroup multicast system by two ways, i.e. SDR-alternating algorithm and SOCP-alternating algorithm.
3.1 SDR-alternating algorithm

In order to facilitate the processing, we first combine the constant terms by introducing two variables, i.e. \( \mathbf{H}_k = \text{diag}(\mathbf{h}_k^H\mathbf{H}_k^H) \) and \( \mathbf{e} = [e_1, \ldots, e_M]^H \), where \( e_m = e_m^e, \forall m = 1, \ldots, M \). Thus we have

\[
\left( \mathbf{h}_k^H + \mathbf{h}_k^H \mathbf{R}_k \right) \mathbf{w}_k = \mathbf{e}^H \mathbf{H}_k^H \mathbf{w}_k. \tag{5}
\]

And then the original problem of (4) can be equivalently expressed as

\[
\begin{align*}
\min_{\mathbf{W}, \mathbf{e}} & \quad \sum_{g=1}^{G} \| \mathbf{w}_g \|^2 \\
\text{s.t.} & \quad \| \mathbf{e}^H \mathbf{H}_k^H \mathbf{w}_k \|^2 \geq r_k, \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G \\
& \quad \sum_{i \neq k} \| \mathbf{e}^H \mathbf{H}_i^H \mathbf{w}_i \|^2 + \delta_k^2 > 0 \\
& \quad C2: |\mathbf{e}| = 1, \ m \in 1, \ldots, M \\
& \quad \mathbf{e}_{M+1} = 1 
\end{align*} \tag{6}
\]

After setting \( \mathbf{W}_g = \mathbf{w}_k \mathbf{w}_k^H \) and \( \mathbf{E} = \mathbf{e} \mathbf{e}^H \), the problem (6) can be further simplified as

\[
\begin{align*}
\min_{\mathbf{W}, \mathbf{E}} & \quad \sum_{g=1}^{G} \text{trace}(\mathbf{W}_g) \\
\text{s.t.} & \quad \text{trace}(\mathbf{H}_g \mathbf{W}_g \mathbf{H}_g^H \mathbf{E}) \geq r_k, \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G \\
& \quad \text{trace}(\mathbf{H}_g \mathbf{W}_g \mathbf{H}_g^H \mathbf{E}) + \delta_k^2 > 0 \\
& \quad C2: \text{diag}(\mathbf{E}) = 1, \ \text{rank}(\mathbf{E}) = 1, \ \mathbf{E} \succeq 0 \\
& \quad \mathbf{W}_g \succeq 0, \ \text{rank}(\mathbf{W}_g) = 1 
\end{align*} \tag{7}
\]

Then we apply the SDR-based alternating algorithm to transform the non-convex problem (7) into two convex subproblems. And the suboptimal \( \mathbf{E} \) and \( \mathbf{W}_g, g = 1, \ldots, G \) can be obtained at each iteration, respectively.

Specifically, \( \mathbf{W}_g, g = 1, \ldots, G \) can be optimized firstly by assuming that \( \mathbf{E} \) is fixed. Based on the problem (7), we can get the following formulation

\[
\begin{align*}
\min_{\mathbf{W}} & \quad \sum_{g=1}^{G} \text{trace}(\mathbf{W}_g) \\
\text{s.t.} & \quad \text{trace}(\mathbf{A}_g \mathbf{W}_g) \geq r_k \left( \sum_{i \neq g} \text{trace}(\mathbf{A}_i \mathbf{W}_i) + \delta_k^2 \right), \\
& \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G \\
& \quad \mathbf{W}_g \succeq 0, \ \mathbf{E}_{m,w} = 1, \ m \in 1, \ldots, M + 1 \\
& \quad \text{rank}(\mathbf{E}) = 1, 
\end{align*} \tag{8}
\]

where \( \mathbf{A}_k = \mathbf{H}_k^H \mathbf{E} \mathbf{H}_k \). Since the rank-one constraint is non-convex, we first ignore it and use the CVX [29] solver, such as MOSEK [30] to find a higher-rank solution. And then we can use Gaussian random algorithm to get the rank-1 solution, i.e. the suboptimal \( \mathbf{w}_g, g = 1, \ldots, G \). The details can be found in [31], and the Gaussian random algorithm can guarantee at least a \( \frac{\pi}{4} \)-approximation of the optimal objective value of problem (8) by sufficient randomizations [8]. And the tightness of SDR algorithm has also been shown in the Theorem 1 of [24].

