Joint Beamforming Design for Intelligent Reflecting Surface Aided Terahertz Wireless Network

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This paper investigates the transmission design in a multiple-input single-output (MISO) Terahertz network assisted by an intelligent reflecting surface (IRS). Specifically, we consider the sum-rate maximization design by jointly optimizing the active beamforming (BF) and the phase shifters. To solve the formulated nonconvex problem, we utilize the Lagrangian dual transform based method to obtain an equivalent problem. Then, an alternating optimization (AO) algorithm is proposed, where the unit modulus constraint (UMC) of the IRS is handled by a computational efficient adaptive gradient descent (AGD) method. Finally, simulation results demonstrate the promising performance of the proposed design.

1. Introduction

Recently, the newly proposed intelligent reflecting surface (IRS) has drawn great attention in industry and academia. An IRS is a planar array with many reflecting elements, which can rotate the phases of the incident electromagnetic (EM) wave passively [1]. Hence, by altering the phase shifters with a programmable controller, the reflected signals can be adjusted to the desired direction [2]. Moreover, since the processing is limited to only reflecting the received signal, IRS consumes much less power than the active transmitter (Tx) or relay [3]. With these advantages, IRS has sparked much interest in recent works.

For example, a single IRS for data transmission was studied in [4], with the goal of either maximizing the system throughput or minimizing the transmit power at Tx. Also, the work in [5] investigated the joint active and passive beamforming (BF) design for IRS-empowered wireless systems while [6] studied the phase shifters design in the case of discrete coefficient. What’s more, the IRS-assisted design has been investigated in the multuser network in [7], the multigroup multicast network in [8], the multicell network in [9], and the wireless energy harvesting network in [10], respectively. Moreover, when the channel state information (CSI) cannot be accurately obtained, the work in [11] studied the outage-constrained robust BF in IRS-aided wireless networks. Then, the work in [12] revealed that exploiting amplitude control in IRS-aided wireless networks can improve the robustness. Recently, in [13, 14], the authors proposed a two-timescale BF scheme in IRS-aided wireless networks, where the passive IRS phase shifters were optimized based on the statistical CSI of all links, and the transmit BF vectors at the access point (AP) were designed based on the instantaneous CSI of the effective channels, thus to reduce the channel training overhead and design complexity. Among these works, the manifold optimization (MO) in [7], the majorization-minimization (MM) method in [9], and the penalty dual decomposition (PDD) in [12] are widely used to handle the passive BF design.

On the other hand, future wireless communications aim to establish higher performance indicators and introduce new application scenarios. To meet the requirements of ultrahigh data rate for emerging applications, Terahertz (THz) wireless communication has emerged as a potential candidate technology for the wireless network [15]. Applying IRS to the THz channel can establish a virtual direct link, which effectively enhances signal reception and reduces the probability of signal blocking. Specifically, an IRS-assisted THz system with orthogonal frequency division multiple accesses was studied in [16]. Then, [17] investigated the THz massive multiple-input
multiple-output (MIMO) network assisted by an IRS. Besides, [18] studied the IRS-empowered THz communications, where a deep reinforcement learning-based BF design was proposed. Recently, the work in [19] investigated the sum-rate maximization design for an IRS-assisted THz network while, in [20], the authors studied the hardware design for IRS-enabled THz networks. These works suggested the potential of IRS in improving the performance of the THz network such as spectrum efficiency and coverage area. However, the optimization methods in this literature maybe too complicated to be achieved. Low computational complexity methods are needed to reduce the hardware cost and power consumption in IRS-enhanced networks, especially for high-frequency THz channel.

