Linear Precoder Design for SWIPT-Enabled Relay Networks With Finite-Alphabet Inputs

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ABSTRACT This paper considers the problem of mutual information maximization in a two-hop relay network with simultaneous wireless information and power transfer (SWIPT), where the relay nodes use the power splitting (PS) scheme to harvest the energy for information forwarding. Unlike previous research, this paper focuses on a more practical scenario, where the inputs to the network are assumed to be finite-alphabet signals. Although each node in the network is assumed to have single antenna, we show that the relay network can be regarded as an effective multiple-input multiple-output (MIMO) system. Our goal is to perform the joint optimization on the precoder at source and PS ratio at relays to maximize the mutual information. Although the formulated problem is nondeterministic polynomial-time (NP)-hard, we theoretically analyze the optimal PS ratio; then, by using the structure of optimization problem, a near optimal precoder design based on semidefinite relaxation (SDR) is proposed; further, to reduce the complexity of algorithm, another precoder design based on search technique, which exploiting the structure of precoder, is developed only with a slight performance degradation. Simulation results verify the efficacy of proposed precoder designs.

INDEX TERMS Finite-alphabet inputs, precoder design, SWIPT, relay network.

I. INTRODUCTION

As is well known, relay communication technology, by elaborately designing the network configuration and relaying strategies, can further improve the channel capacity and reduce the energy consumption in wireless networks [1]. In order to improve the end-to-end performance of relay networks, it is generally necessary to perform precoding operation at the source, relay, or joint source and relay nodes. The goal of precoding is usually to maximize the information rate of the source-destination link. In [2], this goal was achieved by using the source precoder maximizing the signal to noise ratio (SNR) under the constraint of transmit power. For the decode-and-forward (DF) based relay communication networks, [3] proposed a source precoding technique which can balance the direct and relay links and maximize the information rate. For the amplify-and-forward (AF) based networks, [4] developed a relay precoding algorithm, which is designed to maximize the information rate and concurrently reduce the network latency. [5] considered a robust design of relay precoder in a nonregenerative multiple-input multiple-output (MIMO) relay network that consists of multiple source-destination node pairs assisted by a relay node. The works of [6] and [7] showed that there is a potential to further enhance the network performance in MIMO channels when source and relay precoders are applied. In [8] and [9], the authors designed precoding matrices at both the source and relay nodes, and then introduced an iterative algorithm to jointly optimize the precoding matrices to achieve the maximal information rate. For a multiple-relay cooperative MIMO wireless network, [10] proposed a closed-form joint optimization framework of the source precoder, the AF relaying matrices, and the destination equalizer.

In some application scenarios of relay networks, it may be difficult and even impossible to replace the battery of nodes. For this issue, an effective solution is to equip the nodes with the devices which can collect energy from the surrounding environment, such as solar and wind [11]. In recent years, collecting energy from radio frequency (RF) signals has
attracted more and more research interest. In typical scenarios, RF signals can not only transport energy, but also transmit information. This technique is known as simultaneous wireless information and power transfer (SWIPT), which has become a research hotspot [12]. As the combination of relay and SWIPT technologies, SWIPT-enabled relay networks have also been studied in the literature. For example, [13] investigated source and relay precoder designs in the cases of two energy harvesting schemes, namely power splitting (PS) and time switching (TS). In [14], a low-complexity precoder was designed for the full-duplex MIMO relay system, where the RF energy is harvested at the destination node. For a two-hop MIMO system, [15] considered the joint optimization of the source precoder and TS ratio, whose goal is to maximize the mutual information between the source and destination nodes. In a relay network, the joint optimization of precoder and PS ratio is also an important research area. In [16], the achievable transmission rate of the overall link in a MIMO DF relay network was maximized by optimizing the source and relay precoders and the PS ratio, where the optimal PS ratio was obtained by using a search algorithm. [17] considered a scenario similar to [16], and developed an iterative algorithm jointly optimizing the PS ratio and source power allocation, where the optimal PS ratio was obtained by the primal-dual method. In [18], to maximize the transmission rate, the joint optimization of source precoder and PS ratio over a non-regenerative MIMO orthogonal frequency-division multiplexing (OFDM) relay system was studied, where the expression of optimal PS ratio was derived.