After obtaining the precoding vector \( \mathbf{w}_g, g = 1, \ldots, G \) for each group by above procedure, we can move on to find the suboptimal reflecting beamforming \( \mathbf{E} \) in the same way. Specifically, for the fixed \( \mathbf{w}_g, g = 1, \ldots, G \) obtained by (8), problem (7) can be formulated as

\[
\begin{align*}
\min_{\mathbf{W}, \mathbf{E}} & \quad \sum_{i \neq g} \text{trace}(\mathbf{H}_g \mathbf{W}_g \mathbf{H}_g^H \mathbf{E}) \geq r_k \\
\text{s.t.} & \quad \text{trace}(\mathbf{H}_g \mathbf{W}_g \mathbf{H}_g^H \mathbf{E}) + \delta_k^2 > 0 \\
& \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G \\
& \quad \text{diag}(\mathbf{E}) = 1, \ \text{rank}(\mathbf{E}) = 1, \ \mathbf{E} \succeq 0 
\end{align*} \tag{9}
\]

which is a feasible problem. Thus, we only need to find an \( \mathbf{E} \) satisfying the constraints of (9), but that \( \mathbf{E} \) is not always the optimal one.

According to the practical application, if an \( \mathbf{E} \) can make the SINR of each user reach the maximum under a given \( \mathbf{W} \). It can be deduced that under this \( \mathbf{E} \), we can meet the same SINR requirements with the minimal power consumption. Therefore, the feasible problem (9) can be improved as a problem of finding the maximum total SINR residual of all users [8], i.e.

\[
\begin{align*}
\max_{\mathbf{E}_{\lambda_k}, \lambda_k} & \quad \sum_{k=1}^{K} \lambda_k \\
\text{s.t.} & \quad f_k(\mathbf{E}) \triangleq \frac{\text{trace}(\mathbf{H}_k \mathbf{W}_g \mathbf{H}_k^H \mathbf{E})}{\sum_{i \neq g} \text{trace}(\mathbf{H}_g \mathbf{W}_g \mathbf{H}_g^H \mathbf{E}) + \delta_k^2} \geq r_k + \lambda_k \\
& \quad \lambda_k \geq 0, \ \forall k \in \mathcal{K}, \ g \in 1, \ldots, G \\
& \quad \mathbf{E}_{m,w} = 1, \ m \in 1, \ldots, M + 1 \\
& \quad \text{rank}(\mathbf{E}) = 1, 
\end{align*} \tag{10}
\]
where $\lambda_k \geq 0$ is the SINR residual of user $k$. The maximizing SINR residual problem (10) has the same set of solutions as the feasible problem (9), but problem (10) is more efficient than the problem (9) in convergence. It has been proved in [8] and thus are omitted here.

But (10) is not a convex problem due to the non-convex SINR constraints $f_k(E)$, we can use Lemma 1 to transform it into convex.

**Lemma 1.** $f_k(E)$ has the following properties,

$$f_k(E) \geq \frac{\text{trace}(H_k W_k H_k^T E)}{\omega_k} + \eta_k \frac{\sum_{i \neq k} \text{trace}(H_i W_i H_i^T E) + \delta_k^2}{(\omega_k)^2} \triangleq \bar{f}_k(E)$$  

where

$$\omega_k = \sum_{i \neq k} \text{trace}(H_i W_i H_i^T E) + \delta_k^2$$

and $W_{g^*}, (g \in 1, ..., G)$ are fixed, $E^*$ is the solution obtained at iteration $n - 1$.