Motivated by above, in this work, we consider an IRS-aided multiuser THz downlink network. Our goal is to maximize the sum rate of all users by jointly optimizing the TX’s transmit BF and the IRS’s phase shifter. Since the obtained problem is a nonconvex optimization problem with the unit modulus constraint (UMC), we utilize the Lagrangian dual transform method to obtain an equivalent problem. Then, an alternating optimization (AO) algorithm is proposed, where the active BF is obtained by the bisection search method and the phase shifts are solved by an adaptive gradient descent (AGD) method with low computational complexity. Different from the commonly used methods such as MO, MM, and PDD, we formulate an unconstrained programming problem with respect to (w.r.t.) the phase coefficients. Then, we calculate the gradient vector of the objective function and update the coefficients according to the gradient descent algorithm. In fact, the major advantage of the AGD method is that the iterative step size is smartly determined by the second-order Taylor expansion or the Armijo-Goldstein search strategy, thus accelerating the convergence speed. Simulation results suggest the efficiency of the proposed design and reveal that a significant spectrum efficiency improvement can be obtained with the aid of an IRS.

The rest of this work is organized as follows. A system model and problem formulation are given in Section 2. Section 3 investigates the joint design problem, where an AO approach is proposed. Simulation results are illustrated in Section 4. Section 5 concludes this work.

**Notations:** Throughout the work, we use the upper case boldface letters for matrices and lower case boldface letters for vectors. The superscripts \((\cdot)^T, (\cdot)^\dagger\) represent the transpose, conjugate, and conjugate transpose, respectively. The trace of matrix \(A\) is denoted as \(Tr(A)\). \(a = \text{vec}(A)\) denotes to stack the columns of matrix \(A\) into a vector \(a\). Besides, \(I\) denotes an identity matrix with an appropriate size. \(\Re(a)\) denotes the real part of a complex variable \(a\). \(\mathcal{CN}(0, I)\) denotes a circularly symmetric complex Gaussian random vector with mean 0 and covariance matrix \(I\). \(\text{Diag}(a_1, \ldots, a_N)\) represents a diagonal matrix with \(a_1, \ldots, a_N\) on the main diagonal.

2. System Model and Problem Formulation

In this section, we introduce the IRS-aided THz system model and formulate the problem.

2.1. IRS Model. For an IRS with \(M\) elements, let \(\Theta = \text{Diag}(\theta_1, \ldots, \theta_M)\) denote the phase shift matrix at the IRS with \(\theta_m = e^{j\phi_m}, \forall m \in \{1, \ldots, M\}\), where \(\phi_m \in [0, 2\pi)\) represents the reflection coefficient (RC) of the \(m\)-th element. In practice, due to the hardware limitations, the RC of each element can only take a value from a discrete set. Let \(Q_p\) denote the number of bit resolutions for each element. Then, we have \(\theta_m \in \mathcal{F}_d \triangleq \{\theta_m | \theta_m = e^{j\phi_m}, \phi_m \in \mathcal{S}\}, \quad \mathcal{S} \equiv \{0, 2\pi/2Q_p, \ldots, 2\pi(2Q_p - 1)/2Q_p\}\); that is, the discrete phase shift values are assumed to be equally spaced in \([0, 2\pi)\). Furthermore, by setting \(Q_p \rightarrow \infty\), we obtain the continuous phase shifts; that is, \(\theta_m \in \mathcal{F}_c \triangleq \{\theta_m | \theta_m = e^{j\phi_m}, \phi_m \in [0, 2\pi)\}\), which leads to the performance upper bound for discrete phase shifts in practical systems.

2.2. Signal Transmission Model. Let us consider an IRS-aided MISO THz system as shown in Figure 1, which consists of one transmitter (Tx), one IRS, and \(K\) receivers. The Tx has \(N_t\) antennas, and the IRS has \(M\) reflecting elements, respectively. In addition, each receiver (Rx) is equipped with a single antenna, and the sets of these receivers are denoted as \(\mathcal{R} \equiv \{1, \ldots, K\}\). The channel between Tx and the IRS is denoted as \(F \in \mathbb{C}^{M \times N_t}\). Besides, the channel between Tx and the \(k\)-th Rx is denoted as \(h_{T,K} \in \mathbb{C}^{N_t \times 1}\), while the channel between the IRS and the \(k\)-th Rx is denoted as \(h_{R,K} \in \mathbb{C}^{M \times 1}\), respectively. In addition, an IRS controller is used to coordinate the information exchange and signal transmission between Tx and IRS.