Note that all of the aforementioned studies on SWIPT-enabled relay networks are based on the assumption of Gaussian input signals. However, in practical systems, input signals are typically taken from finite-alphabet constellations, such as phase shift keying (PSK) and quadrature amplitude modulation (QAM), which are not Gaussian distributed. Due to the difference between Gaussian signals and finite-alphabet signals, significant performance loss occurs when the precoder designs based on Gaussian inputs are used in systems with finite-alphabet inputs [19], [20]. To improve the performance of systems with finite-alphabet inputs, some investigations have been carried out. To maximize the mutual information over independent parallel Gaussian channels with finite-alphabet inputs, [19] provided an optimal algorithm called mercury-waterfilling. For general MIMO channels with perfect channel state information (CSI) known at the transmitter, [20] developed an optimal precoder design; subsequently, in [21], the complexity of designing the optimal precoder was significantly reduced by using the lower bound of mutual information. When the transmitter only knows the statistical CSI, the optimal precoder design for MIMO channels was studied in [22]. For a relay network with finite-alphabet inputs, [23] proposed an appropriately optimal precoder design, in which all the nodes are assumed to be equipped with constant power supply. Nowadays, research on precoding with finite-alphabet inputs has been extended to massive MIMO systems [24], [25], multiple access channel (MAC) systems [26] and multiantenna secure cognitive radio networks [27]. All the results of these works verified the superiority of the precoder, which is designed based on finite-alphabet inputs instead of Gaussian inputs, in the practical systems with finite-alphabet inputs.

This paper investigates the precoder design in a SWIPT-enabled relay network. Different from previous research [13]–[18], we assume that the inputs to the network are finite-alphabet signals, which, as mentioned above, are used in practical systems for transmission. In the considered relay network, the source, relay, and destination nodes are assumed to be equipped with a single antenna. Our analysis shows that this network can be regarded as an effective MIMO system and thus precoding can be implemented. Our goal is to jointly optimize the precoder, which performs precoding on signal blocks, at the source and the PS ratio at the relays to maximize the mutual information. The optimization problem is nondeterministic polynomial-time (NP)-hard. However, by theoretical analysis, we derive the optimal PS ratio; then, by employing the structures of optimization problem and precoder, we propose two near optimal precoding algorithms: one is based on semidefinite relaxation (SDR) technique, and the other is based on search technique. The latter shows slight performance degradation but with low complexity. Simulation results verify the efficacy of the proposed precoder designs.

The main contributions of this paper are as follows: first, we investigate the problem of maximizing mutual information in a SWIPT-enabled relay network with finite-alphabet inputs, where the relay nodes have no constant power supply and they need to harvest energy from the RF signals for information forwarding. To the best of our knowledge, the research on this scenario has not been reported in literature. Moreover, due to the complexity of the mutual information calculation for finite-alphabet inputs, this research is more challenging. Second, in the considered relay network with SWIPT, we theoretically analyze the optimal PS ratio maximizing the mutual information, which is verified by simulation results. Different from the previous works, in this paper, the optimal PS ratio is analyzed based on practical finite-alphabet inputs rather than ideal Gaussian inputs. Third, two near optimal precoder designs, which are based on SDR and search, respectively, are developed, and their performance is compared.

The structure of this paper is as follows. Section II describes the system model. Section III formulates the optimization problem. Section IV provides the problem solving framework. Section V presents the simulation results, and Section VI concludes this paper.

Notation: Boldface letters denote matrices or vectors, and italics denote scalars. The superscripts $(\cdot)^H$, $(\cdot)^T$ and $(\cdot)^*$ represent Hermitian, transpose and conjugate operations, respectively; $\text{Tr}(\cdot)$ and $\text{det}(\cdot)$ denote the trace and determinant of a matrix, respectively; $E_x(\cdot)$ represents the expectation over $x$; $\| \cdot \|$ denotes the Euclidean norm; $\mathbb{C}$ and $\mathbb{R}$ stand for the complex and real spaces, respectively; $\log$ and $\ln$ denote the base two logarithm and natural logarithm, respectively;
II. SYSTEM MODEL

Consider a SWIPT-enabled relay network with one source-and-destination pair, as shown in Fig. 1, where there is no direct link between the source and the destination and they communicate by means of $N$ relay nodes $R_1, R_2, \ldots, R_N$. We assume that the source and destination nodes have constant power supply, while the relay nodes have no constant power supply and they have to harvest energy from the RF signals before forwarding information, which is similar to [15] and [16], i.e., the harvest-then-forward protocol [11] is applied at the relays. Assume that all the nodes are equipped with a single antenna and operate in half-duplex mode. The channel gain matrices from the source to the $i$-th relay $R_i$ and from the $i$-th relay $R_i$ to the destination are denoted as $h_i$ and $g_i$, respectively. At the source node, the signals are transmitted in blocks with block length $L$, where $L \geq 1$. Therefore, the original signal block $x \in \mathbb{C}^{L \times 1}$ at the source node can be given by

$$x = [x_1 \ x_2 \ \cdots \ x_l \ \cdots \ x_L]^T$$

where $x_l, l = 1, \ldots, L$, are drawn from the equiprobable discrete constellations, such as PSK and QAM, with a unit covariance matrix, i.e., $E(xx^H) = I$.

![FIGURE 1. SWIPT-enabled relay system model.](image)

At the source node, the original signal block is processed by a precoding matrix before transmission, which is expressed as

$$s = [s_1 \ s_2 \ \cdots \ s_l \ \cdots \ s_L]^T = Ps$$

where $P \in \mathbb{C}^{L \times L}$ denotes the precoding matrix and $s \in \mathbb{C}^{L \times 1}$ is the precoded signal block for transmission.