**Proof.** Set $\phi = \text{trace}(H_k W_k H_k^T E)$ and $\varphi = \sum_{i \neq k} \text{trace}(H_i W_i H_i^T E) + \delta_k^2$, where $\phi$ and $\varphi$ are real numbers. Then we have

$$f_k(E) = f_k(\phi, \varphi) = \frac{\phi}{\varphi},$$

and $f_k(E^*) = f_k(\phi^*, \varphi^*)$. Since $f_k(\phi, \varphi)$ is a biconvex function w.r.t $\phi$ and $\varphi$, then we can get

$$f_k(\phi, \varphi) \geq f_k(\phi^*, \varphi^*) + \frac{\partial f}{\partial \phi} \bigg|_{\phi = \phi^*} (\phi - \phi^*)$$

$$+ \frac{\partial f}{\partial \varphi} \bigg|_{\phi = \phi^*} (\varphi - \varphi^*)$$

$$= \frac{\phi^*}{\varphi^*} + (\phi - \phi^*) - \frac{\varphi^*}{\varphi^*} (\varphi - \varphi^*)$$

$$= \frac{\phi}{\varphi} - \frac{\phi^*}{\varphi^*} + \frac{\varphi^*}{\varphi^*}.$$ (15)

Substitute $\varphi = \sum_{i \neq k} \text{trace}(H_i W_i H_i^T E) + \delta_k^2$.

| Table 1 | The proposed SDR-alternating algorithm |
|----------------|--------------------------------------|
| **Initialization**: | Initialize a set of precoding vector $w_k, (g \in 1, ..., G)$ and a reflection coefficient vector $e$ randomly, then multiply them to generate $W_k, (g \in 1, ..., G)$ and $E$, i.e., $W_k = w_k e^H, E = ee^H$. And set iteration counter $n = 0$. |
| **Iteration**: | 1) Under the given $E^*$, calculate $W_k, (g \in 1, ..., G)$ by solving problem (8), and set $W_k = W_k^*$. |
| | 2) Under the obtained $W_k^*, (g \in 1, ..., G)$, calculate $E$ by solving problem (16), and set $E^* = E$. |
| | 3) $n = n + 1$. |
| **Stop**: | Until the convergence condition is satisfied, i.e., $\left| \sum_{n=1}^{\infty} (W_k^{n+1}) - \sum_{n=1}^{\infty} (W_k^n) \right| < \varepsilon$. |
| **Output**: | $W_k, E$. |

**Decomposition:** If $\text{rank}(E) = 1$, the IRS's reflection coefficient vector $e$ can be obtained by eigenvalue decomposition. If $\text{rank}(E) > 1$, $e$ can be obtained by Gauss randomization method. The precoding vector $w_{g^*}, (g \in 1, ..., G)$ can be obtained in the same way.

$$\phi = \text{trace}(H_k W_k H_k^T E), \quad \varphi = \sum_{i \neq k} \text{trace}(H_i W_i H_i^T E) + \delta_k^2$$

and

$$\phi^* = \text{trace}(H_k W_k H_k^T E^*)$$

into (15), we can get the inequality (11), which completes the proof.

Thus, the non-convex problem (10) can be transformed into a convex problem

$$\max_{E, \lambda_k} \sum_{k=1}^{K} \lambda_k$$

s.t. $f_k(E) \geq r_k + \lambda_k, \quad \lambda_k \geq 0, \forall k \in x_{g^*}, g \in 1, ..., G$

$$E_{m,m} = 1, m \in 1, ..., M + 1$$

$$\text{rank}(E) = 1.$$ (16)

Just like the previous process of optimizing $w_{g^*}, g = 1, ..., G$, we can also get a rank-1 suboptimal $E$ by Gaussian random algorithm. The proposed SDR-alternating algorithm is described as Table 1.