Now, we present the THz channel model. Although there are a few scattering components in THz network, their power is much lower (more than 20 dB) than that of the line-of-sight (LoS) component, and thus, we only consider the LoS component and ignore the other scattering components [16]. Accordingly, \(F\) can be expressed as \(F = q(f, d)\mathcal{F}\), where \(q(f, d)\) is the complex path gain satisfying \(q(f, d) = ce^{-1/2\pi(\tau f)^d}\), where \(c\) is the speed of light, \(\ell\) is the central frequency, \(\tau(f)\) represents the medium absorption factor, and \(d\) is the link distance. Besides, \(\mathcal{F}\) can be expressed as \(\mathcal{F} = a_t(\varphi^{\text{inc}})a_r^H(\varphi^{\text{dec}})\), with \(a_t(\varphi^{\text{inc}})\) and \(a_r(\varphi^{\text{dec}})\) are the steer vectors of Tx and IRS;
for example, \( a_0(\theta_{\text{AoD}}) = 1/\sqrt{N_t} \), \( a_{\text{AoA}}(\theta) = 1/\sqrt{\lambda} \), \( e^{i2\pi/\lambda(N_t-1)\sin\theta_{\text{AoD}}} \), \( e^{i2\pi/\lambda(N_t-1)\sin\theta_{\text{AoA}}} \), \( \ldots \), \( e^{i2\pi/\lambda(N_t-1)\sin\theta_{\text{AoD}}} \), respectively, while \( d_i \) and \( d_r \) are the antenna separation distance at Tx and IRS, respectively, \( \lambda \) is the wavelength, \( \theta_{\text{AoD}} \) and \( \theta_{\text{AoA}} \) are the angle of departure and arrival, respectively. The rest channel can be defined similarly.

The transmit signal \( x \) can be written as

\[
x = \sum_{k=1}^{K} w_k s_k,
\]

where \( s_k \in \mathbb{C} \) is the information for the \( k \)-th Rx, and \( w_k \in \mathbb{C} \) is the transmit BF for the \( k \)-th Rx, respectively.

Then, the signals received by the \( k \)-th Rx are given by

\[
y_k = (h_{T,k}^H + h_{R,k}^H \gamma F) x + n_k,
\]

where \( n_k \) denotes the antenna noise at the \( k \)-th Rx with \( n_k \sim \mathcal{CN}(0, \sigma_n^2) \).

In fact, by defining \( \theta = [\theta_1, \ldots, \theta_M]^T \), we have

\[
h_{T,k}^H + h_{R,k}^H \Theta^H F = h_{T,k}^H \Theta^H F + \Theta^H \text{Diag}(h_{R,k}^H) F = \begin{bmatrix} H_{R,k} \end{bmatrix} \begin{bmatrix} \Theta^H \end{bmatrix} \begin{bmatrix} H_{T,k} \end{bmatrix}.
\]

Thus, the signal-to-interference-noise-ratio (SINR) for the \( k \)-th Rx can be written as

\[
Y_k = \frac{\| \Theta^H H_k w_k \|^2}{\sum_{j=1,j \neq k}^{K} \| \Theta^H H_k w_j \|^2 + \sigma_{n,k}^2} = \frac{\| \Theta^H H_k w_k \|^2}{\sum_{j=1,j \neq k}^{K} \| \Theta^H H_k W_{-k} \|^2 + \sigma_{e,k}^2},
\]

where \( W_{-k} \equiv [w_1, \ldots, w_{k-1}, w_{k+1}, \ldots, w_K] \).