In this paper, we assume that the relay network uses the two-hop AF protocol [23], in which the transmission from the source to the destination is divided into two phases. In the first phase, the source node transmits the signal $\sqrt{P_s} s$ with the power $P_s$ to the relays; in the second phase, the relays forward the signal to the destination. Now let us focus on the first phase. Let $h_i^t$ denote the channel gain from the source to relay $R_i$ at the $l$-th time slot, and $y_i^l$ be the received signal at relay $R_i$ at the $l$-th time slot. Then, we have

$$y_i^l = h_i^l \sqrt{P_s} s_i + n_i^l_{SR},$$

where $n_i^l_{SR}$ represents the zero-mean Gaussian noise with covariance $\sigma^2$ received by $R_i$ at the $l$-th time slot. Further, the received signal at $R_i$ over the $L$ time slots can be rewritten in matrix form as

$$y_i = h_i \sqrt{P_s} s + n_{SR},$$

where $y_i = [y_i^1, y_i^2, \ldots, y_i^L]^T$, $h_i = \text{diag}(h_i^1, h_i^2, \ldots, h_i^L)$, and $n_{SR} = [n_{SR}^1, n_{SR}^2, \ldots, n_{SR}^L]^T$.

As mentioned earlier, the relay nodes need to harvest energy from the received signals, and then use it to forward the information to the destination. In this paper, we assume that the relay nodes employ the PS scheme [18], [33] for energy harvesting, and that the PS ratios are identical among all the relays for simplicity. Under these assumptions, the received signal $y_i$ at relay $R_i$ is divided into two parts: one is $y_i^\prime_i$ used for information forwarding with PS ratio $\rho \in (0, 1)$, and the other is $y_i^\prime\prime_i$ used for energy harvesting with ratio $1 - \rho$. That is

$$y_i^\prime_i = \sqrt{\rho}(h_i \sqrt{P_s} s + n_{SR})$$

and

$$y_i^\prime\prime_i = \sqrt{1 - \rho}(h_i \sqrt{P_s} s + n_{SR}).$$

According to [39], [40], and [41], the energy harvesting efficiency has a non-linear relationship to the input power level. In this paper, for simplicity, we assume a linear relationship between them. Let $\eta$ denote the power conversion efficiency, and then the harvested energy at $R_i$ is $\eta \text{Tr} \left( E \left[ y_i^\prime\prime_i y_i^\prime\prime_i^H \right] \right)$ over the $L$ time slots. Here, assume that all the energy harvested by $R_i$ is used for the information forwarding in the second phase. Then, for the transmit power at $R_i$ for information forwarding, we have

$$b_i^t \text{Tr} \left( E \left[ y_i y_i^H \right] \right) = \eta \text{Tr} \left( E \left[ y_i^\prime\prime_i y_i^\prime\prime_i^H \right] \right)$$

where $b_i$ denotes a scaling factor, which is used to guarantee that the transmit power at $R_i$ does not exceed the
harvested power. Solving (3) yields
\[ b_i = \sqrt{\frac{\eta(1-\rho)}{\rho}}. \] (4)

Now, let us turn to the second phase, in which the relay node \( R_i \) transmits the signal \( b_i y_{R_i} \) to the destination. Let \( g_{ij} \) denote the channel gain from relay \( R_i \) to the destination at the \( l \)-th time slot. We can use an approach similar to [29] and [30] to combat the time delays, so the signal \( y_{D} \in \mathbb{C}^{L \times 1} \) received at the destination node is the superposition of the transmission signals from all the relay nodes, i.e.,
\[ y_{D} = \sum_{i=1}^{N} (b_i g_i y_{R_i} + n_{R,D}) \] (5)

where \( g_i = \text{diag}(g_{i1}^1, g_{i2}^2, \ldots, g_{iL}^L) \) and \( n_{R,D} \in \mathbb{C}^{L \times 1} \) denotes the independent and identically distributed (i.i.d.) zero-mean additive Gaussian noise vector with covariance \( \sigma^2 \mathbf{I} \) over the channel from \( R_i \) to the destination. Substituting (1) and (4) into (5), we have
\[ y_{D} = \sum_{i=1}^{N} \sqrt{\eta(1-\rho)} P_{s_i} g_i h_i s_i + n_{SD} \] (6)

where \( n_{SD} \) denotes the effective end-to-end noise, which satisfies complex Gaussian distribution \( \mathcal{CN}(0, N_0 \sigma^2 \mathbf{I}) \) with
\[ N_d = N I + \eta (1-\rho) \sum_{i=1}^{N} g_i g_i^H. \] (7)

Let
\[ F = \left( N I + \eta (1-\rho) \sum_{i=1}^{N} g_i g_i^H \right)^{-\frac{1}{2}}. \] (8)

Then, we can use \( F \) to normalize noise \( n_{SD} \) for convenience. After normalization, (6) can be written as
\[ y_{D} = \sum_{i=1}^{N} F \sqrt{\eta(1-\rho)} P_{s_i} g_i h_i s + F n_{SD}. \] (9)

Let \( n = F n_{SD} \), and it is easy to verify \( n \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}) \).