### 3.1.1 Complexity analysis

Problem (8) contains $K$ rate constraints of size $N$, $G$ positive semi-definite constraints of size $N$ and $n_1 = GN^2$ decision variables. Therefore, according to the Lecture 6 of [32] and [33], the complexity of solving problem (8) per iteration is $O(\sqrt{GN} + 2KN_1 (GN^2 + n_1 GN^2 + KGN^2 + n_1^2))$. Similarly, the complexity of solving problem (10) per iteration can be calculated as $O(\sqrt{3(M + 1)} + 2KN_2 ((M + 1)^3 + n_2 (M + 1)^2 + ...)$.
where \( n_2 = (M + 1)^2 \) and \( n_1 = K \). When the BS and IRS have more antennas and reflectors than the number of users, i.e., \( M \geq K \), the approximate complexity of SDR algorithm per iteration can be written as \( \mathcal{O}(M^{6.5} + G^{3.5}N^{6.5}) \) by neglecting the lower order terms.

### 3.1.2 Convergence analysis

Denote the total transmit power calculated by problem \((p)\) based on \((W, E)\) as \( f(W, E) \). Specifically, the total transmit power of problem \((8)\) based on \((W, E)\) can be written as \( f(W, E) = \sum_{i=1}^{G} \text{trace}(W_i) \). Thus, at the \( n_{th} \) iteration, with given \((W^*, E^*)\) we have

\[
f(W^*, E^*)_g \triangleq f(W^{*+1}, E^*)_g = f(W^{*+1}, E^*)_g \geq f(W^{*+1}, E^*)_g = f(W^{*+1}, E^{*+1})_g \geq f(W^{*+2}, E^{*+2})_g \quad (17)
\]

where \((a1)\) holds since for given \( E^* \), \( W^{*+1} \) is the optimal solution to problem \((8)\), and \((a2), (a3), (a4)\) hold because the total transmit power of BS is regardless of \( E \) and only depends on \( W \). However the optimal solution \( E^{*+1} \) of problem \((16)\) which is also feasible to problem \((10), (9)\) and \((8)\) can generate a larger total SINR residual than problem \((9)\). Thus \((a5)\) can be guaranteed by two ways, i.e., the larger SINR residual and the optimal solution of problem \((8)\). And due to the SINR constraints, there exist a lower bound for transmit power. Therefore, the proposed SDR-alternating algorithm is convergent.

The convergence behaviour of SDR-alternating algorithm is shown in Figure 3.

### 3.2 SOCP-alternating algorithm

In the algorithm 1, we use SDR to optimize the precoding vector of each group, and Gaussian random algorithm to get the rank-1 solution. But doing so will multiply the dimension of variables and increase the computational complexity. Therefore, in this section, we first vectorize the precoding matrix, and then turn the original non-convex problem into two SOCP problems to find the optimal precoding matrix \( W \) and reflection coefficient vector \( e \) directly.

For a given \( e \), we have

\[
\sum_{j=1}^{G} \| e^{H_j} H_k w_j \|^2 = \sum_{j=1}^{G} w_j^H e^{H_j} H_k e^{H_j} H_k w_j = \text{trace}(W^{H_j} H_k e^{H_j} H_k W)
\]

\[
= f^{H_j} I \otimes \hat{\beta}_k f, \quad (18)
\]

where \( \hat{\beta}_k = H_k^H e H_k \), \( f = \text{vec}(W) \) and \( I \) is an identity matrix with the same dimension as the number of user groups. Similarly, we have

\[
| e^{H_j} H_k w_j |^2 = \text{trace}(f^{H_j} e H_k W) \text{trace}(W^{H_j} H_k e^{H_j} H_k W)
\]

\[
= \text{vec}(W^{H_j} e^{H_j} H_k W) \text{vec}(H_k^H e H_k W)
\]

\[
= \text{vec}(H_k^H e H_k W) \text{vec}(W^{H_j} e H_k W)
\]

\[
= f^{H_j} N_k f, \quad (19)
\]

where \( N_k = \text{vec}(H_k^H e H_k W) \text{vec}(W^{H_j} e H_k W) \geq 0 \) is a positive semi-definite matrix, and \( f \) is a selection vector whose \( g_{th} \) term is 1 and all other terms are 0.

