Reflection Resource Management for Intelligent Reflecting Surface Aided Wireless Networks

Yulan Gao, Chao Yong, Zehui Xiong, Student Member, IEEE, Jun Zhao, Member, IEEE, Yue Xiao, Member, IEEE, Dusit Niyato, Fellow, IEEE

Abstract

Intelligent reflecting surface (IRS) exploits large reflection elements to proactively steer the incident radio-frequency wave towards destination terminals (DTs), which is a promising solution to build a programmable wireless environment for 5G and beyond systems. In this paper, the adoption of an IRS for multiple single-antenna source terminal (ST)-DT pairs in two-hop networks is investigated. Different from the previous studies on IRS that merely focused on tuning the reflection coefficient of all the reflection elements at IRS, in this paper, we consider the true reflection resource (elements) management. Specifically, the true reflection resource management can be realized via trigger module selection based on our proposed IRS architecture that all the reflection elements are partially controlled by multiple parallel switches of controller. As the number of reflection elements increases, the true reflection resource management will become urgently needed in this context, which is due to the non-ignorable energy consumption. Moreover, the proposed modular architecture of IRS is designed to make the reflection elements part independent and controllable. As such, our goal is to maximize the minimum signal-to-interference-plus-noise ratio (SINR) at DTs via a joint trigger module subset selection, transmit
power allocation of STs, and the corresponding passive beamforming of the trigger modules, subject to per ST power budgets and module size constraint. Whereas this problem is NP-hard due to the module size constraint, to deal with it, we transform the hard module size constraint into the group sparse constraint by introducing the mixed row block $\ell_{1,2}$-norm, which yields a suitable semidefinite relaxation. Additionally, the parallel alternating direction method of multipliers (PADMM) is proposed to identify the trigger module subset, and then subsequently the transmit power allocation and passive beamforming can be obtained by solving the original minimum SINR maximization problem without the group sparse constraint via partial linearization for generalized fractional programs. Simulation results demonstrate the effectiveness of the proposed PADMM algorithm. Finally, performance comparison as a function of the system parameters confirms that the proposed PADMM is highly efficient since each iteration of it can be calculated in closed-form.

Index Terms

Intelligent reflecting surface (IRS), transmit power allocation, passive beamforming, reflection resource management, parallel alternating direction and method of multipliers (PADMM), group sparsity, modular architecture.

I. INTRODUCTION

A. Background and Motivation

It is evident that the fast prolific spread of Internet-enabled mobile devices will bring to a 1000-fold increment of network capacity by 2020 [1], which can not be supported by the forth-generation (4G) mobile networks, i.e., long-term evolution (LTE) and LTE-advanced (LTE-A) technologies. Therefore, a lot of attention from research community was mainly focused on the design of fifth generation (5G) wireless technologies, e.g., heterogeneous networks (HetNets), peer-to-peer (P2P) communications, massive multiple-input multiple-output (mMIMO), and mmWave communication, which should address high quality of service (QoS), coverage, seamless connectivity with a high user speed, and limited power consumption [2]–[4]. However, due to the highly demanding of forthcoming and future wireless networks (5G and beyond), a serious issue in the wireless industry today is to meet the soaring demand at the cost of resulting power consumption [2], [5]. For instance, for mMIMO, adopting a higher amount of base station antennas to serve multiple users concurrently not only entails the increased radio frequency chains and maintenance cost, but also significantly decreases the overall performance level. Therefore, addressing this issue means introducing innovation technologies in future/beyond-5G wireless
networks, which are spectral-energy efficient and cost-effective [6]. As a result, intelligent reflecting surface (IRS) has been treated as a promising innovation technology for future/beyond-5G wireless networks supporting reconfigurable wireless environment via exploiting large software-controlled reflection elements [7]–[10]. The IRS provides a new degree of freedom to further enhance the wireless link performance via proactively steering the incident radio-frequency wave towards destination terminals (DTs) as its important feature, which is expected to play an important role for beyond-5G networks in future.

The IRS-aided communications refer to the scenario that a large number of software-controlled reflection elements with adjustable phase shifts for reflecting the incident signal. As such, the phase shifts of all reflection elements can be tuned adaptively according to the state of networks, e.g., the channel conditions and the incident angle of the signal by the source terminal (ST). Notably, different from the conventional half and full-duplex modes, in IRS-aided communication, the propagation environment can be improved without incurring additional noise at the reflector elements. Currently, considerable research attention has been paid for IRS-aided communications [6], [11]–[17]. Among the early contributions in this area, [6] summarized the main communication applications and competitive advantages of the IRS technology. For the IRS-aided point-to-point multiple-input-single-output (MISO) wireless system with single user, [11] investigated the total received signal power maximization problem by jointly optimizing the transmit beamforming and the passive beamforming. In the spirit of these works, a vast corpus of literature focused on optimizing active-passive beamforming for unilateral spectral efficiency (SE) maximization subject to power constraint. For instance, [12] proposed a fractional programming based alternating optimization approach to maximize the weighted SE in IRS-aided MISO downlink communication systems. In particular, three assumptions for the feasible set of reflection coefficient (RC) were consider at IRS, including the ideal RC constrained by peak-power, continuous phase shifter, and discrete phase shifter. Meantime, in MISO wireless systems, the problem of minimizing the total transmit power at the access point was considered to energy-efficient active-passive beamforming [13], [16]. [13] formulated and solved the total transmit power minimization problem by joint active-passive beamforming design, subject to the signal-to-interference-plus-noise ratio (SINR) constraints, where each reflection element is a continuous phase shifter. Along this direction, considering the discrete reflect phase shifts at the IRS, the same optimization problem was further studied in [16]. Notably, the aforementioned studies for IRS-aided communications were based on the premise of ignoring the power consumption at
IRS. In contrast, in [17], an energy efficiency (EE) maximization problem was investigated by developing a realistic IRS power consumption model, where IRS power consumption relies on the type and the resolution of meta-element.

The common assumption in the existing studies for IRS-aided communications is that all the reflection elements are used to reflect the incident signal, i.e., adjusting RC of each meta-element simultaneously each time. However, along with the use of a large number of high-resolution reflection elements, especially with continuous phase shifters, triggering all the reflection elements every time may result in significant power consumption. Moreover, the hardware support for the IRS implementation is the use of a large number of tunable metasurfaces. Specifically, the tunability feature can be realized by introducing mixed-signal integrated circuits (ICs) or diodes/varactors, which can vary both the resistance and reactance, offering complete local control over the complex surface impedance [7]–[9]. According to the IRS power consumption model presented in [17], triggering the entire IRS not only incurs increased power consumption, but also entails the increased latency of adjusting phase-shift. Therefore, realizing true reflection resource management is significantly important for IRS-aided communications.

B. Novelty and Contribution

In this paper, we consider the two-hop peer-to-peer (P2P) network in which multiple single-antenna STs reaches the corresponding single-antenna DTs through an IRS that forwards a suitably phase-shifted version of the transmitted signal. The goal is to maximize the minimum SINR at DTs under the maximum transmit power constraints for STs and RC constraints, via joint reflection resource management, transmit power allocation, and the corresponding passive beamforming. Specifically, the novelty and contributions of this paper mainly lie in the following aspects.

1) Modular Architecture of IRS: For the first time, we develop a modular architecture of IRS that divides all the reflection elements into multiple modules which can be independently controlled by parallel switches. Each module contains multiple reflection elements, since the unit meta-element size is subwavelength [8]. As mentioned in [6], the IRS is programmatically controlled by controller, and hence, from an operational standpoint, independent module triggering can be implemented easily. Therefore, the proposed architecture of IRS allows the realization of the true reflection resource management, since each module is independently controlled by its switch.
2) Trigger Module Selection: The true reflection resource management can be realized via trigger module selection, which is based on the architecture that all the reflection elements are partially controlled by parallel switches of controller. Specifically, we formulate the minimum SINR maximization problem to optimize the trigger module selection, transmit power allocation, and the corresponding passive beamformer design under maximum transmit power and module size constraints. To the best of our knowledge, this is the first work that studies the trigger module selection.

3) Module Size Constraint Convex Relaxation: The joint optimization problem is NP-hard due to the module size constraint, there is no known efficient and standard method to solve the problem. Furthermore, an exhaustive combinatorial search over all possible cases to obtain a globally optimal solution with high computational complexity which is prohibitive in practice. Thus, we aim to develop a low complexity and effective method to obtain a near-optimal solution of the formulated problem. Specifically, to deal with the joint optimization problem, we transform the hard module size constraint into the group sparse constraint by introducing the mixed row block $\ell_{1,2}$-norm [18], which yields a suitable semidefinite relaxation. Based on this insight, a tractable convex problem can be formulated from the perspective of group sparse optimization. To solve this problem, the parallel alternating direction method of multipliers (PADMM) is used to identify the trigger modules subset, and subsequently both the transmit power allocation and the corresponding passive beamforming can be obtained by solving the original max-min problem via generalized fractional programs. Specifically, in the second part of this procedure, an algorithm based on partial linearization is proposed to deal with generalized fractional programs. Finally, an efficient custom-made algorithm is developed to distributively solve the trigger module identification problem. In particular, a simple closed solution can be derived in each iteration.

4) Simulations: For IRS-aided communications, the main applications and competitive advantages over existing technologies, e.g., half-duplex and full-duplex relay, were investigated in vast literature [11], [13], [17]. The goal of this paper is to investigate the true reflection resource management not to compare the communication performance of IRS and relay mechanisms. Therefore, in this paper, in order to assess the performance of the PADMM algorithm, we compare it with two methods, i.e., method of exhaustive search (MES) and method of randomly select (MRS) the trigger modules. From the simulation results, we can conclude that the PADMM algorithm achieves the performance very close to that of
C. Paper Outline and Notation

The reminder of this paper is organized as follows. The modular architecture of IRS, trigger module selection, the hard sparsity constraint convex relaxation, and optimization problem formulation are presented in Section II. Section III describes the trigger module identification and minimum SINR maximization. Section IV reports numerical results that are used to assess the performance of the proposed PADMM algorithm and to make comparisons with alternatives. Conclusions are presented in Section V.