Now we are in a position to give the effective input-output relationship for the two-hop relay transmission, that is
\[ y_{D} = H P x + n \] (10)

where \( n \) denotes the effective end-to-end noise; \( H \) is the effective channel matrix of the two-hop relay channel, which is given by
\[ H = \sum_{i=1}^{N} F \sqrt{\eta(1-\rho)} P_{s_i} g_i h_i. \] (11)

Actually, equation (10) describes an effective MIMO system. So an appropriate precoder can be constructed to improve the system performance. In this paper, our objective is to maximize the overall mutual information of the system described by (10) by jointly optimizing the precoder and PS ratio when the inputs are finite-alphabet signals.

**III. PROBLEM FORMULATION**

In this paper, we assume that signal \( x \) is equiprobably drawn from discrete constellations of cardinality \( M \), and that perfect CSI is known at the source. In this case, the mutual information \( \bar{I}(x; y_{D}) \) between input \( x \) and output \( y_{D} \) in (10) is given by [36]
\[ \bar{I}(x; y_{D}) = L \log M - \frac{1}{M^L} \sum_{m=1}^{M^L} \log \sum_{k=1}^{M^L} \exp \left(-\frac{C_{mk} C_{mk}}{2\sigma^2}\right) \] (12)

where \( f_{mk} = \left( \| H P (x_m - x_k) + n \|^2 - \| n \|^2 \right) / \sigma^2 \). Here, \( x_m \) and \( x_k \) are input signal blocks containing \( L \) symbols taken independently from the \( M \)-ary signal constellation. Strictly speaking, the righthand side of (12) should be multiplied by \( 1/2L \), which has no effect on the optimal choice of the solution; so it is ignored here for convenience.

However, equation (12) involves the expectation over noise \( n \), which implies the evaluation of \( 2L \) integrals; so it is very difficult to directly compute the mutual information with finite-alphabet inputs according to (12). In [21], an approximate expression for the mutual information \( \bar{I}(x; y_{D}) \) is derived, which is
\[ \bar{I}(x; y_{D}) = L \log M - \frac{1}{M^L} \sum_{m=1}^{M^L} \log \sum_{k=1}^{M^L} \exp \left(-\frac{C_{mk} C_{mk}}{2\sigma^2}\right) \] (13)

where \( C_{mk} = H P e_{mk} = H P (x_m - x_k) \). \( \bar{I}(x; y_{D}) \) is a closed form expression according to [21], and it provides a very accurate approximation to the mutual information \( I(x; y_{D}) \). Therefore, in this paper, we use \( \bar{I}(x; y_{D}) \) instead of \( \bar{I}(x; y_{D}) \) to analyze the mutual information with finite-alphabet inputs.

In practical relay networks with SWIPT, PS ratio \( \rho \) cannot be 1 or 0. The reason is obvious: \( \rho = 1 \) means that no energy can be harvested for the signal transmission in the second phase, while \( \rho = 0 \) means that no information is received at the relays. Let \( \rho_{\text{min}} \) and \( \rho_{\text{max}} \), where \( \rho_{\text{min}} > 0 \) and \( \rho_{\text{max}} < 1 \), denote the minimum and maximum values of permitted \( \rho \), respectively. Then we have \( \rho \in [\rho_{\text{min}}, \rho_{\text{max}}] \).

Now we consider the relay network with SWIPT described earlier, whose input-output relationship is given by (10). Our goal is to find the optimal precoder \( P \) and PS ratio \( \rho \) to maximize \( \bar{I}(x; y_{D}) \) under the constraints of transmit power at the source node and permitted PS ratio, that is,
\[ \max_{P, \rho} \bar{I}(x; y_{D}) \] (14a)
\[ \text{s. t. } \text{Tr}\left(E\left[ss^H\right]\right) = \text{Tr}\left(PP^H\right) \leq L \] (14b)
\[ \rho_{\text{min}} \leq \rho \leq \rho_{\text{max}}. \] (14c)

The optimization problem (14) is difficult to solve because it is an NP-hard problem with two optimization variables. So we can not achieve its optimal solution in polynomial-time complexity. However, by analyzing the optimization problem, we derive the optimal PS ratio, and develop two algorithms that can yield near optimal precoders.

**IV. PROBLEM SOLVING**

In this section, we analyze optimization problem (14), and then perform optimizations on the PS ratio and precoder, respectively. Based on our analysis results, two near optimal solving algorithms for problem (14) are proposed.