Thus, we have

\[
\sum_{j=1}^{G} | e^{H_j} H_k w_j |^2 = f^{H_j} (I \otimes \hat{\beta}_k - N_k) f = f^{H_j} M_k f \geq 0, \quad (20)
\]

where \( M_k = I \otimes \hat{\beta}_k - N_k \geq 0 \) is also a positive semi-definite matrix. And the objective function of \((6)\) can be rewritten as

\[
\sum_{j=1}^{G} | w_j |^2 = | W |^2 = \text{trace}(W^H W) = f^{H_j} f. \quad (21)
\]

Therefore, for a given \( e \), the original problem \((6)\) can be expressed as

\[
\min_{f} f^{H_j} f
\]

\[
s.t. \frac{f^{H_j} N_k f}{f^{H_j} M_k f + \delta_k^2} \geq r_{k}, \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G. \quad (22)
\]

The non-convex constraints of \((22)\) can be further transformed into

\[
f^{H_j} N_k f \geq r_{k}(f^{H_j} M_k f + \delta_k^2). \quad (23)
\]

Then we can use the first-order approximation technique on the left side of the inequality to transform \((23)\) into convex. Thus, the non-convex problem of \((22)\) can be approximated as a convex one

\[
f = \text{arg min}_{f} f^{H_j} f
\]

\[
s.t. 2 \text{real} \left( f^{H_j} N_k f \right) - f^{H_j} N_k f \geq r_{k}(f^{H_j} M_k f + \delta_k^2). \quad \forall k \in \mathcal{K}, \ g \in 1, \ldots, G, \quad (24)
\]

which is a SOCP problem and can be easily solved by CVX. Then, the optimal \( f \) of the \( n + 1_{st} \) iteration is

\[
f^{(n+1)} = \begin{cases} f, \text{if } f(f^{*+1})_{24} \leq f(f^{(n)} f^{*+1})_{24} \\ f, \text{otherwise.} \end{cases} \qquad (25)
\]
Just like the algorithm 1, we will get a feasible problem about \( e \) after obtaining the optimal \( f \) from (25), and that feasible problem can also be transformed into a problem of finding the maximum total SINR residual of all users.

We first make some modifications on the terms related to \( e \), i.e.,

\[
\left| e^H H_k w \right|^2 = e^H H_k w, w^H H_k^H e = e^H P_k e, \tag{26}
\]

where \( P_k = H_k w w^H H_k^H \).

Thus

\[
\sum_{i \neq g} |e^H H_k w_j| = \left( \sum_{i=1}^G |e^H H_k w_j| \right) - |e^H H_k w_i|^2 = e^H (H_k WW^H H_k^H - P_k) e = e^H J_k e, \tag{27}
\]

where \( J_k = H_k WW^H H_k^H - P_k \).

Therefore, after getting the optimal \( W \) by reshaping the vector \( f \), we have

\[
\max_{\lambda_k} \sum_{k=1}^K \lambda_k
\]

s.t. \( \text{SINR}_k(e) \triangleq \frac{e^H P_k e}{e^H J_k e + \delta_k^2} \geq r_k + \lambda_k \)

\( \lambda_k \geq 0, \forall k \in \mathcal{K}, g \in \{1, \ldots, G\} \)

\( |e_m| = 1, m \in \{1, \ldots, M\} \)

\( e_{M+1} = 1 \) \( \tag{28} \)