Matrices and vectors are denoted by bold letters. I_N, 0_N, and e_n are the N x N identity matrix, the N x 1 all-zero column vector, and the N x 1 elementary vector with a one at the n-th position, respectively. A^T, A^†, A^{-1}, and ||A||_2 denote transpose, Hermitian, inverse, and Frobenius norm of matrix A, respectively. Re(·) and |·| denote real part and modulus of the enclosed vector, respectively.
II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

As shown in Fig. 1, we consider a two-hop link of slowly-varying P2P network where an IRS is adjoined to $K$ user pairs, where a user pair includes one ST and one DT, and each user terminal is equipped with a single antenna. Let $\mathcal{S} := \{s_1, s_2, \ldots, s_K\}$ and $\mathcal{D} := \{d_1, d_2, \ldots, d_K\}$ be the sets of STs and DTs, respectively. The index set of user pairs is denoted by $\mathcal{K} := \{1, 2, \ldots, K\}$. The modular architecture of the IRS is shown in Fig. 2 for which multiple parallel controlled switches (on/off) are considered. The setting can be regarded as generalization of the IRS architecture introduced in [6]. Specifically, the total $N$ reflecting elements are divided into $M$ modules controlled by parallel switches, each module consists of $L$ elements, and $N = ML$. Define $\mathcal{M} := \{1, 2, \ldots, M\}$ as the index set of reflection modules. Consequently, reflection resource management of IRS can be realized by the modular of reflection elements and the parallel switches design. The channels of two-hop communications are assumed to experience quasi-static block fading, i.e., the channel coefficient from the STs to the IRS and the IRS to the DTs remain constant during each time slot, but may vary from one to another [19]. Let $h_{k,m} \in \mathbb{C}^{L \times 1}$ and $g_{m,k} \in \mathbb{C}^{L \times 1}$ denote the uplink channel vector from ST $k$ to the $m$th module of IRS and the downlink channel vector from reflection module $m$ to DT $k$, respectively. The associated passive beamformer at the $m$th module of IRS denoted by $\Phi^m = \text{diag}\{\phi_{(m-1)L+1}, \ldots, \phi_{(m-1)L+L}, \ldots, \phi_{mL}\} \in \mathbb{C}^{L \times L}$, where $\phi_{(m-1)L+l}$ is the entry of reflecting coefficient matrix, $\forall m \in \mathcal{M}, l = 1, 2, \ldots, L$. We assume that all the modules can potentially serve the BS transmitting. Note that if all modules are triggered to serve the ST-DT communications, the problem becomes a special case which is simpler to solve. The passive beamformer at IRS denoted by $\Phi \in \mathbb{C}^{N \times N}$, and the associated channel from ST $k$ to the IRS and the downlink channel from the IRS to DT $k$, denoted by $h_k \in \mathbb{C}^{N \times 1}$ and $g \in \mathbb{C}^{N \times 1}$, respectively, are defined as

$$\Phi := \text{diag}\{\Phi^1, \Phi^2, \ldots, \Phi^M\},$$

$$h_k := [(h_{k,1})^T, (h_{k,2})^T, \ldots, (h_{k,M})^T]^T, \forall k \in \mathcal{K},$$

$$g_k := [(g_{1,k})^T, (g_{2,k})^T, \ldots, (g_{M,k})^T]^T, \forall k \in \mathcal{K}.$$ 

In addition, in the following analysis—for the sake of simplicity—we consider that the reflection coefficient is peak-power constrained [12]: $\mathcal{X} \triangleq \{\phi_{(m-1)L+l} : |\phi_{(m-1)L+l}| \leq 1, \forall m =$
In practice, the feasible set of reflecting coefficient $\mathcal{X}$ might be more complicated, such as in [10], [12], [17], but this feature is beyond the focus of this paper. The main purpose of this paper is to realize the true reflection resource management by introducing the modular architecture of IRS. Specifically, for the formulated maximization problem under module size constraint, the true reflection resource management can be implemented via trigger module selection.

Remark 1: As mentioned in [8], an intelligent surface can be realized by a control computer if it can determine the optimal reflection coefficient of IRS. Specifically, by introducing diodes or tunable integrated circuits (ICs) in each unit element [8], [9], the independently tuning reactive and absorption can be controlled by the computer. Therefore, the use of IRS in wireless communication systems is also energy consuming. Among the contributions in the mainstream research direction on IRS-aided communication systems, most studies assumed that the energy consumption on IRS is negligible, but this assumption is not realistic when the reflection size is large enough. In our proposed IRS architecture, we design the modularity to trigger the reflection resource rather than directly triggering the unit element, considering that the size of unit element is subwavelength. Different from the existing studies on IRS that merely focus on how to exploit the total reflection elements to proactively modify the wireless communication environment, we consider the true reflection resource management besides tuning the passive beamformer at the
IRS. The main purpose of this paper is to realize the management of the reflection resources (or elements) themselves by partially reflecting elements controlled by parallel switches.

Let $z_k$ denote the data symbol of ST $k$ and write $p_k$ for its corresponding power. The signal received at DT $k$ via IRS-aided link is expressed by

$$y_k = g_k^\dagger \Phi \sum_{k=1}^{K} \sqrt{p_k} h_k z_k + u_k$$

$$= g_k^\dagger \Phi \sqrt{p_k} h_k z_k + g_k^\dagger \Phi \sum_{j=1,j \neq k}^{K} \sqrt{p_j} h_j z_j + u_k, \forall k \in \mathcal{K},$$

where $u_k \sim \mathcal{CN}(0, \sigma^2)$ is the thermal noise experienced by DT $k$ and the second term accounts for the interference experienced by user pair $k$ from other user pairs $j \in \mathcal{K}, j \neq k$. Then, the SINR is achieved by user pair $k$ takes the form:

$$\text{SINR}_k = \frac{p_k \left| g_k^\dagger \Phi h_k \right|^2}{\sum_{j=1,j \neq k}^{K} p_j \left| g_j^\dagger \Phi h_j \right|^2 + \sigma^2}, \forall k \in \mathcal{K}.$$  \hspace{1cm} (3)

The problem design is to maximize the minimum SINR at all DTs, while satisfying the STs’ transmit power constraint $p_k^\text{max}, \forall k \in \mathcal{K}$, and the reflecting coefficient constraint $\Phi$; that is

\begin{equation}
\begin{align*}
(\text{O}) \quad & \max_{\{\Phi, \{p_k\}_{k=1}^{K}\}} \min_{k} \text{SINR}_k \\
\text{s. t.} \quad & p_k \leq p_k^\text{max}, \forall k \in \mathcal{K} \hspace{1cm} (5) \\
& \text{and} \ \Phi. \hspace{3cm} (6)
\end{align*}
\end{equation}

(\text{O}) is a non-convex optimization problem due to the non-convex objective function w.r.t. $\{p_k\}_{k=1}^{K}$ and $\Phi$, and there is no known efficient and standard method to obtain an optimal solution for (O). Instead, the focus is to design a low complexity and effective method for a suboptimal solution via exploiting the special structure of problem itself. The most suitable tool for this similar problems is the generalized fractional programs [20]–[22], since the numerator and denominator of SINR are continuous functions on variables. For this IRS-aided two-hop communication, the suboptimal solution of (O) can be obtained effectively by using generalized fractional programs and the alternating optimization technique [23] to separately and iteratively solve for $\{p_k\}_{k=1}^{K}$ and $\Phi$ [6], [10], [13], [17].
B. Trigger Module Selection

Here, we develop an optimization problem design to maximize the minimum SINR at DTs subject to the trigger module size constraint. Different from the previous studies that mainly focused on designing the appropriate transmit beamforming at the source nodes and passive beamforming at IRS, we design the trigger module selection at the IRS besides the active-passive beamforming optimization. As aforementioned before, in our proposed IRS architecture, all reflection elements are divided into modules which are triggered by multiple control switches in parallel. In the proposed modular architecture of IRS, the reflection elements management can be implemented instead of tuning all the entries at IRS. In this context, suppose now that only \(Q \leq M\) reflection modules are available, and thus only \(QL\) reflection elements can be serving the BS simultaneously. Inspired by \([18]\), the design problem is to jointly trigger the best \(Q\) out of \(M\) modules, and designing the transmit power \(\{p_k\}_{k=1}^{K}\) and the corresponding beamformer at IRS so that the minimum SINR among DTs is maximized, subject to the maximum transmit constraint and reflection coefficient.

Define the \(N \times 1\) vector \(\phi := [(\phi^1)^T, (\phi^2)^T, \ldots, (\phi^M)^T]^T\), where \(\phi^m := [\phi^m_{(m-1)L+1}, \ldots, \phi^m_{mL}]^T \in \mathbb{C}^{L \times 1}\) is the \(m\)th block of vector \(\phi\), \(\forall m = 1, 2, \ldots, M\). Denote the \(M \times 1\) vector \(\tilde{\phi} := [||\phi^1||_2, ||\phi^2||_2, \ldots, ||\phi^M||_2]^T\). For each module \(m \in \mathcal{M}\) at IRS not to be triggered, vector \(\phi^m\) must be set to zero, consequently, \(||\phi^m||_2 = 0\). Hence, the maximization of minimum SINR among DTs problem via joint reflection module trigger and active-passive beamformer design can be expressed by

\[
\text{(P0)} \max_{\{\phi, \{p_k\}_{k=1}^{K}\}} \min_k \text{SINR}_k \tag{7}
\]

\[
\text{ s. t. } p_k \leq p_k^{\max}, \forall k \in \mathcal{K} \tag{8}
\]

\[
||\tilde{\phi}||_0 \leq Q, \text{ and } \mathcal{X}, \tag{9}
\]

where the \(\ell_0\)-norm denotes the number of triggered reflection modules, i.e., \(||\tilde{\phi}||_0 := |\{m : ||\phi^m||_2 \neq 0\}|\), and \(Q \leq M\) is the upper bound of this number. Note that (P0) is NP-hard problem due to the non-convex \(\ell_0\)-norm, solving (P0) requires an exhaustive combinatorial search over all \(\binom{Q}{M}\) possible patterns of \(\tilde{\phi}\). Thus, in the following, we aim to develop computationally efficient method to obtain a sub-optimal solution. Specifically, we first study the trigger module selection via a convex sparsity-inducing approximation \([18], [24]\), i.e., identifying the trigger modules at IRS.
Then, the joint transmit power and the corresponding phase-shift can be obtained by using the generalized fractional programs and Taylor expansion.