According to (13), optimization problem (14) can be rewritten as

\[
\begin{align*}
\min_{P, \rho} & \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( -\frac{C_{mk}^H C_{mk}}{2\sigma^2} \right) \\
\text{s. t.} & \quad \text{Tr} \left( PP^H \right) \leq L \\
n & \quad \rho_{\text{min}} \leq \rho \leq \rho_{\text{max}}.
\end{align*}
\] (15a)

(15b)

(15c)

Now consider the exponential terms of (15a). Substituting (11), we have

\[
C_{mk}^H C_{mk} = \mathbf{e}_{mk}^H \mathbf{P}^H \mathbf{F} \sqrt{\eta \left( 1 - \rho \right)} \mathbf{P} \mathbf{g} \mathbf{h}_i^H \mathbf{P} \mathbf{g} \mathbf{h}_i \\
\times \left( \sum_{i=1}^{N} \mathbf{F} \sqrt{\eta \left( 1 - \rho \right)} P \mathbf{g} \mathbf{h}_i \right)^H.
\] (16)

From (16), we can find that the effects of PS ratio \( \rho \) and precoding matrix \( \mathbf{P} \) on the value of (15a) are actually independent, which motivates us to solve problem (16) by individually optimizing \( \rho \) and \( \mathbf{P} \).

**A. PS RATIO OPTIMIZATION**

Now, we consider the optimization of PS ratio \( \rho \). For a given feasible precoding matrix \( \mathbf{P} \), optimization problem (15) can be rewritten as

\[
\begin{align*}
\min_{\rho} & \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( -\frac{C_{mk}^H C_{mk}}{2\sigma^2} \right) \\
\text{s. t.} & \quad \rho_{\text{min}} \leq \rho \leq \rho_{\text{max}}. \quad (17a)
\end{align*}
\]

(17b)

For optimization problem (17), we have the following proposition:

**Proposition 1:** When precoding matrix \( \mathbf{P} \) is given, the optimal PS ratio at the relay nodes is

\[ \rho_{\text{opt}} = \rho_{\text{min}}. \] (18)

**Proof:** see Appendix.

Given the optimal PS ratio, the effective channel matrix (refer to (11)) is given by

\[ \hat{\mathbf{H}} = \sum_{i=1}^{N} \hat{\mathbf{F}} \sqrt{\eta \left( 1 - \rho_{\text{opt}} \right)} P \mathbf{g} \mathbf{h}_i \] (19)

where

\[ \hat{\mathbf{F}} = \left( N \mathbf{I} + \eta \left( 1 - \rho_{\text{opt}} \right) \sum_{i=1}^{N} \mathbf{g} \mathbf{h}_i^H \right)^{-\frac{1}{2}}. \] (20)

In the proof of Proposition 1, according to (44), we know that \( \omega \) is a monotonously decreasing function of \( \rho \). When \( \mathbf{P} \) is given, which means \( d_i \), \( l = 1, \ldots, L \), in (45) are fixed, it follows from (46) that \( C_{mk}^H C_{mk} \) also a monotonously decreasing function of \( \rho \). Therefore, according to (13), the \( \mathbf{I} (\mathbf{x}; \mathbf{y}_D) \) monotonously increases as the power ratio \( \rho \) decreases.

After achieving the optimal PS ratio, we next investigate the optimization of precoder \( \mathbf{P} \).

**B. NEAR OPTIMAL PRECODER DESIGN**

With the optimal PS ratio, we can rewrite the optimization problem (15) as

\[
\begin{align*}
\min_{\mathbf{P}} & \quad \Phi(\mathbf{P}) \\
\text{s. t.} & \quad \text{Tr} \left( \mathbf{P} \mathbf{P}^H \right) \leq L
\end{align*}
\] (21a)

(21b)

where

\[ \Phi(\mathbf{P}) = \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( -\frac{\mathbf{e}_{mk}^H \mathbf{P}^H \hat{\mathbf{H}} \mathbf{P} \mathbf{e}_{mk}}{2\sigma^2} \right). \] (22)

For problem (21), we develop two near optimal precoding design methods, which are based on SDR and search technique, respectively.