**Lemma 2.** The SINR of each user has the following properties,

\[
\text{SINR}_k(e) \geq 2 \text{real} \left( a_k e^H H_k w \right) e - b_k \delta_k^2 - e^H \left( \sum_{i \neq g} H_k w_i \right) e \tag{29}
\]

where

\[
a_k = \frac{\left( e^H H_k w \right)^H}{e^H \left( \sum_{i \neq g} H_k w_i \right) e + \delta_k^2}, \tag{30}
\]

\[
b_k = \frac{e^H H_k w \left( H_k^H H_k \right) e}{\left( e^H \left( \sum_{i \neq g} H_k w_i \right) e + \delta_k^2 \right)^2}, \tag{31}
\]

and \( w_g \) \( (g \in \{1, \ldots, G\}) \) are fixed, \( e^* \) is the solution obtained at iteration \( n - 1 \).

**Proof:**

\[
\text{SINR}_k(e) = \frac{e^H P_k e}{e^H J_k e + \delta_k^2} = \frac{\left| e^H H_k w \right|^2}{\sum_{i \neq g} |e^H H_k w_i|^2 + \delta_k^2}, \tag{32}
\]

where \( w_g \) \( (g \in \{1, \ldots, G\}) \) can be obtained by reshaping the vector \( f \). After setting \( t_k = e^H H_k w \) and \( y_k = \sum_{i \neq g} |e^H H_k w_i|^2 + \delta_k^2 > 0 \), we have

\[
\text{SINR}_k(e) = \text{SINR}_k(t_k, y_k) = \frac{|t_k|^2 - t_k H_k}{y_k}, \tag{33}
\]

and \( \text{SINR}_k(e^*) = \text{SINR}_k(t_*^*, y_*^*) \). Since \( \text{SINR}_k(t_k, y_k) \) is a biconvex function w.r.t. \( t_k \) and \( y_k \), then \( \text{SINR}_k(t_k, y_k) \) has the following properties,

\[
\text{SINR}_k(t_k, y_k) \geq \text{SINR}_k \left( t^*, y^* \right) + \frac{\partial \text{SINR}_k}{\partial y_k} |y_k - y^*| + 2 \text{real} \left( \frac{\partial \text{SINR}_k}{\partial t_k} \right) \left( t_k - t^* \right) - \frac{\partial^2 \text{SINR}_k}{\partial t_k^2} |t_k - t^*|^2 \frac{\partial^2 \text{SINR}_k}{\partial y_k^2} (y_k - y^*)^2
\]

Substitute \( t_k = e^H H_k w, y_k = \sum_{i \neq g} |e^H H_k w_i|^2 + \delta_k^2 \), \( t^* = e^H H_k w \) and \( y^* = \sum_{i \neq g} |e^H H_k w_i|^2 + \delta_k^2 \) into (34), we can get the inequality (29), which completes the proof.

Therefore, the non-convex problem (28) can be relaxed as

\[
\max_{\lambda_k} \sum_{k=1}^K \lambda_k
\]

s.t. \( 2 \text{real} \left( a_k e^H H_k w \right) e - b_k \delta_k^2 - e^H \left( \sum_{i \neq g} H_k w_i \right) e \geq r_k + \lambda_k \)

\( \lambda_k \geq 0, \forall k \in \mathcal{K}, g \in \{1, \ldots, G\} \)

\( |e_m| \leq 1, m \in \{1, \ldots, M\} \)