C. Convex Relaxation and Problem Formulation

Define $A_k = \text{diag}(g_k^\dagger) \in \mathbb{C}^{N \times N}$, the $N \times 1$ vector $\mathbf{h}_{j,k} = A_k \mathbf{h}_j$, and the $(KN) \times 1$ vector $\mathbf{H}^k = [ (\mathbf{h}_{1,k})^T, (\mathbf{h}_{2,k})^T, \ldots, (\mathbf{h}_{k,k})^T, \ldots, (\mathbf{h}_{K,k})^T ]^T$. Thus, the expression of SINR$_k$ in (3) can be rewritten as

$$\text{SINR}_k = \frac{p_k \phi_k^\dagger \mathbf{h}_{k,k} \mathbf{h}_{k,k}^\dagger \phi_k}{\sigma^2 + \sum_{j=1, j \neq k}^K p_j \phi_j^\dagger \mathbf{h}_{j,k} \mathbf{h}_{j,k}^\dagger \phi_j}, \quad (10)$$

where $\phi_k = \sqrt{p_k} \phi$, $\forall k \in K$. Define the $N \times K$ matrix $\Phi = [\phi_1, \phi_2, \ldots, \phi_K]$. By introducing the mixed $\ell_{1,2}$-norm, which was first presented in the context of the group least-absolute selection and shrinkage operator (group Lasso) [25], the triggered module size can be effectively appropriated by replacing the $\ell_{0,2}$-norm with $\ell_{1,2}$-norm, i.e., $||\phi||_{1,2} \triangleq \sum_{m=1}^M ||\phi^m||_2$. Moreover, similar to the group-sparsity inducing norm $\ell_{1,2}$-norm of vectors, we define the mixed convex norm $\ell_{1,2}$ of matrix [26] as

$$||\Phi||_{1,2} = \sum_{m=1}^M ||\Phi^m||_2, \quad (11)$$

where $\Phi^m \in \mathbb{C}^{L \times K}$ represents the $m$th row block of matrix $\Phi$, i.e., $\Phi^m = [\sqrt{p_1} \phi^m_1, \ldots, \sqrt{p_K} \phi^m_K]$, $\forall m \in \mathcal{M}$. Notably, the mixed $\ell_{1,2}$-norm of matrix $\Phi$, which implies that each $||\Phi^m||_2$ (or equivalently $\phi^m$) is encouraged to be set to zero, therefore inducing group-sparsity. Thus, instead of using the hard sparsity constraint (9), the $\ell_{1,2}$-norm can be employed to promote sparsity, leading to

$$(P1-1) \quad \max_{\Phi} \min_k \frac{\phi_k^\dagger \mathbf{h}_{k,k} \mathbf{h}_{k,k}^\dagger \phi_k}{\sigma^2 + \sum_{j=1, j \neq k}^K \phi_j^\dagger \mathbf{h}_{j,k} \mathbf{h}_{j,k}^\dagger \phi_j} \tag{12}$$

$$\text{s.t.} \quad \sum_{m=1}^M \alpha_m ||\Phi^m||_2 \leq \delta, \tag{13}$$

$$\phi_k^\dagger \mathbf{e}_n e_k^\dagger \phi_k \leq p_k^\text{max}, \quad \forall k = 1, 2, \ldots, K; n = 1, 2, \ldots, N, \tag{14}$$
where $e_n \in \mathbb{R}^{N \times 1}$ is an elementary vector with a one at the $n$-th position; $\alpha_m > 0$ is the weighting factor reflecting the cost of keeping module $m$ triggering. Larger $\alpha_m$ means that module $m$ is more likely to be excluded from the IRS. Moreover, $\delta > 0$ controls the row block sparsity of $\Phi$.

By introducing an auxiliary variable $\gamma$, the joint trigger reflection module selection, transmit power, and the corresponding passive beamformer design problem (P1–1) can thus be equivalent to

$$(P1–2) \quad \max_{\Phi, \gamma} \gamma$$

$$\text{s.t.} \quad \frac{\Phi_k^\dagger h_{k,k} h_{k,k}^\dagger \Phi_k}{\sigma^2 + \sum_{j=1, j \neq k}^K \phi_j^\dagger h_{j,k} h_{j,k}^\dagger \phi_j} \geq \gamma, \forall k = 1, 2, \ldots, K$$

$$\sum_{m=1}^M \alpha_m \|\Phi^m\|_2 \leq \delta, \quad (17)$$

$$\phi_k^\dagger e_n e_n^\dagger \phi_k \leq p^{\max}_k, \forall k = 1, 2, \ldots, K; n = 1, 2, \ldots, N. \quad (18)$$

Clearly, for large $\gamma$, problem (P1–2) can be infeasible due to the resulting stringent SINR constraints, strong interference, and insufficient number of triggered reflection modules. Thus, in the following, problem (15)–(18) can be solved efficiently via bisection method for feasibility checking. Notably, this is a sufficient condition only, and the feasibility checking of (15)–(18) also can be solved directly by using CVX [27]. For the centralized algorithms as above, e.g., CVX, the problem dimension may be transformed to an additional big issue, due to the increasing collected information of all the user pairs and IRS, when the number of them is larger. In the next section, to develop a distributed algorithm, we fit (15)–(18) into the ADMM framework [23] and then reformulate it as a separable group Lasso problem. Finally, a custom-made partially distributed algorithm is developed. The proposed algorithm is computationally efficient since each step of ADMM can be computed in closed-form.

## III. Trigger Module Identification and the Minimum SINR Maximization

### A. Trigger Module Identification

As mentioned early, for a given $\gamma > 0$, the design problem (15)–(18) becomes the feasibility test one. In this context, the challenge in solving problem (P1–2) lies in the fact that its objective is non-differentiable and that the feasible set is nonconvex. To proceed further, for the fixed $\gamma$, we...
obtain the augmented Lagrangian duality theory, its augmented duality problem is zero. This means that the optimal solution of (P1–4) can be obtained by applying the augmented Lagrangian duality theory. (P1–4) is a convex minimization problem, and therefore, the duality gap between (P1–4) and (P1–3) is lower than δ, where (P1–3) is given by

\begin{equation}
(P1–3) \min_{\Phi} \sum_{m=1}^{M} \alpha_m \|\Phi^m\|_2
\end{equation}

\begin{equation}
\text{s.t. } \sqrt{(1 + \gamma^{-1})} \sum_{k=1}^{K} \mathbf{h}_{k,k}^\dagger \bar{\Phi} \leq \|\mathbf{H}^k \bar{\Phi}, \sigma\|_2, \forall k = 1, 2, \ldots, K
\end{equation}

\begin{equation}
\sum_{k=1}^{K} \|\bar{\Phi}_{k,k}\|_2 \leq \mathbf{p}_k^{\max}, n = 1, 2, \ldots, N; k = 1, 2, \ldots, K.
\end{equation}

The constraint (20) of (P1–3) is the reformulation of SINR constraint (16) relies on the second-order cone program [28], where the \((NK) \times K\) matrix \(\bar{\Phi}\) is defined as

\begin{equation}
\bar{\Phi} = \begin{bmatrix}
\bar{\Phi}_1 & 0 & \cdots & 0 \\
0 & \bar{\Phi}_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \bar{\Phi}_K
\end{bmatrix}.
\end{equation}

Let us define \(\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_K] \in \mathbb{C}^{(NK) \times K}\), and then introduce a \(K \times (K+1)\) auxiliary matrix \(\mathbf{F} = [\mathbf{H}^\dagger \bar{\Phi}, \sigma \mathbf{1}_K]\). Furthermore, define \(f_{k,k} = \mathbf{h}_{k,k}^\dagger \bar{\Phi}_k\) and \(f_k = [\mathbf{H}^k \bar{\Phi}, \sigma] \in \mathbb{C}^{1 \times (K+1)}\) as the \(k\)-th diagonal element and the \(k\)-th row vector of \(\mathbf{F}\), respectively. Using these definitions and introducing a matrix variable \(\mathbf{W} = \bar{\Phi} \in \mathbb{C}^{N \times K}\), problem (19)–(21) can be reformulated as the following problem:

\begin{equation}
(P1–4) \min_{\{\Phi_k\}_{k \in \mathcal{K}}, \mathbf{W}, \mathbf{F}} \sum_{m=1}^{M} \alpha_m \|\mathbf{W}^m\|_2
\end{equation}

\begin{equation}
\text{s. t. } \sqrt{(1 + \gamma^{-1})} f_{k,k} \geq \|f_k\|_2, \forall k \in \mathcal{K}
\end{equation}

\begin{equation}
\sum_{k=1}^{K} \|\bar{\Phi}_{k,k}\|_2 \leq \mathbf{p}_k^{\max}, \forall n = 1, 2, \ldots, N; k = 1, 2, \ldots, K,
\end{equation}

\begin{equation}
\mathbf{W} = \bar{\Phi} \quad \mathbf{F} = [\mathbf{H}^\dagger \bar{\Phi}, \sigma \mathbf{1}_K].
\end{equation}