1) SDR BASED DESIGN

In problem (21), the objective function can be rewritten as [32]

\[ \Phi(\mathbf{P}) = \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( -\text{vec}(\mathbf{P})^H \left( \mathbf{B}_{mk}^T \otimes \hat{\mathbf{H}}^H \mathbf{H} \right) \cdot \text{vec}(\mathbf{P}) \right). \] (23)

where \( \mathbf{B}_{mk} = \mathbf{e}_{mk} \mathbf{e}_{mk}^H / (2\sigma^2) \). Let

\[ \mathbf{p} = \begin{bmatrix} \Re\{\text{vec}(\mathbf{P})\} \\
\Im\{\text{vec}(\mathbf{P})\} \end{bmatrix} \in \mathbb{R}^{2L^2} \] (24)

and

\[ \mathbf{A}_{mk} = \begin{bmatrix} \Re\{\mathbf{B}_{mk}^T \otimes \hat{\mathbf{H}}^H \mathbf{H} \} \\
\Im\{\mathbf{B}_{mk}^T \otimes \hat{\mathbf{H}}^H \mathbf{H} \} \end{bmatrix}. \] (25)

Then (23) can be rewritten as

\[ \Phi(\mathbf{P}) = \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( \mathbf{p}^T \mathbf{A}_{mk} \mathbf{p} \right). \] (26)

According to (23)-(26), optimization problem (21) can be transformed equivalently into

\[
\begin{align*}
\min_{\mathbf{P}} & \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp \left( \mathbf{p}^T \mathbf{A}_{mk} \mathbf{p} \right) \\
\text{s. t.} & \quad \mathbf{p}^T \mathbf{p} \leq L.
\end{align*}
\] (27a)

(27b)
Let $G = pp^T$, which is a symmetric PSD matrix with rank one. Then problem (27) can be reformulated equivalently as
\begin{equation}
\min_G \sum_{m=1}^{M_L} \sum_{k=1}^{M_L} \log \exp(\text{Tr}(A_{mk} G)) \quad (28a)
\end{equation}
subject to
\begin{align}
\text{Tr}(G) &\leq L \quad (28b) \\
G &\in S, \ G \succeq 0 \quad (28c) \\
\text{rank}(G) & = 1 \quad (28d)
\end{align}

By dropping the rank constraint (28d), we obtain the following relaxed version of problem (28):
\begin{equation}
\min_G \sum_{m=1}^{M_L} \sum_{k=1}^{M_L} \log \exp(\text{Tr}(A_{mk} G)) \quad (29a)
\end{equation}
subject to
\begin{align}
\text{Tr}(G) &\leq L \quad (29b) \\
G &\in S, \ G \succeq 0 \quad (29c)
\end{align}

As the SDR of problem (28), problem (29) is an instance of the semidefinite programming (SDP), and thus, it can be solved efficiently by interior-point method (IPM) [28] or existing general solvers like CVX [34].

Now we briefly describe the IPM for solving problem (29). Using the barrier method [38], we can rewrite problem (29) as
\begin{equation}
\min_G f(G) = f_o(G) + \varphi(L - \text{Tr}(G)) + \varphi(\text{det}(G)) \quad (30)
\end{equation}
where
\begin{equation}
f_o(G) = \sum_{m=1}^{M_L} \sum_{k=1}^{M_L} \exp(\text{Tr}(A_{mk} G)) \quad (31)
\end{equation}
In problem (30), $\varphi(u)$ denotes the logarithmic barrier function given by
\begin{equation}
\varphi(u) = \begin{cases} 
-\frac{1}{t} \ln(u), & u > 0 \\
+\infty, & u \leq 0
\end{cases} \quad (32)
\end{equation}
with barrier parameter $t > 0$.

For problem (30), the gradient of $f(G)$ at feasible point $G$ is given by
\begin{equation}
\nabla_G f(G) = \nabla_G f_o(G) - \frac{1}{t} (-\frac{I}{L - \text{Tr}(G)} + G^{-1}) \quad (33)
\end{equation}
where
\begin{equation}
\nabla_G f_o(G) = \sum_{m=1}^{M_L} \sum_{k=1}^{M_L} \frac{\exp(\text{Tr}(A_{mk} G)) \cdot A_{mk}^T}{2} \quad (34)
\end{equation}
In the iterations, the negative gradient of $f(G)$ is chosen as the descent direction, i.e.,
\begin{equation}
\Delta G = -\nabla_G f(G) \quad (35)
\end{equation}
By combining descent direction (35) with the backtracking line search [38], the optimal solution to SDP problem (29), which is denoted by $G_{opt}$, can be obtained. The details are given in Algorithm 1. Note that, after the optimal solution to (29) is obtained, the Gaussian randomization technique [35] needs to be used to extract an approximate solution $p_{opt}$ to problem (27). The Gaussian randomization technique and the corresponding precoder design based on SDR are presented in detail in Algorithms 2 and 3, respectively.

**Algorithm 1 IPM for Optimization Problem (29)**

1. **Initialization**: Given tolerance $\xi > 0$, $t := t(0) > 0$, $\alpha > 1$, and feasible initial point $G_0 = \frac{1}{2} I$.
2. **Search direction**: Compute the gradient of $f(G)$ at $G$ as (33) and the descent direction $\Delta G$ as (35). Evaluate $||\Delta G||^2 = \text{Tr}(\Delta G^T \Delta G)$. If it is sufficiently small, go to step 5.
3. **Search step**: Choose step size $\mu$ by backtracking line search.
4. **Update**: Set $G := G + \mu \Delta G$. Go to step 2.
5. **Iteration and stop**: Stop if $\frac{1}{t} < \xi$, else $t := \alpha t$, and go to step 2.
6. **Output**: Optimal solution $G_{opt} := G$ to problem (29).