\( e_{M+1} = 1 \) \( \tag{35} \)

where \( \bar{b}_k = b_k \sum_{i \neq g} H_k w_i \). We can use CVX to solve this SOCP problem (35), and then set the last element of \( e \) to be
TABLE 2  The proposed SOCP-alternating algorithm

| Initialization: | Initialize the precoding matrix $\mathbf{W}$ and the reflection coefficient vector $\mathbf{e}$ randomly, set $f = \text{vec}(\mathbf{W})$ and iteration counter $\sigma = 0$. |
|-----------------|----------------------------------------------------------------------------------------------------------------------------------|
| Iteration:      | 1) Under the given $\mathbf{e}^\sigma$, calculate $f$ by solving problem (24), and get the $f^{\sigma+1}$ by (25).  
                     2) Under the given $f^{\sigma}$, calculate $\mathbf{e}$ by solving problem (35), and set $\mathbf{e}^{\sigma+1} = \exp(j\angle(\mathbf{e}^{\sigma+1})).$
                     3) $\sigma = \sigma + 1$.  
| Stop:           | Until the convergence condition is satisfied, i.e. $|f^{\sigma+1} - f^{\sigma}| < \epsilon$. |
| Output:         | $f$, $\mathbf{e}$ |

one by normalization, i.e.

$$e_{opt} = \exp\left(j\angle\left(\frac{\mathbf{e}}{\mathbf{e}^{(\sigma+1)}}\right)\right),$$ (36)

where $\mathbf{e}$ is the optimal solution of (35). The proposed SOCP-alternating algorithm is described as Table 2.

3.2.1 Complexity analysis

The complexity of solving problem (24) per iteration is $O(\sqrt{2KN_aK(NG + 1)^2})$, where $N_a = GN$. And the complexity of solving problem (35) per iteration is $O(\sqrt{2(M + 1) + 2KN_aK(M + 2)^2 + (M + 1)(M + 1)^2 + \sqrt{4K(N_aK + N_bK)}})$, where $N_a = M + 1$ and $N_b = K$. When the BS and IRS have more antennas and reflectors than the number of users, i.e. $M \geq K, N \geq K$, the approximate complexity of SOCP algorithm per iteration can be written as $O(M^{4.5} + C^3N^{4.5})$ by neglecting the lower order terms. Therefore, the SOCP-alternating algorithm is more efficient than SDR-alternating algorithm with complexity $O(M^{6.5} + C^3N^{6.5})$, which is shown in Figure 3.

3.2.2 Convergence analysis

Using the same method as the SDR algorithm convergence analysis, we have

$$f(\mathbf{f}^{\sigma}, \mathbf{e}^{\sigma})_{24} \geq f(\mathbf{f}^{\sigma+1}, \mathbf{e}^{\sigma+1})_{24} \geq f(\mathbf{f}^{\sigma+1}, \mathbf{e}^{\sigma})_{24} \geq f(\mathbf{f}^{\sigma+1}, \mathbf{e}^{\sigma+1})_{24},$$ (63)

where (b1) holds since for given $\mathbf{e}^\sigma$, $\mathbf{f}^{\sigma+1}$ is the optimal solution to problem (24). And (b2), (b3) hold because the total transmit power of BS is regardless of $\mathbf{e}$ and only depends on $f$. (b4) can be guaranteed not only by (25) but also by the SINR residual of (35). And due to the SINR constraints, there exist a lower bound for transmit power. Therefore, the proposed SOCP algorithm is convergent.

4 SIMULATION RESULTS

In this section, numerical results are provided to illustrate the BS's power consumption of multigroup multicast system. The simulation setting is shown in Figure 2. And all experiments are performed on a PC with a 2.90GHz i5-9400 CPU and 16GB RAM.

We assume that there are two groups where each group has two users, i.e. $G = 2, \kappa_x = 2$. And all users are randomly distributed in a circular area with a radius of 2m and a center at (100m, 10m). Denote the distance between BS and IRS by $d_{br}$ m, and the position of BS and users are fixed while IRS moves from the place near the BS to the distance. Thus the distance between IRS and user $\kappa$ can be calculated as

$$d_{ux} = \sqrt{(\sqrt{d_{wr}^2 - d_{x}^2} - d_{br})^2 + d_{x}^2}.$$
The path loss model is set as

$$L = C_0 \left( \frac{d_s}{D_0} \right)^{-\alpha},$$

where $d_s$ is the distance between any two nodes, $D_0$ is the reference distance, $\alpha$ is the path loss exponent and $C_0$ is the path loss coefficient. We adopt Rayleigh fading model for all channels.