(P1–4) is a convex minimization problem, and therefore, the duality gap between (P1–4) and its augmented duality problem is zero. This means that the optimal solution of (P1–4) can be obtained by applying the augmented Lagrangian duality theory [29]. The partial augmented Lagrangian function of (P1–4) can be written as

\begin{equation}
L_c(\{\Phi_k\}_{k \in \mathcal{K}}, \mathbf{W}, \mathbf{F}, \Lambda, \Psi) = \sum_{m=1}^{M} \alpha_m \|\mathbf{W}^m\|_2 + \text{Re} \left\{ \text{Tr} \left[ \Lambda^\dagger (\mathbf{W} - \bar{\Phi}) \right] \right\} + \frac{c}{2} \|\mathbf{W} - \bar{\Phi}\|_F^2
\end{equation}

\begin{equation}
+ \left( \text{Re} \left\{ \text{Tr} \left[ \Psi^\dagger (\mathbf{F} - [\mathbf{H}^\dagger \bar{\Phi}, \sigma \mathbf{1}_K]) \right] \right\} + \frac{c}{2} \|\mathbf{F} - [\mathbf{H}^\dagger \bar{\Phi}, \sigma \mathbf{1}_K]\|_F^2 \right),
\end{equation}
where \( c > 0 \) is the penalty factor; \( \Lambda \in \mathbb{C}^{N \times K} \) and \( \Psi \in \mathbb{C}^{K \times (K+1)} \) are the Lagrangian matrix multipliers for \( W = \tilde{\Phi} \) and \( F = [\tilde{H}^t \tilde{\Phi}, \sigma 1_K] \), respectively. Note that the reformulated SINR constraints (24) as well as the boundary constraint (25) are not taken into the augmented Lagrangian function and they will be integrated into the optimal solution in the following. Particularly, we focus on solving:

\[
\begin{align*}
(\text{P1–5}) \quad & \max_{\{A, \Psi\}} \min_{\{\phi_k\}_{k \in K}, W, F} \quad L_c \left( \{\phi_k\}_{k \in K}, W, F, A, \Psi \right) \\
\text{s. t.} \quad & \sqrt{1 + \gamma^{-1}} f_{k,k} \geq ||f_k||_2, \forall k \in K \\
& \bar{\phi}_k e_n e_n^t \tilde{\phi}_k \leq p_k^{\text{max}}, \forall n = 1, 2, \ldots, N; k = 1, 2, \ldots, K.
\end{align*}
\]

We need decouple the optimization variables in \( L_c \) to make (P1–5) intractable. To be specific, dividing \( \{\phi_k\}_{k \in K}, W, \) and \( F \) into two blocks of \( \{\phi_k\}_{k \in K} \) and \( \{W, F\} \), we can apply the two-block ADMM framework [23] to solve (P1–4). In each iteration \( t \), we first update \( \{\phi_k\}_{k \in K} \) by solving \( \mathcal{P}_{\phi_k}(L_c) \)

\[
\begin{align*}
\mathcal{P}_{\phi_k}(L_c) : \min_{\phi_k} \Re \left\{ \Tr \left[ \lambda^{k\dagger} (w^k(t) - \bar{\phi}_k) \right] \right\} + & \frac{c}{2} ||w^k(t) - \bar{\phi}_k||^2_2 \\
+ & \left( \Re \left\{ \Tr \left[ \psi^{k\dagger} \left( f^k(t) - \tilde{H}^{k\dagger} \bar{\phi}_k \right) \right] \right\} + \frac{c}{2} ||f^k(t) - \tilde{H}^{k\dagger} \bar{\phi}_k||^2_F \right) \\
\text{s. t.} \quad & \bar{\phi}_k e_n e_n^t \tilde{\phi}_k \leq p_k^{\text{max}}, \forall k = 1, 2, \ldots, K; n = 1, 2, \ldots, N,
\end{align*}
\]

where \( w^k \in \mathbb{C}^{N \times 1} \) and \( \lambda^k \in \mathbb{C}^{N \times 1} \) represent the \( k \)-th column of matrices \( W \) and \( \Lambda \), respectively; and \( \psi^k \in \mathbb{C}^{K \times 1} \) and \( f^k \in \mathbb{C}^{K \times 1} \) are the \( k \)-th column of matrices \( \Psi \) and \( F \), respectively. With the obtained \( \tilde{\Phi} \) (or \( \{\phi_k\}_{k \in K} \)), and then better solutions for \( W \) and \( F \) can be updated by solving the following problem:

\[
\begin{align*}
\mathcal{P}_{W,F}(L_c) : \min_{W, F} \quad & L_c(\tilde{\Phi}(t + 1), W, F, A, \Psi) \\
\text{s. t.} \quad & \sqrt{1 + \gamma^{-1}} f_{k,k} \geq ||f_k||_2, \forall k = 1, 2, \ldots, K.
\end{align*}
\]

Then, as shown in Appendix A, the optimal \( \tilde{\Phi}_k \) and \( W \) can be obtained as in Theorem 1.

**Theorem 1:** For given \( \Lambda \) and \( \Psi \), the optimal \( \{\phi_k\}^K_{k=1} \) of minimizing \( \mathcal{P}_{\phi_k}(L_c) \) is given by

\[
\begin{align*}
\bar{\phi}_k(t + 1) = \left( cI_{N \times N} + c\tilde{h}^k \tilde{h}^{k\dagger} + 2 \sum_{n=1}^{N} \mu^k_n e_n e_n^t \right)^{-1} \left( \lambda^k(t) + c w^k(t) + \tilde{h}^k \psi^k(t) + c \tilde{h}^k f^k(t) \right),
\end{align*}
\]

where \( \tilde{h}^k = [\tilde{h}_{k,1}, \tilde{h}_{k,2}, \ldots, \tilde{h}_{k,K}] \), and \( \mu^k_n \geq 0 \) is the Lagrangian multiplier of boundary constraint in (25). Moreover, the optimal \( W \) is given by solving the following unconstrained problem

\[
\begin{align*}
\min_W \sum_{m=1}^{M} \alpha_m ||W^m||_2 + \Re \left\{ \Tr[\Lambda^t (W - \tilde{\Phi}(t + 1))] \right\} + \frac{c}{2} ||W - \tilde{\Phi}(t + 1)||^2_2. \quad (32)
\end{align*}
\]
Using the first-order optimality condition for the optimal solution $W^m(t + 1)$, we have

$$W^m(t + 1) = \begin{cases} 0, & \text{if } ||\Xi(t)||_F \leq \alpha_m \\ \frac{(||\Xi^m(t)||_F - \alpha_m)||\Xi^m(t)||_F}{c||\Xi^m(t)||_F}, & \text{otherwise,} \end{cases}$$

(33)

where $\Xi^m(t) = c\Phi^m(t + 1) - \Lambda^m(t)$, and $\Lambda^m \in \mathbb{C}^{N \times K}$, $W^m \in \mathbb{C}^{N \times K}$, and $\Phi^m \in \mathbb{C}^{N \times K}$ are the $m$-th row blocks of matrices $\Lambda$, $W$, and $\Phi$, respectively, $\forall m = 1, 2, \ldots, M$.

**Proof 1:** See Appendix A.

With the obtained optimal $\{\Phi_k\}_{k \in K}$, the optimal multiplier $\mu_n^k$ of the boundary constraint (25) can be optimally obtained by

$$\mu_n^k = \left( p_k^{max} - \bar{\Phi}_k(t + 1)e_n e_n^T \bar{\Phi}_k(t + 1) \right)^+, \forall k = 1, 2, \ldots, K; n = 1, 2, \ldots, N,$$

(34)

where $(x)^+ = \max\{x, 0\}$.

Finally, we optimize $F$ in (30) given fixed $\Phi$. The problem of $F$ of (30) is expressed as

$$\mathcal{P}_F(L_c) : \min_F \left\{ \text{Re} \left\{ \text{Tr} \left[ \Psi^T(t) \left( F - [\bar{H}^T \Phi(t + 1), \sigma 1_K] \right) \right] \right\} + \frac{c}{2} ||F - [\bar{H}^T \Phi(t + 1), \sigma 1_K]||_F^2 \right\}$$

s.t. $\sqrt{\gamma}^{-1} f_{k,k} \geq ||f_{-k,k}||_2, \forall k \in K,$

(35)

where $f_{-k,k} \in \mathbb{C}^{1 \times K}$ denotes the remaining subvector of $f_k \in \mathbb{C}^{1 \times (K + 1)}$ after removing the element $f_{k,k}$, i.e.,

$$f_{-k,k} = [f_{1,k}, \ldots, f_{k-1,k}, f_{k+1,k}, \ldots, f_{K+1,k}] \in \mathbb{C}^{1 \times K}.$$  

(36)

Similar to [26], in order to find the optimal $F$ for $\mathcal{P}_F(L_c)$ with low computational complexity, we divide the optimization problem of $F$ into $K$ independent subproblems of $f_k, \forall k \in K$, which are solved in parallel, where the subproblem is given by

$$\min_{f_k} \text{Re} \left\{ \text{Tr} \left[ \psi_k(t)^T(f_k - b_k(t + 1)) \right] \right\} + \frac{c}{2} ||f_k - b_k(t + 1)||_2^2$$

s.t. $\sqrt{\gamma}^{-1} f_{k,k} \geq ||f_{-k,k}||_2,$

(37)

where $\psi_k \in \mathbb{C}^{1 \times (K + 1)}$ and $b_k \in \mathbb{C}^{1 \times (K + 1)}$ denote the $k$-th row vectors of $\Psi$ and $[\bar{H}^T \Phi, \sigma 1_K]$, respectively. Define $\psi_{k,k}$ as the $k$-th element of $\psi_k$ and $\psi_{-k,k}$ as the remaining subvector after removing $\psi_{k,k}$. Similarly, we define $b_{k,k}$ and $b_{-k,k}$.