### 3. Problem Formulation.

In this work, we aim to maximize the sum rate of all the users by jointly designing \( w_k \) and \( \hat{\theta} \), subject to the transmit power constraint and the UMC. Thus, the problem is formulated as

\[
P1: \max_{w_k, \hat{\theta}} f_1(w_k, \hat{\theta}) = \sum_{k=1}^{K} \log_2 (1 + Y_k), \tag{5a}
\]

s.t. \( \sum_{k=1}^{K} \| w_k \|^2 \leq P_s, \tag{5b} \)

\[
|\hat{\theta}_m| = 1, \quad \forall m \in \{1, \ldots, M\}, \tag{5c}
\]

where \( P_s \) is the power budget at the Tx.

It is generally difficult to solve (5a)–(5c) due to the nonconcave objective function \( f_1(w_k, \hat{\theta}) \) and the nonconvex constraint (5c). In this work, we try to solve P1 efficiently. First, we decouple the optimization variables to make P1 tractable.

### 3.3. The Lagrangian Dual AO Method

In this section, we decouple \( P1 \) into several tractable subproblems and obtain the solution to these subproblems.

#### 3.3.1. The Lagrangian Dual Transformation.

To tackle the logarithm function in (5a), we apply the newly proposed Lagrangian dual transform method in [21]. To be specific, \( P1 \) can be equivalently rewritten as

\[
%P1': \max_{w_k, \hat{\theta}, \alpha} f_1(w_k, \hat{\theta}, \alpha), \tag{6a}
\]

s.t. (5b), \tag{6b}

where \( \alpha \) refers to \([\alpha_1, \ldots, \alpha_K]^T\), and \( \alpha_k \) is an auxiliary variable w.r.t. \( y_k \), and the new objective function is defined by

\[
f_{1\alpha}(w_k, \hat{\theta}, \alpha) = \sum_{k=1}^{K} \log_2 (1 + \alpha_k) - \sum_{k=1}^{K} \alpha_k - \sum_{k=1}^{K} \frac{(1 + \alpha_k)Y_k}{1 + Y_k} \tag{7}
\]

With the conclusion in [21], it is known that for \( P1' \), when \( \{w_k, \hat{\theta}\} \) is fixed, the optimal \( \alpha_k \) is \( \alpha_k^* = Y_k \). Besides, for a fixed \( \alpha \), optimizing \( \{w_k, \hat{\theta}\} \) is reduced to

\[
%P1'': \max_{\alpha, \hat{\theta}} \sum_{k=1}^{K} \frac{(1 + \alpha_k)Y_k}{1 + Y_k} \tag{8a}
\]

s.t. (5b). \tag{8b}

Using \( Y_k \) in (4), the objective function (8a) is rewritten as a new function of \( \{w_k, \hat{\theta}\} \) as

\[
f_{2}(F, \theta, \alpha) = \sum_{k=1}^{K} (1 + \alpha_k)Y_k/1 + Y_k = \sum_{k=1}^{K} \frac{|\Theta^H H_k w_k|^2}{\sum_{j=1,j \neq k}^{K} |\Theta^H H_k W_{-k}|^2 + \sigma^2_n} \tag{9}
\]

Thus, with given \( \alpha \), optimizing \( \{w_k, \hat{\theta}\} \) becomes

\[
P2: \max_{w_k, \hat{\theta}} f_2(w_k, \hat{\theta}) \tag{10a}
\]

s.t. (5b). \tag{10b}

In this subsection, we have introduced the Lagrangian dual method to transform (5a)–(5c) into (10a)–(10b). In the next subsection, we will propose an AO method to solve (10a)–(10b) efficiently.

### 3.2. The AO Method

It is known that \( P2 \) is the multiple-ratio fractional programming (FP) problem. By introducing the auxiliary variable \( \beta_k \in \mathbb{C} \) and utilizing the quadratic transform proposed in [22], we reformulate \( f_2(w_k, \hat{\theta}) \) as
\[ f_{2\beta}(w_k, \hat{\theta}, \beta) = \sum_{k=1}^{K} 2\sqrt{(1 + \alpha_k) \Re \{ \beta_k^* \hat{\theta} H_k w_k \}}, \]  
(11)

\[ -\sum_{k=1}^{K} |\beta_k|^2 \left( \sum_{i=1}^{K} |\hat{\theta} H_k w_i|^2 + \sigma_k^2 \right), \]  
(12)

where \( \beta = [\beta_1, \ldots, \beta_K]^T \).