**Algorithm 2 Gaussian Randomization Algorithm**

1. Calculate the eigen-decomposition of $G_{opt} = U_G \Sigma_G U_G^T$.
2. For $r = 1$ to $K$ do
3. Generate vector $q_r \in \mathbb{R}^{M_L2}$ of zero-mean, unit-variance Gaussian random variables;
4. Let $\hat{p}_r := U_G \Sigma_G^{1/2} q_r$, which means $\hat{p}_r \sim \mathcal{N}(0, G_{opt})$;
5. Rescale $\hat{p}_r$ to obtain $p_r$, that is, $p_r := \hat{p}_r / \sqrt{\text{Tr}(p_r^T p_r) / L}$;
6. If $p_r$ satisfies $p_r^T p_r / L \leq 1$, then calculate $\sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp(p_r^T A_{mk} p_r)$;
7. Else, return to 2.
8. End for
9. Extract an approximate solution $p_{opt} := p_r$, where $r = \arg \min \sum_{m=1}^{M_L} \log \sum_{k=1}^{M_L} \exp(p_r^T A_{mk} p_r)$.

2) SEARCH BASED DESIGN

The precoder design based on SDR technique has high complexity due to the usages of IPM and Gaussian randomization technique. Next we develop another precoding algorithm with low complexity. Applying singular value decomposition (SVD) to the precoding and effective channel matrices, respectively, we have $P = U_P \Sigma_P V_P^T$ and $H = U_H \Sigma_H V_H^T$, where $U_P$, $V_P$, $U_H$, and $V_H$ are unitary matrices, and $\Sigma_P$ and $\Sigma_H$ are nonnegative diagonal matrices containing singular values. According to [21], the left singular matrix of the optimal precoder can always be chosen to be the same as the right singular matrix of the effective channel matrix, i.e., $V_H = U_P$.

On the other hand, according to [37], the right singular matrix $V_P$ can be simply set to be the modulation diversity.
After keying (BPSK), quadrature phase shift keying (QPSK), and modulation, and it equals 1, (37), the rotation angle optimized, is only the diagonal matrix $V$. With SWIPT and Finite-Alphabet Inputs, according to our previous work [28] for details. Then a near optimal solution, where $G_{opt}$ is optimal, is approximately optimal solution to problem (14). Finally, a near optimal precoder is obtained according to (38). Unlike the precoder design based on SDR, this algorithm is designed through searching in the feasible region instead of using iterative IPM. So the search based precoding algorithm has lower complexity than the SDR based one. The details of search based algorithm are shown in Algorithm 4.

Algorithm 3 SDR Based Precoder Design for Relay Network With SWIPT and Finite-Alphabet Inputs

1. Given block length $L$, relay node number $N$, relay channel gain matrices $h_i$, $g_i$, and permitted PS ratio region $[\rho_{min}, \rho_{max}]$;
2. Let optimal PS ratio $\rho_{opt} = \rho_{min}$, and compute the corresponding effective channel matrix $\hat{H}$ according to (19);
3. Use the IPM to solve problem (29), and obtain the optimal $G_{opt}$;
4. Use the Gaussian randomization technique to obtain approximate solution $p_{opt}$ to problem (27);
5. Rewrite $p_{opt}$ in complex matrix form and thus yield the approximately optimal solution to problem (14).

Algorithm 4 Search Based Precoder Design for Relay Network With SWIPT and Finite-Alphabet Inputs

1. Given block length $L$, relay node number $N$, relay channel gain matrices $h_i$, $g_i$, and permitted PS ratio region $[\rho_{min}, \rho_{max}]$;
2. Let optimal PS ratio $\rho_{opt} = \rho_{min}$, and compute the corresponding effective channel matrix $\hat{H}$ according to (19);
3. Employ the search strategy to find an appropriately optimal solution $\Sigma_p$ to problem (40);
4. Obtain a near optimal precoder according to (38).

3) COMPLEXITY OF BOTH ALGORITHMS

For the SDR based algorithm, when problem (29) is solved, the number of iterations is linear in $\sqrt{2L^2}$, where $2L^2$ is the dimension of optimization variable $G$ [38]. Let $C_{SDR}$ denote the complexity of calculating the objective function and its gradient in each iteration, then the complexity of solving SDP problem (29) is $O(\sqrt{2L^2} \cdot C_{SDR})$. In the subsequent randomization process with $K$ randomizations, the operation complexity is $O(K \cdot C_{RAN})$ where $C_{RAN}$ is the complexity of calculating (27a) for each randomization. Therefore, the complexity of the SDR based algorithm is

$$O\left(\sqrt{2L^2} \cdot C_{SDR} + K \cdot C_{RAN}\right).$$

Similarly, for the search based algorithm, the complexity of solving problem (40) is given by

$$O\left(J \cdot C_{SE}\right).$$
where $J$ is the number of iterations and $C_{\text{SE}}$ denotes the complexity of calculating (40a) in each iteration.