Problem (37) is a convex minimization problem. Moreover, it can be verified that the Slater’s constraint qualification is satisfied [28]. Therefore, the duality gap between problem (37) and its duality problem is zero. This means that the optimal solution of problem (37) can be obtained
by applying the Lagrange duality theory [28]. In the following Theorem 2, the optimal \( f_k \) can be obtained via exploiting the Karush-Kuhn-Tucker (KKT) conditions of problem (37).

**Theorem 2:** Given \( \Psi \), fixing \( \Phi(t+1) \), the optimal \( f_k \) is

\[
\begin{align*}
\left\{
\begin{array}{ll}
f_{k,k}(t+1) &= \frac{cb_{k,k}(t+1) - \psi_{k,k}(t)}{c + \varepsilon_k \rho_k} + \sqrt{\gamma - 1} \\
f_{-k,k}(t+1) &= \frac{cb_{-k,k}(t+1) - \psi_{-k,k}(t)}{c + \varepsilon_k \rho_k}
\end{array}
\right.
\end{align*}
\]

(38)

where \( \rho_k = (||f_{-k,k}(t+1)||_F)^{-1} \), \( \varepsilon_k \geq 0 \) is the dual variable introduced for the SINR constraint, which is optimally determined by

\[
\varepsilon_k = \frac{1}{1 + \gamma} \left[ \gamma ||cb_{-k,k}(t+1) - \psi_{-k,k}(t)||_2 - \sqrt{\gamma}(cb_{k,k}(t+1) - \psi_{k,k}(t)) \right].
\]

(39)

**Proof 2:** See Appendix B.

After obtaining the optimal \( \Phi, W, \) and \( F \), we update the Lagrangian matrix multipliers in problem (P1–5), i.e., \( \Lambda \) and \( \Psi \). It has been shown in [30] that the well known subgradient based method can be employed iteratively to find the optimal solutions of \( \Lambda \) and \( \Psi \). Similar to the updating of variables \( \{W^m\}_{m=1}^M \) and \( \{f_k\}_{k=1}^K \), updating \( \Lambda \) and \( \Psi \) are also separable. Specifically, for \( \Lambda^m \) and \( \psi_k \), the pointwise update equations are given by

\[
\begin{align*}
\Lambda^m(t+1) &= \Lambda^m(t) + c \left( W^m(t+1) - \Phi^m(t+1) \right) \\
\psi_k(t+1) &= \psi_k(t) + c \left( f_k(t+1) - [H_k^t \Phi(t+1), \sigma] \right)
\end{align*}
\]

(40)

(41)

We summarize the proposed PADMM algorithm for trigger module identification in Algorithm 1. In Algorithm 1, \( \gamma \) and \( \gamma \) represent the upper bound and the lower bound of SINR in bisection. The key step is solving (P1–5) on PADMM, and the whole PADMM algorithm can be implemented distributively.

**B. Minimum SINR Maximization**

In this section, we solve joint transmit power and passive beamforming when the trigger modules are identified. To be specific, for the original minimum SINR maximization problem (P0), we drop the sparsity constraint and make the phase-shift matrix \( \Phi \) with the value for the diagonal blocks corresponding to the remaining non-triggered modules equal to zero. For convenience to illustrate, the identified phase-shift matrix denoted by \( F_\Phi \), where the non-triggered modules reflection coefficients are forced to be zero. Particularly, we focus on solving:

\[
\begin{align*}
\max_{\{p_k\}_{k \in \mathcal{K} \ominus F_\Phi}} \min_{k \in \mathcal{K}} \frac{p_k|\mathbf{s}_k^t F_\Phi \mathbf{h}_k|^2}{\sum_{j=1,j \neq k}^K p_j|\mathbf{s}_k^t F_\Phi \mathbf{h}_j|^2 + \sigma^2}
\end{align*}
\]

s.t. (8) and (9).

(42)
Algorithm 1: PADMM Algorithm Summary for Trigger Module Identification

**Initialization:**

Input communication system configurations and algorithm parameters;

**I. Identify the active blocks of each IRS**

(1.1) Set outer (bisection) iteration index \( \tau = 0 \);

(1.2) Update \( \gamma = \frac{\underline{\gamma} + \bar{\gamma}}{2} \), where \( \underline{\gamma} \) and \( \bar{\gamma} \) are the lower bound and upper bound of SINR in bisection.

(1.3) Set inner (ADMM) iteration index \( t = 0 \);

(1.4) Initialize \( \{ \bar{\phi}_k(t) \}_{k \in K}, W(t), \{ F(t) \}, \Lambda(t), \{ \Psi(t) \} \);

(1.5) Update \( \bar{\phi}_k(t+1) \) as (31); \( W^m(t+1) \) as (33); \( f_k(t+1) \) as (38); \( \Lambda^m(t+1) \) as (40); \( \psi_k(t+1) \) as (41) in parallel; \( \forall k = 1, 2, \ldots, K; m = 1, 2, \ldots, M \)

(1.6) if not converge and max iteration number not achieved,

\[
  t = t + 1, \text{ go to (1.5)};
\]

else if convergence, compare \( \sum_{m=1}^{M} \alpha_m ||W^m||_2 \) with \( \delta \),

if “\( \leq \)”, (P1–4) feasible for \( \gamma \), update \( \underline{\gamma} = \gamma \);

else (P1–4) infeasible for \( \gamma \), update \( \bar{\gamma} = \gamma \);

(1.7) if \( \gamma \) converges, go to (1.12)

else, \( \tau = \tau + 1, \text{ go to (1.2)}; \)

(1.8) Identify the trigger module at IRS by exploring the sparse pattern of \( W \);

Note that (P0) can be transformed into the conventional minimum SINR maximization problem, which can be efficiently and optimally solved by employing the alternating optimization technique [31] to separately and iteratively solve for \( \{ p_k \}_{k \in K} \) and \( F_\Phi \). In the rest of this section, the optimization with respect to \( F_\Phi \) for fixed \( \{ p_k \}_{k \in K} \), and with respect to \( \{ p_k \}_{k \in K} \) for fixed \( F_\Phi \) will be treated separately.

\( \begin{aligned}
1) \text{Optimizing Phase-Shift Matrix } F_\Phi: \text{ Let } & F_\phi \in \mathbb{C}^{N \times N} \text{ denote the vectorization of diagonal matrix } F_\phi. \text{ Substituting } \bar{h}_{j,k} \text{ into the objective function of (42), then, } \quad p_k |g_k^\dagger F_\phi h_k|^2 = p_k F_\phi^\dagger \bar{h}_{k,k} F_\phi, \quad \sum_{j=1,j \neq k}^{K} p_j |g_j^\dagger F_\phi h_j|^2 + \sigma^2 = \sum_{j=1,j \neq k}^{K} p_j F_\phi^\dagger \bar{h}_{j,k} F_\phi + \sigma^2 \text{ for all } k \text{ and } j. \quad \text{Utilizing the method of partial linearization for generalized fractional programs [22], introducing}
\end{aligned} \)
the continuous functions w.r.t. $F_\phi$, are defined as

$$u_k(F_\phi) = p_k^{\text{T}}h_{k,k}^{\text{T}}F_\phi h_{k,k}, \forall k = 1, 2, \ldots, K \tag{43}$$

$$v_k(F_\phi) = \sum_{j=1, j\neq k}^{K} p_j^{\text{T}}h_{j,k}^{\text{T}}F_\phi + \sigma^2, \forall k = 1, 2, \ldots, K. \tag{44}$$

By introducing parameter $\gamma_{\text{out}}$, then the optimization with respect to phase-shift matrix is equivalent to

$$\max_{\gamma_{\text{out}}} \gamma_{\text{out}} \tag{45}$$

$$\text{s.t. } u_k(F_\phi) - \gamma_{\text{out}} v_k(F_\phi) \geq 0, \forall k \in \mathcal{K} \tag{46}$$

$$\text{and } \mathcal{A}. \tag{47}$$

For $1 \leq k \leq K$, denote $G_k(F_\phi, \gamma_{\text{out}}) = u_k(F_\phi) - \gamma_{\text{out}} v_k(F_\phi)$, and consider the following partial linearization of $G_k(F_\phi, \gamma_{\text{out}})$ at a point $(F_\phi^{(\tau)}, \gamma_{\text{out}}^{(\tau)})$

$$G_k^{(\tau)}(F_\phi, \gamma_{\text{out}}) = G_k(F_\phi, \gamma_{\text{out}}^{(\tau)}) + (\gamma_{\text{out}} - \gamma_{\text{out}}^{(\tau)}) \nabla_{\gamma_{\text{out}}} G(F_\phi^{(\tau)}, \gamma_{\text{out}}^{(\tau)}) \tag{48}$$

$$= u_k(F_\phi) - \gamma_{\text{out}} v_k(F_\phi) - (\gamma_{\text{out}} - \gamma_{\text{out}}^{(\tau)}) v_k(F_\phi^{(\tau)}).$$

The following sub-problem specified with this partial linearization of the $G_k$ is to be solved by CVX at each iteration $\tau$ of the algorithm.

$$\max_{\gamma_{\text{out}}} \gamma_{\text{out}} \tag{49}$$

$$\text{s.t. } G_k^{(\tau)}(F_\phi, \gamma_{\text{out}}) \geq 0, \forall k = 1, 2, \ldots, K; \text{ and } \mathcal{A}. \tag{50}$$

2) Optimization with Respect to the Power Allocation $\{p_k\}_{k \in \mathcal{K}}$: Likewise, for the case where $F_\phi$ is fixed and the objective is the optimization over $p = [p_1, p_2, \ldots, p_K]^T$, we introduce continuous functions of $p$, denoted by $\xi_k(p)$ and $\eta_k(p)$, respectively, and are defined as

$$\xi_k(p) = p_k|g_{k,k}^{\text{T}}F_\phi h_{k,k}|^2, \forall k = 1, 2, \ldots, K \tag{50}$$

$$\eta_k(p) = \sum_{j=1, j\neq k}^{K} p_j|g_{j,k}^{\text{T}}F_\phi h_{j,k}|^2 + \sigma^2, \forall k = 1, 2, \ldots, K. \tag{51}$$