Then, based on [22], solving problem P2 is equivalent to solving the following problem over \( \{w_k, \hat{\theta}\} \) and \( \beta \):

\[
P_2' \quad \max_{w_k, \hat{\theta}, \beta} f_{2\beta}(w_k, \hat{\theta}, \beta).
\]  
(13a)

s.t. (5b).  
(13b)

In fact, with given \( \{w_k, \hat{\theta}\} \), P2' is convex w.r.t. \( \beta \), since the objective is the difference between the linear function and the quadratic function, thus the constraint is convex.

Then, with given \( \{\beta, \hat{\theta}\} \), P2' is convex w.r.t. \( w_k \), since the objective is convex and the constraint is convex. However, with given \( \{w_k, \beta\} \), P2' is nonconvex w.r.t. \( \hat{\theta} \). The main reason is that the UMC constraint is nonconvex w.r.t. \( \hat{\theta} \).

A common method for solving P2' is alternatively updating the variables by solving the corresponding subproblems w.r.t. one of them while fixing the others [23]. To obtain the solution in an efficient way, we introduce the following lemma.

**Lemma 1** [23]: The optimal \( \beta_k \) for a given \( \{w_k, \hat{\theta}\} \) is

\[ \beta_k^* = \sqrt{(1 + \alpha_k) \hat{\theta} H_k w_k / \sum_{i=1}^{K} |\hat{\theta} H_k w_i|^2 + \sigma_k^2} \]  
(14)

Proof: \( \beta_k^* \) can be obtained by setting \( \partial f_{2\beta} / \partial \beta_k \) to zero.

In addition, by the first-order condition, the optimal \( f_k \) for (11) is

\[ w_k^* = \sqrt{(1 + \alpha_k) \beta_k \left( \lambda I + \sum_{i=1}^{K} |\beta_i|^2 H_i^H \hat{\theta} H_i H_k \right)^{-1}} H_k^H \hat{\theta}, \]  
(15)

where \( \lambda \) is the dual variable introduced for the power constraint, which is determined by

\[ \lambda^* = \min_{\lambda \geq 0} \sum_{K} \|w_k\|^2 \leq P, \]  
(16)

and can be obtained by the bisection search method [24].

In the following part, we will solve the subproblem w.r.t. \( \hat{\theta} \).

\[ \Box \]

### 3.3. The Optimization of the Phase Shifter

In fact, the main difficulty part of (11) is the UMC for \( \hat{\theta} \). According to (11) and doing some mathematical operations, we obtain the following problem w.r.t. \( \hat{\theta} \):

\[
\min_{\hat{\theta}} \hat{\theta}^H U \hat{\theta} + 2 \Re \{ t^T \hat{\theta} \},
\]  
(17a)

s.t. \([\theta]_m = e^{j\varphi_m}, \varphi_m \in S,\]  
(17b)

where

\[
\varphi = [\varphi_1, \ldots, \varphi_M]^T
\]  

consider \( \theta \) as a function of \( \varphi \), which is given by \( \theta = [\varphi_j, \varphi_k]^T \). Then, by assuming \( Q_{\varphi} \rightarrow \infty \), we have the following problem:

\[
\min_{\varphi} h(\varphi) = g(\varphi)^H U g(\varphi) + 2 \Re \{ t^T g(\varphi) \},
\]  
(19)

which is an unconstrained function w.r.t. \( \varphi \). Thus, the AGD algorithm is able to find a locally optimal solution for (19). Specifically, the partial derivative \( \partial h(\varphi) / \partial \varphi_m \) is given as

\[
\frac{\partial h(\varphi)}{\partial \varphi_m} = j \sum_{n=1}^{M} \Re \{ U_{m,n} e^{j(\varphi_n - \varphi_m)} \} - j \sum_{n=1}^{M} \Re \{ U_{m,n} e^{j(\varphi_n - \varphi_m)} \} + j[t]^m e^{j\varphi_m} - j[t]^m e^{-j\varphi_m}.
\]  
(20)