Unless otherwise stated, the parameters are set as follows: $C_0 = -30\text{dB}$, $D_0 = 1\text{m}$, $r_k = 10\text{dB}$, ($k \in 1, \ldots, K$) and the convergence accuracy $\varepsilon = 10^{-4}$. The path loss exponent of the BS-user link, BS-IRS link and IRS-user link are set as $\alpha_{BU} = 4$ and $\alpha_{IR} = \alpha_{RU} = 2$, respectively. Transmission bandwidth is 10 MHz, noise power density is $-174 \text{dBm/Hz}$. We assume that the noise of each user is the same.

In Figure 3, we set the number of IRS’s reflector as $M = 40$, the antenna number of BS as $N = 40$ and the distance between BS and IRS as 15m. We can see from this figure that both SDR-alternating and SOCP-alternating algorithms can converge with a small number of iterations, but the convergence time of SOCP-alternating algorithm is less than that of SDR.

The relationship between the total transmit power at the BS and the distance of BS-IRS is illustrated in Figure 4. In this figure, we have set the number of IRS’s reflection unit as $M = 20$, and the antenna number of BS as $N = 20$. It can be seen that compared with the system without IRS or random phase-shifting IRS, the IRS with optimal reflection beamforming can significantly reduce the power consumption, which is due to the fact that IRS can not only bring the array gain but also the beamforming gain. Due to the array gain, the IRS with random phase-shifting can also reduce some power consumption. However, this power consumption reduction will disappear when IRS is far away from the BS and users.

From Figure 4, we can also find that there exists a local minimal power consumption when IRS is near the user, which means that the coverage of communication can be improved by IRS without increasing the transmission power.

The relationship between the BS transmitting power and the number of IRS’s reflectors, the number of BS’s transmit antennas and the distance between BS and IRS can be found from Figures 5, 6, and 7 in which the distance between BS and IRS are set as 50m, 100m and 200m, respectively.

We can find that for the random phase-shifting IRS, the performance of increasing the number of BS antennas is always better than that of the IRS under the same conditions, but for the IRS designed by the two proposed algorithms, its performance is related to the distance. When the distance between IRS and BS is the same as the distance between IRS and users, the performance of adding antenna at BS is similar to that of adding reflector at IRS. When IRS is near the user, the performance of adding reflector is better than adding antenna;
when IRS is far away from the BS and users, the performance of adding antenna is better than that of adding reflector. This phenomenon is caused by the passivity of the IRS. That is to say, in the fading environment, the array gain and beamforming gain from the passive IRS will decrease with the increase of distance.

5 CONCLUSION AND FUTURE WORK

This paper examines the application of an IRS in the multigroup multicast communication system, and proposed two algorithms based on alternating optimization techniques to minimize the transmission power consumption of base station. Specifically, given each user SINR constraints, the precoding matrix at BS and the passive reflecting beamforming at IRS were jointly optimized to minimize the transmit power of BS. In algorithm 1, we use SDR to optimize precoding vector for each group, and then apply the Gaussian random algorithm to get rank-1 solution. In order to reduce the variable dimension and simplify complication, in algorithm 2, we transform the original problem into two SOCP sub-problems to directly optimize the precoding matrix of BS and the reflection coefficient vector of IRS. At the same time, in order to find the optimal reflection coefficient vector more efficient, we transform the feasible problem of finding IRS's reflector and BS's transmit antennas, the distance between BS and IRS is 200m

FIGURE 7 Total transmit power versus the number of IRS's reflector and BS's transmit antennas, the distance between BS and IRS is 200m

CONFLICT OF INTEREST STATEMENT

We declare that we have no any possible conflicts of interest.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.
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