Denote $\Omega_k(p, \gamma_{\text{out}}) = \xi_k(p) - \gamma_{\text{out}} \eta_k(p)$. The partial linearalization of $\Omega_k$ at a point $(p^{(\tau)}, \gamma_{\text{out}}^{(\tau)})$ is

$$\Omega_k^{(\tau)}(p, \gamma_{\text{out}}) = \Omega_k(p, \gamma_{\text{out}}) + (\gamma_{\text{out}} - \gamma_{\text{out}}^{(\tau)}) \nabla_{\gamma_{\text{out}}} \Omega_k(p^{(\tau)}, \gamma_{\text{out}}^{(\tau)}) \tag{52}$$

$$= \xi_k(p) - \gamma_{\text{out}} \eta_k(p) - (\gamma_{\text{out}} - \gamma_{\text{out}}^{(\tau)}) \eta_k(p^{(\tau)}). \tag{53}$$
Consequently, we focus on solving:

\[
\begin{align*}
\max_{p, \gamma_{\text{out}}} & \quad \gamma_{\text{out}} \\
\text{s.t.} & \quad \Omega_k^{(r)}(p, \gamma_{\text{out}}) \geq 0, \quad \text{and} \quad (8).
\end{align*}
\]

(54)

In the proposed alternating optimization algorithm, we solve \(p\) and \(F_\phi\) by addressing problems (49) and (54) alternately in an iterative manner, where the solution obtained in each iteration is used as the initial point of the next iteration. The details of the proposed algorithm are summarized in Algorithm 2.

**Algorithm 2** Alternating optimization algorithm for \(p\) and \(F_\phi\) when the trigger modules are identified

**Step 0:** Initialize \(F_\phi^{(0)}\) and \(p^{(0)}\) to feasible values, and let \(\gamma_{\text{out}}^{(0)} = \min_{1 \leq k \leq K} \left\{ \frac{u_k(F_\phi^{(0)})}{v_k(F_\phi^{(0)})} \right\} \), and set the iteration number \(\tau = 0\).

**repeat**

**Step 1:** Solve (49) by CVX for given \(p^{(\tau)}\), and denote \(F_\phi^{(\tau)}\) be an optimal solution.

**Step 2:** Solve problem (54) for given \(F_\phi^{(\tau)}\), and denote the optimal solution as \(p^{(\tau+1)}\).

**Step 3:** Update \(\tau = \tau + 1\).

**Step 4. until** \(\gamma_{\text{out}}\) converges or problem becomes infeasible.

**IV. Simulation Results**

**A. Simulation Environments and Settings**

We now evaluate the performance of the proposed joint trigger reflection module selection, transmit power allocation, and the corresponding passive beamformer design in the IRS-aided P2P networks. The convergence property and effectiveness of the PADMM algorithm are verified. Numerical simulations are presented to assess the performance of the PADMM algorithm under different operating conditions. To keep the complexity of the simulations tractable, we focus on the scenario, where the \(K\) STs are randomly employed within a circle cell centered at \((0, 0)\) m, and the cell radius is 20 m, and the corresponding \(K\) DTs are located within a circle cell with radius 20 m centered at \((300, 0)\) m. The primary purpose of this paper is to improve the worst communication performance between ST and DT that are far from each other. Therefore, similar to the simulation settings in [12] we suppose that the IRS is employed at \((200, 50)\) m, where the number of reflection elements of each module is set as \(L = 8\). We assume quasi-static block
fading channels in this paper, i.e., the channels from the STs to the IRS and the IRS to the DTs remain constant during each time block, but may vary from one to another [32]. To include the effects of fading and shadowing, we use the path-loss model introduced in [33]. Throughout the simulations, unless otherwise specified, we adopt the parameters reported in Table I (see [33], [34] and references therein), where, for simplicity, all the STs are assumed to have the same maximum transmit power $p^{\text{max}}$. All the simulation results are obtained by averaging over $10^4$ channel realizations.

### TABLE I

**SIMULATION PARAMETERS**

| Parameters                      | Descriptions     | Parameters                      | Descriptions     |
|---------------------------------|------------------|---------------------------------|------------------|
| Number of STs, $K$              | 4(or 6)          | Number of DTs, $K$              | 4(or 6)          |
| Number of modules, $M$          | 4(or 8)          | Number of reflection elements at each module, $L$ | 8                |
| Maximum transmit power of ST, $p^{\text{max}}$ | 100dBm          | Noise power, $\sigma^2$         | $-174$dBm        |
| Bandwidth                       | 1.8MHz           | Carrier frequency               | 2.3GHz           |
| Lognormal Shadowing             | 8dB              | Path-loss exponent              | 3                |
| Fading distribution             | Lognormal shadow fading+ Rayleigh fading | Rayleigh fading standard deviation | 8dB |
| The reference distance          | 50m              | Weighted factor, $\{\alpha_m\}_{m=1}^{M}$ | 1                |

### B. Convergence Verification of PADMM Algorithm

**TABLE II**

**PERFORMANCE OF THE PADMM ALGORITHM AND THE CVX METHOD FOR DIFFERENT SPARSITY CONSTRAINTS**

$\delta \in \{1, 5, 10, 20\}$ with $K = \{4, 6\}$.

| $K = 4, M = 4, L = 8$ | $K = 6, M = 4, L = 8$ | $K = 4, M = 4, L = 8$ | $K = 6, M = 4, L = 8$ |
|-----------------------|-----------------------|-----------------------|-----------------------|
| Triggered module index if $\delta = 1$ | $\{2, 3\}$           | $\{2, 3, 4\}$        | $\{2, 3\}$           | $\{2, 3, 4\}$        |
| Triggered module index if $\delta = 5$ | $\{1, 3, 4\}$        | $\{1, 3, 4\}$        | $\{1, 3, 4\}$        | $\{1, 3, 4\}$        |
| Triggered module index if $\delta = 10$ | $\{2, 3, 4\}$        | $\{1, 2, 3, 4\}$    | $\{2, 3, 4\}$        | $\{1, 2, 3, 4\}$    |
| Triggered module index if $\delta = 20$ | $\{1, 2, 3, 4\}$    | $\{1, 2, 3, 4\}$    | $\{1, 2, 3, 4\}$    | $\{1, 2, 3, 4\}$    |

Table II shows the converging properties of the PADMM algorithm proposed for identifying the trigger modules, i.e., comparing the results obtained by solving (P1–5) using the PADMM
algorithm and by solving problem (P1–3) via CVX method. Specifically, Table II shows the impacts of the sparsity parameter $\delta$ and the number of user pairs $K$ on the trigger modules for both PADMM algorithm and CVX method, where the value of $K = 4$ and 6. From the results, we observe that for both the PADMM algorithm and CVX method, the number of trigger modules increases, when $K$ or $\delta$ increases. Comparing the results from the CVX method, one can verify that the PADMM algorithm can converge to the CVX solution. Moreover, as shown in the last row of Table II, all the modules tend to be triggered at the IRS to maximize the performance, when the sparsity parameter $\delta = 20$.

To measure the effect of sparsity parameter $\delta$, Figs. 3 and 4 depict the average number of trigger modules at IRS and the trigger ratio of each module in terms of the sparsity parameter $\delta$, averaged over 1000 independent channel realizations per marker. As shown in Fig. 3, as expected, it is difficult to distinguish the curves for the PADMM algorithm and CVX method, varying sparsity parameter $\delta$ from 1 to 80, i.e., the PADMM algorithm provides a close-to-optimal solution as the CVX based method. And the average trigger modules at IRS for both PADMM algorithm and CVX method increases as the sparsity parameter, $\delta$, increases. In addition, we observe in Fig. 3 that the average number of triggered modules identified by both PADMM algorithm and CVX based method first increases and then approaches the constant value 8. This in essence attributes to the fundamental effect of parameter $\delta$ to control the group sparsity at IRS, precisely, the number of trigger modules at IRS becomes less and less sensitive to sparsity constraint, as the parameter, $\delta$, increases.

C. Performance Comparison

In this section, we evaluate the performance of the PADMM algorithm by comparing with two conventional methods, denoted as method of exhaustive search (MES) and method of randomly selecting the trigger modules (MRS), respectively. The premise of performance comparison between the three methods is to use the same sparsity constraint to control the size of triggered modules. In this paper, the number of trigger modules is determined by PADMM algorithm. Specifically, both MES and MRS perform their respective trigger modules selection and solve the conventional minimum SINR maximization problem via partial linearization for generalized fractional programs [22]. In Figs. 5 and 6, fixing $M = 4$ and $L = 8$, we evaluate and compare the max-min SINR and the average module trigger ratio versus the sparsity parameter $\delta$ for the PADMM, MES, and MRS with different user numbers $K = 4$ and $K = 6$, respectively. From
the results, we observe that for all the mentioned methods, the max-min SINR first increases and then approaches to a constant value, when the sparsity parameter $\delta$ increases. As shown in Fig. 5, for $K = 6$, $M = 4$, and $L = 8$, it is difficult to distinguish the curves of the PADMM algorithm, MES, and MRS, when we vary parameter $\delta$ from 1 to 80. Moreover, as shown in Fig. 6, for $K = 6$, almost all the modules are triggered regardless of the value of parameter $\delta$, i.e., the sparsity constraint is not sensitive to parameter $\delta$. This is mainly because when $\delta$ is
Fig. 7. Max-min SINR versus sparsity parameter $\delta$ for $M = 4$ and $K = 4$ with $L \in \{6, 8\}$, and the maximum transmit power of STs $p_{\text{max}} = 100$dB.