After computing all the \( \partial h(\varphi) / \partial \varphi_m \), we obtain the following gradient vector \( \nabla_{\varphi} h(\varphi) \).
\[ \nabla_{\phi} h(\phi) = \begin{bmatrix} \partial h(\phi) \over \partial \phi_1 , \partial h(\phi) \over \partial \phi_2 , \ldots , \partial h(\phi) \over \partial \phi_M \end{bmatrix}^T. \]  

(21)

Following the gradient direction \( \nabla_{\phi} h(\phi) \), the value of \( h(\phi) \) will descend by updating \( \phi \) with \( \phi - \lambda \nabla_{\phi} h(\phi) \), where \( \lambda \) is the iterative step size. Thus, in the \( i \)-th iteration, the update of \( \phi^{(i+1)} \) and \( h(\phi^{(i+1)}) \) can be, respectively, given as

\[ \phi^{(i+1)} = \phi^i - \lambda \nabla_{\phi} h(\phi^i), \]  

(22a)

\[ h(\phi^{(i+1)}) = h(\phi^i) - \lambda \nabla_{\phi} h(\phi^i). \]  

(22b)

In fact, (22a)–(22b) is the main idea of the conventional gradient descent (CGD) algorithm, where \( \lambda \) is commonly a constant determined by the simulation experiment, which suffers high complexity and low efficiency. Thus, we propose a novel AGD algorithm to choose a suitable step size \( \lambda' \) for each step during the iterative process. Specifically, we first expand (22b) as

\[ h(\phi^{(i+1)}) = g(\phi^{(i+1)})^H U g(\phi^{(i+1)}) + 2R \{ t^T g(\phi^{(i+1)}) \}, \]  

(23)

\[ = R \left( \sum_{q=1}^{M} e^{-j\phi_q} \sum_{p=1}^{M} \left[ \phi_q + 1 \right] \{ U \} q,p + 2 \{ t \} q \right) \left( \sum_{q=1}^{M} e^{-j\phi_q} \sum_{p=1}^{M} \left[ \phi_q + 1 \right] \{ U \} q,p + 2 \{ t \} q \right), \]  

(24)

where \( \Delta \phi = -\lambda \partial h(\phi)/\partial \phi \), \( \forall m \in \{ 1, \ldots , M \} \).

According to (22), the partial derivative terms \( \partial h(\phi^i)/\partial \phi_q \) and \( \partial h(\phi^i)/\partial \phi_q \) of the gradient vector \( \nabla_{\phi} h(\phi^i) \) are obtained in the \( i \)-th iteration. For the \( (i+1) \)-th iteration, \( h(\phi^{(i+1)}) \) is only determined by the step size \( \lambda' \). To minimize the value of \( h(\phi^{(i+1)}) \), we try to find a better \( \lambda' \) by solving the following problem:

\[ \lambda^i = \arg \min \{ h(\phi^{(i+1)}) \}, \]  

(25)

\[ = \arg \min \{ R \left( \sum_{q=1}^{M} e^{-j\phi_q} \sum_{p=1}^{M} \left[ \phi_q + 1 \right] \{ U \} q,p + 2 \{ t \} q \right) \left( \sum_{q=1}^{M} e^{-j\phi_q} \sum_{p=1}^{M} \left[ \phi_q + 1 \right] \{ U \} q,p + 2 \{ t \} q \right) \}, \]  

(26)

For the quadratic form \( C_0 + C_1 \lambda^i + C_2 (\lambda^i)^2 \) in (27), if \( C_2 > 0 \), the optimal \( \lambda^i \) is given by \( \lambda^i = -C_1/(2C_2) \). On the other hand, if \( C_2 < 0 \), we can find an appropriate \( \lambda' \) by certain advanced line search method such as the Armijo-Goldstein search strategy [4].