Fig. 8. Average module trigger ratio versus sparsity parameter $\delta$ for $M = 4$ and $K = 4$ with $L \in \{6, 8\}$, and the maximum transmit power of STs $p_{\text{max}} = 100$dB.

relatively small, instead of using a magnitude that increases the reflection coefficient, maximizing minimum SINR mainly relies on triggering a large number of modules and tuning the reflecting angles. By contrast, considering relatively small $\delta$ (e.g., $\delta \leq 40$), for $K = 4$, $M = 4$, and $L = 8$, the MES outperforms the remaining two methods. In addition to our observations in Fig. 5 with respect to $\delta$, it can be shown that the max-min SINR decreases for a given value of $\delta$, as the number of user pairs, $K$, increases. The reason is that multiple access interference may be serious, as the number of user pairs increases.

Fixing the user pair number $K = 4$ and the number of modules $M = 4$, Fig. 7 shows the impacts of the reflection elements number of each module and the sparsity parameter on the max-min SINR for all the mentioned methods, where $L = 6$ and 8. As expected, the max-min SINR of the three methods first increases and then approaches to a constant value for a given value of $L$, as the sparsity parameter, $\delta$, increases. According to Fig. 7, considering the sparsity parameter $\delta \leq 40$ for $L = 8$, the SINR performance order is “MES>PADMM>MRS”. MES achieves the highest SINR by exhaustively searching overall possible modules subset selections, while the performance gain of MRS is the worst, since the trigger modules subset at the IRS is not optimized, where the subset is selected randomly and the useful information of channels is ignored. PADMM outperforms MRS due to the joint optimization of trigger module, transmit power allocation, and passive beamformer design at IRS. It can be shown that for a given sparsity
Fig. 9. Max-min SINR versus the maximum transmit power of STs $p^{\text{max}}$ for $K = 4$, $M = 4$, and $L = 8$ with the sparsity parameter $\delta \in \{1, 20\}$.

parameter $\delta$, the max-min SINR increase apparently, as the number of reflection elements of each module increases from 6 to 8, which is straightforward since the power of the signal reflected by the IRS becomes stronger. Correspondingly, in Fig. 8, the average module trigger ratio of all the mentioned methods first increases and then remains constant, with the increase of the sparsity parameter $\delta$. Consistent with the results in previous simulations, the increase of sparsity parameter encourages more modules to serve the STs, thereby improving the performance gain.

Finally, Fig. 9 shows the impacts of the sparsity parameter $\delta$ and the maximum transmit power of STs $p^{\text{max}}$ on the SINR performance for the three methods, where $\delta = 1$ and 20. As expected, the max-min SINR achieved by the three methods for sparsity parameter $\delta = 1$ and 20 monotonically increases with increasing the maximum transmit power of STs. Consistent with the previous simulations, the highest and worst SINR are achieved by MES and MRS, respectively. From the results, we observe that for any given maximum transmit power $p^{\text{max}}$, the max-min SINR increases significantly, as the sparsity parameter, $\delta$, increases from 1 to 20. The reason is that more modules are triggered to serve the STs when setting sparsity parameter $\delta = 20$, according Fig. 8 and Fig. 9. Notably, for $\delta = 20$, there exists the same outcome of the three methods, when the maximum transit power of STs $p^{\text{max}}$ is sufficient large ($p^{\text{max}} \geq 125$ W). The reason is that when $p^{\text{max}}$ is relatively large, the transmit power allocation dominates the maximizing minimum SINR of STs in this regime.
V. CONCLUSIONS

In this paper, we studied the joint problem of transmit power allocation and passive beamforming to IRS-aided P2P communication networks with reflection resource management. Specifically, the true reflection resource management can be realized via trigger module selection based on the architecture that all the reflection elements are partially controlled by parallel switches of controller. The objective is to jointly select sparse passive beamforming matrix and allocate transmit power such that the minimum SINR is maximized, subject to both the maximum transmit power and the reflection coefficients constraints. Instead of using the hard module size constraint, we relaxed that by the mixed $\ell_{1,2}$-norm, transforming it to the group sparse constraint. The appropriate problem was formulated from the perspective of group sparse optimization. To solve this problem, the PADMM was used to identify the trigger modules subset firstly, and then both the transmit power allocation and the corresponding passive beamforming can be obtained by solving the original max-min problem via generalized fractional programs. Finally, the simulation results demonstrated the convergence and effectiveness of the PADMM algorithm. The performance comparison indicated that PADMM is highly efficient since each step can be calculated in closed-form.

APPENDIX A

THE PROOF OF THEOREM 1

1) Optimization for problem $P_{\phi_k}(L_c)$: We rewrite $W$, $\Lambda$, $\Psi$, and $F$ in forms of $W = [w^1, w^2, \ldots, w^K]$, $\Lambda = [\lambda^1, \lambda^2, \ldots, \lambda^K]$, $\Psi = [\psi^1, \psi^2, \ldots, \psi^{K+1}]$, and $F = [f^1, f^2, \ldots, f^K]$, respectively. And $w^k \in \mathbb{C}^{N \times 1}$ and $\lambda^k \in \mathbb{C}^{N \times 1}$ represent the $k$-th column of matrices $W$ and $\Lambda$, respectively. $\psi^k \in \mathbb{C}^{K \times 1}$ and $f^k \in \mathbb{C}^{K \times 1}$ are the $k$-th column of matrices $\Psi$ and $F$, respectively.

Introducing auxiliary matrix $\tilde{h}^k = [h_{k,1}, h_{k,2}, \ldots, h_{k,K}]$, then, $\Phi$ is separable in $P_{\phi_k}(L_c)$. The optimization problem of $\phi_k$, $\forall k \in K$ is

$$
\min_{\phi_k} \text{Re} \left\{ \text{Tr} \left[ \lambda^{k+} (w^{k}(t) - \overline{\phi}_k) \right] \right\} + \frac{c}{2} \|w^{k}(t) - \overline{\phi}_k\|_2^2 
+ \left( \text{Re} \left\{ \text{Tr} \left[ \psi^{k+} (f^{k}(t) - \overline{\phi}_k) \right] \right\} \right) + \frac{c}{2} \|f^{k}(t) - \overline{\phi}_k\|_2^2
$$

s. t. $\phi_k e_n e_n^H \phi_k \leq p_{\text{max}}^n$, $\forall n = 1, 2, \ldots, N; k = 1, 2, \ldots, K,$
which can be easily solved by exploiting the first-order optimality condition. Specifically, we have
\[-\lambda_k + c(\phi_k - w_k^k(t)) - \tilde{h}^k \psi^k(t) + c \left( \tilde{h}^k \tilde{h}^k \phi_k - \tilde{h}^k f^k(t) \right) + 2 \left( \sum_{n=1}^{N} \mu_n^k e_n e_n^T \right) \phi_k = 0, \]  
and consequently, the optimal solution of \( \phi \) is given by
\[ \phi_k(t + 1) = \left( cI_{N \times N} + c\tilde{h}^k \tilde{h}^k + 2 \sum_{n=1}^{N} \mu_n^k e_n e_n^T \right)^{-1} \left( \lambda_k(t) + c w_k^k(t) + \tilde{h}^k \psi^k(t) + c \tilde{h}^k f^k(t) \right), \]  
where \( \mu_n^k \) is the Lagrangian multipliers of \( \phi_k^T e_n e_n^T \phi_k \leq p_n^\text{max}, \forall n = 1, 2, \ldots, N, \) and should be properly chosen to satisfy the KKT condition \([28]\). And the dual variable \( \mu_n^k \) is optimally determined by
\[ \mu_n^k = \max \{ p_n^\text{max} - \phi_k^T(t + 1) e_n e_n^T \phi_k(t + 1), 0 \}. \]  

2) Optimization for Problem \( \mathcal{P}_W \): The problem of \( W \) is an unconstrained group Lasso problem, i.e.,
\[ \mathcal{P}(W) : \min_W \sum_{m=1}^{M} \alpha_m ||W^m||_2 + \text{Re} \left\{ \text{Tr} [\Lambda^m(t) (W - \bar{\Phi}(t + 1))] \right\} + \frac{c}{2} ||W - \bar{\Phi}(t + 1)||_2^2. \]  
Let \( \Lambda^m \in \mathbb{C}^{N \times K}, W^m \in \mathbb{C}^{N \times K}, \) and \( \bar{\Phi}^m \in \mathbb{C}^{N \times K} \) be the \( m \)-th row block of matrices \( \Lambda, W, \) and \( \bar{\Phi} \), respectively, \( \forall m = 1, 2, \ldots, M \). Then, \( \mathcal{P}_W \) can be divided into \( M \) independent problems of \( W^m \) for \( m = 1, 2, \ldots, M \)
\[ \mathcal{P}(W^m) : \min_{W^m} \alpha_m ||W^m||_2 + \text{Re} \left\{ \text{Tr} [\Lambda^m(t) (W^m - \bar{\Phi}^m(t + 1))] \right\} + \frac{c}{2} ||W^m - \bar{\Phi}^m(t + 1)||_2^2 \]  
The first-order optimality condition for the optimal solution \( W^m(t + 1) \) we have
\[ \alpha_m \partial ||W^m(t + 1)||_2 = c \bar{\Phi}^m(t + 1) - \Lambda^m(t) - c W^m(t + 1) \]  
where \( \partial ||W^m(t + 1)||_2 \) is the subgradient of \( ||W^m(t + 1)||_2 \) defined as
\[ \partial ||W^m(t + 1)||_2 = \frac{W^m(t + 1)}{||W^m(t + 1)||_2} \]  
Inserting (62) into (61), we can easily obtain
\[ W^m(t + 1) = \begin{cases} 0, & \text{if } ||\Xi(t)||_2 \leq \alpha_m \\ \frac{||\Xi(t)||_2 - \alpha_m}{c} ||\Xi(t)||_2 \Xi(t), & \text{otherwise} \end{cases} \]
APPENDIX B

THE PROOF OF THEOREM 2

The first-order optimality conditions for $f_k(t + 1)$ are listed as follows:

$$
\psi_{k,k}(t) + c \left[ f_{k,k}(t + 1) - b_{k,k}(t + 1) \right] - \frac{\varepsilon_k}{\sqrt{\gamma^{-1}}} = 0 \tag{64}
$$

$$
- \psi_{-k,k}(t) - c \left( f_{-k,k}(t + 1) - b_{-k,k}(t + 1) \right) = \varepsilon_k \partial \| f_{-k,k}(t + 1) \|_2 \tag{65}
$$

$$
\varepsilon_k \left( \frac{f_{k,k}(t + 1)}{\sqrt{\gamma^{-1}}} - \| f_{-k,k}(t + 1) \|_2 \right) = 0 \tag{66}
$$

$$
\varepsilon_k \geq 0 \tag{67}
$$

$$
\frac{f_{k,k}(t + 1)}{\sqrt{\gamma^{-1}}} - \| f_{-k,k}(t + 1) \|_2 \geq 0, \tag{68}
$$

where $\varepsilon_k$ is the Lagrangian multiplier for $\sqrt{\gamma^{-1}} f_{k,k} \geq \| f_{-k,k} \|_2$.