At the end of the AGD process, each entry of \( \phi^* \) is mapped into the nearest discrete phase shift from \( \mathcal{F} \), which is given by

\[ \phi_m \leftarrow \text{round} \left( \frac{-\phi_m}{2\pi/2^{Q}} \right) \times \frac{2\pi}{2^{Q}}, \]  

(32)

where \( \text{round} \{ \} \) means rounding to the nearest integer.

The whole procedure of the AGD algorithm is illustrated in Algorithm 1, where \( \epsilon \) denotes the accuracy.

Thus, we have finished the joint BF and phase shifters design. The whole AO procedure is summarized in Algorithm 2, where \( SR^i \) is the obtained optimal value in the \( I \)-th iteration for (5a)–(5c).

### 4. Simulation Results

The simulation scenario is shown in Figure 2, where there are one Tx, one IRS, and 4 users. A three-dimensional (3D) coordinate system is considered, where the Tx and the IRS are located at \((0, m, 0, m)\) and \((30, m, 10, m)\), respectively. Besides, we assume that the users are randomly distributed in a circle centered at \((40, 0, m, 2 m)\) with a radius of 5 m. Unless otherwise specified, the following settings are assumed: \( f = 340 \text{ GHz} \), \( N_t = 8 \), \( M = 50 \), \( P_s = 20 \text{ dB} \), \( \sigma_k = -70 \text{ dBm} \), \( \forall k \), and the medium absorption factor is 0.0033/m [16].
Firstly, the convergence behaviour of the AGD and CGD algorithms is tested. From Figures 3 and 4, we can see that for different $N_t$ and $M$, the sum rate increases with the iteration numbers and gradually converges almost in 50 iterations for the AGD algorithm. However, the CGD method needs almost 200 iterations to converge, which leads to lower efficiency. This comparison demonstrates the efficiency of the AGD method.

Then, we study the convergence behaviour of the AO algorithm. From Figure 5, we can see that for different $N_t$ and $M$, the sum rate always converges almost in 20 iterations, which suggests the practicability of the AO algorithm.

4.1. Performance Evaluation. To highlight the superiority of the proposed scheme, we compare the proposed algorithm with the following methods: (1) the random IRS method, for example, choosing the phase shifter randomly; (2) the no IRS-assisted case; (3) the continuous RC case, which can be seen as the upper bound of the proposed design. These designs are labeled as “Proposed method,” “Random IRS,” “No IRS,” and “Continuous RC,” respectively.
Firstly, in Figure 6, we show the sum rate versus the transmit power budget $P_s$. From this figure, we can see that the sum rate increases with $P_s$ for all these methods, while the proposed method achieves better performance than other schemes, and the performance gap between the discrete RC case and the continuous RC case is relatively small, which suggests the superiority of the discrete RC design.

Then, in Figure 7, we plot the sum rate versus the number of reflecting elements $M$. From this figure, we can see that more $M$ leads to a higher sum rate, since with larger $M$, the signal power received by the IRS is improved, and the reflected signal power received by the users will increase when the phase shifter is optimized properly. Besides, with large $M$, the performance gap between the proposed method and the random IRS scheme is enlarged, since the random IRS manner only exploits the array gain; thus, the sum rate increases slowly. This result suggests that properly optimizing the phase shifter can improve the spectrum efficiency apparently.

5. Conclusions
In this paper, we have investigated the joint BF and phase shifters design in an IRS-aided THz network. The formulated nonconcave sum-rate maximization design was recast by the Lagrangian dual transform. Then, an AO algorithm...
was proposed to solve the equivalent problem, where the phase shifters design was addressed by a computational efficient AGD method. Simulation results showed the effectiveness of the proposed scheme.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

A preprint has previously been published in [16].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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References