Assume that $f_{k,-k}(t + 1) \neq 0$ first, from (64) and (65), we can easily get

$$
\begin{cases}
  f_{k,k}(t + 1) = \frac{c b_{k,k}(t + 1) - \psi_{k,k}(t)}{c + \varepsilon_k \rho_k} \\
  f_{-k,k}(t + 1) = \frac{c b_{-k,k}(t + 1) - \psi_{-k,k}(t)}{c + \varepsilon_k \rho_k}
\end{cases} \tag{69}
$$

where $\rho_k = (\| f_{-k,k}(t + 1) \|_F)^{-1}$, $\varepsilon_k$ should be properly chosen such that KKT complementary condition should be satisfied. If $\left( \frac{f_{k,k}(t + 1)}{\sqrt{\gamma^{-1}}} - \| f_{-k,k}(t + 1) \|_2 \right) |_{\varepsilon_k = 0} \geq 0$ or equivalently $\sqrt{\gamma^{-1}} (c b_{k,k}(t + 1) - \psi_{k,k}(t)) \geq \| c b_{-k,k}(t + 1) - \psi_{-k,k}(t) \|_2$, we have $\varepsilon_k = 0$. Otherwise, we have $\sqrt{\gamma^{-1}} f_{k,k}(t + 1) = \| f_{-k,k}(t + 1) \|_2$ for some $\varepsilon_k > 0$. In the case of $\| c b_{-k,k}(t + 1) - \psi_{-k,k}(t) \|_2 > \sqrt{\gamma^{-1}} (c b_{k,k}(t + 1) - \psi_{k,k}(t))$, Combining $\rho_k \| f_{-k,k} \|_2 = 1$ and $\sqrt{\gamma^{-1}} f_{k,k}(t + 1) = \| f_{-k,k}(t + 1) \|_2$, we obtain

$$
\varepsilon_k = \frac{1 + \gamma}{c + \gamma} \left[ \gamma \| c b_{-k,k}(t + 1) - \psi_{-k,k}(t) \|_2 - \sqrt{\gamma} (c b_{k,k}(t + 1) - \psi_{k,k}(t)) \right] \tag{70}
$$

$$
\rho_k = \frac{1 + \gamma}{c^{-1} + \gamma} \left[ \gamma \| c b_{-k,k}(t + 1) - \psi_{-k,k}(t) \|_2 + \sqrt{\gamma} (c b_{k,k}(t + 1) - \psi_{k,k}(t)) \right].
$$

REFERENCES

[1] “European telecommunications standards institute,” Mobile-edge computing–Introductory technical white paper, 2014.

[2] A. Grassi, G. Piro, G. Bacci, and G. Boggia, “Uplink resource management in 5g: When a distributed and energy-efficient solution meets power and qos constraints,” IEEE Transactions on Vehicular Technology, vol. 66, pp. 5176–5189, June 2017.

[3] S. Chen and J. Zhao, “The requirements, challenges, and technologies for 5g of terrestrial mobile telecommunication,” IEEE Communication Magazine, vol. 52, pp. 36–43, May 2014.

[4] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, “Five disruptive technology directions for 5g,” IEEE Communication Magazine, vol. 52, pp. 74–80, February 2014.
[5] “5Gmm alliance 5g white paper,” 2015.

[6] Q. Wu and R. Zhang, “Towards smart and reconfigurable environment: intelligenet reflecting surfaces aided wireless network,” 2019.

[7] X. Tan, Z. Sun, D. Koutsonikolas, and J. M. Jornet, “Enabling indoor mobile millimeter-wave networks based on smart reflect-arrays,” in 2018 IEEE Conference on Computer Communications, (Honolulu, HI, USA), pp. 1–9, April 2018.

[8] F. Liu, O. Tsilipakos, A. Pitilakis, A. C. Tasolamprou, M. S. Mirmoosa, N. V. Kantartzis, and et. al., “Intelligent metasurfaces with continuously tunable local surface impedance for multiple reconfigurable functions,” Physical Review Applied, vol. 11, pp. 044024–1–044024–1, April 2019.

[9] L. Li, C. T. Jun, W. Ji, S. Liu, J. Ding, X. Wan, L. Y. Bo, M. Jiang, C. Qiu, and S. Zhang, “Electromagnetic reprogrammable coding-metasurface holograms,” Nature Communications, vol. 8, pp. 1–7, August 2017.

[10] B. Di, H. Zhang, L. Song, Y. Li, Z. Han, and H. Vincent Poor, “Hybrid beamforming for reconfigurable intelligent surface based multi-user communications: Achievable rates with limited discrete phase shifts,” 2019.

[11] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design,” in 2018 IEEE Global Communications Conference, (Abu Dhabi, United Arab Emirates, United Arab Emirates), pp. 1–6, December 2018.

[12] H. Guo, Y. C. Liang, J. Chen, and E. G. Larsson, “Weighted sum-rate optimization for intelligent reflecting surface enhanced wireless networks,” 2019.

[13] Q. Wu and R. Zhang, “Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts,” pp. 1–30, June 2019.

[14] E. Bjornson, O. Ozdogan, and E. G. Larsson, “Intelligent reflecting surface vs. decode-and-forward: How large surfaces are needed to beat relaying?,” pp. 1–5, August 2019.

[15] Y. Han, W. Tang, S. Jin, C. K. Wen, and X. Ma, “Large intelligent surface-assisted wireless communication exploiting statistical csi,” IEEE Transactions on Vehicular Technology, vol. 68, August 2018.

[16] Q. Wu and R. Zhang, “Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming design,” IEEE Transactions on Wireless Communications, August 2019.

[17] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” 2019.

[18] O. Mehanna, N. D. Sidiropoulos, and G. B. Giannakis, “Joint multicast beamforming and antenna selection,” IEEE Transactions on Signal Processing, vol. 61, pp. 2660–2674, May 2013.

[19] D. Feng, Y. Lu, Y. Yuan-Wu, G. Y. Li, G. Feng, and S. Li, “Device-to-device communications underlaying cellular networks,” IEEE Transactions on Communications, vol. 61, pp. 3541–3551, August 2013.

[20] J. P. Crouzeix, J. A. Ferland, and S. Schaible, “An algorithm for generalized fractional programs,” Journal of Optimization Theory and Application, vol. 47, pp. 35–49, September 1985.

[21] J. Borde and J. P. Crouzeix, “Convergence of a dinkelbach-type algorithm in generalized fractional programming,” Zeitschrift fur Operations Research, vol. 31, pp. A 31–A 54, January 1987.

[22] Y. Benadada and J. A. Fedand, “Partial linearization for generalized fractional programming,” ZOR–Zeitschrift fur Operations Research, vol. 31, pp. 101–106, March 1988.

[23] M. Fukushima, “Application of the alternating direction method of multipliers to separable convex programming problems,” Computing Optimization Application, vol. 1, pp. 93–111, October 1992.

[24] E. Candes, M. Wakin, and S. Boyd, “Enhancing sparsity by reweighted $\ell_1$ minimization,” Journal Fourier Analysis Application, vol. 14, pp. 877–905, December 2008.
[25] M. Yuan and Y. Lin, “Model selection and estimation in regression with grouped variables,” *Journal Royal Statistical Society*, vol. 68, pp. 49–67, December 2006.

[26] J. Lin, Q. Li, C. Jiang, and H. Shao, “Joint multirelay selection, power allocation, and beamformer design for multiuser decode-and-forward relay networks,” *IEEE Transactions on Vehicular Technology*, vol. 65, pp. 5073–5087, July 2016.

[27] M. C. Grant and S. P. Boyd, “The cvx users’ guide,” 2014.

[28] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge University Press, 2009.

[29] M. R. Hestenes, “Multiplier and gradient methods,” *Journal Optimization Theory and Application*, vol. 4, pp. 303–320, November 1969.

[30] R. Ramamonjison and V. K. Bhargava, “Energy efficiency maximization framework in cognitive downlink two-tier networks,” *IEEE Transactions on Wireless Communications*, vol. 14, pp. 1468–1479, March 2015.

[31] I. Csiszar and G. Tusnady, “Information geometry and alternating minimization procedures,” *Statistic Decisions*, vol. 1, pp. 205–237, December 1984.

[32] Z. Yang and M. Dong, “Low-complexity coordinated relay beamforming design for multi-cluster relay interference networks,” *IEEE Transactions on Wireless Communications*, vol. 18, no. 4, pp. 2215–2228, 2019.

[33] Y. Gao, Y. Xiao, M. Wu, M. Xiao, and J. Shao, “Dynamic social-aware peer selection for cooperative relay management with d2d communications,” *IEEE Transactions on Communications*, vol. 67, pp. 3124–3139, May 2019.

[34] G. Bacci, E. V. Belmega, P. Mertikopoulos, and L. Sanguinetti, “Energy-aware competitive power allocation for heterogeneous networks under QoS constraints,” *IEEE Transactions on Wireless Communications*, vol. 14, pp. 4728–4742, September 2015.