The calculation of (27a) is with respect to a matrix with $2L^2$ dimensions; in comparison, calculating (40a) only involves an $L$-dimensional matrix, which means $C_{\text{SE}} < C_{\text{RAN}}$. In general, the number of randomizations in the SDR based algorithm is larger than the number of iterations in the search based algorithm, that is, $J < K$. Comparing (42) and (43), we can see that the search based algorithm offers higher efficiency than the SDR based algorithm.

V. SIMULATION RESULTS

In this section, the performance of the proposed joint optimization algorithms maximizing mutual information in the SWIPT-enabled relay network with finite-alphabet inputs is evaluated by simulations. In the simulations, a relay network is considered with $N = 2$ relay nodes. The cases of block length $L = 2$ and 3 are simulated, respectively. When $L = 2$, the channel gain matrices are, respectively, given by $\mathbf{h}_1 = \text{diag}(-1.9 + 1.3i, 1.2 + 0.3i)$, $\mathbf{h}_2 = \text{diag}(2.4 - 1.6i, 1.4)$ and $\mathbf{g}_1 = \text{diag}(-1.2 + 0.9i, 0.6)$, $\mathbf{g}_2 = \text{diag}(1.7 - 0.7i, 0.5)$; when $L = 3$, the channel gain matrices are, respectively, given by $\mathbf{h}_1 = \text{diag}(-1.9 + 1.3i, 1.3 + 0.3i, 1.2 - 0.3i)$, $\mathbf{h}_2 = \text{diag}(2.4 - 1.6i, 1.2, 1.1)$ and $\mathbf{g}_1 = \text{diag}(-1.2 + 0.9i, 0.5, 0.6)$, $\mathbf{g}_2 = \text{diag}(1.7 - 0.7i, 0.6, 0.7)$. In the search based algorithm, $W$ is assumed to be 10. At the source, the power $P_s$ is 30 dBm; the minimum PS ratio, maximum PS ratio and energy conversion efficiency are set to be $\rho_{\text{min}} = 0.16$, $\rho_{\text{max}} = 0.92$ and $\eta = 80\%$, respectively. The SNR is defined as $\text{SNR} = \frac{\text{Tr}((\mathbf{H}\mathbf{H}^H))}{(L\sigma^2)}$, where $\sigma^2$ is the end-to-end noise power.

Fig. 3 shows the mutual information versus SNR for the SWIPT-enabled relay system with BPSK inputs and $L = 3$.

Fig. 2 shows the mutual information versus PS ratio $\rho$ for a given precoder, where the precoder is assumed to be an identity matrix. The signal block length $L$ is set to be 2. Two modulation formats, i.e., BPSK and QPSK, are employed, respectively. In section IV-A, our analysis shows that, given a precoder, the achievable mutual information monotonically decreases as the PS ratio increases. In Fig. 2, this trend is observed; moreover, when $\rho$ is equal to $\rho_{\text{min}}$, i.e., 0.16, the mutual information achieves the maximum. Therefore, the simulation results coincide with the earlier analysis, which verifies the correctness of our theoretical analysis on PS ratio $\rho$. 
SNR regions, the corresponding performance is even worse than the finite-alphabet inputs without precoding.

Fig. 4 illustrates the mutual information versus SNR when the inputs are changed to QPSK signals with $L = 2$. The results are similar to Fig. 3. Specifically, the SDR based precoder is slightly superior to the search based one in mutual information performance, but both of them clearly outperform the precoder developed in [31] when the inputs are finite-alphabet signals. On the other hand, since QPSK has a higher modulation order than BPSK, the performance of the precoders proposed in this paper is more close to the upper bound for a wide range of SNR.

Note that, in Figs. 3 and 4, the triangle curves, which denote the performance of the precoder proposed in [31], are not smooth. This phenomenon results from the threshold effect due to the signal mismatch of the precoder designing method. The precoder in [31] was developed for Gaussian signals. When the inputs are replaced by finite-alphabet signals, there exists a threshold effect. Specifically, when the SNR is less than a threshold (2.5 dB in Fig. 3 and 5 dB in Fig. 4), the precoder in [31] allocates all the power to the strongest subchannel of the effective two-hop relay MIMO channel, which leads to a slow increase of mutual information. In contrast, when the SNR exceeds the threshold, the precoder starts to allocate power to the weaker subchannels and therefore makes the mutual information increase rapidly. So the non-smoothness of curves occurs. Refer to [22] for details.

Fig. 5 presents the block error rate (BLER) performance of the proposed precoders, where BLER denotes the error rate of blocks transferred from the source to the destination. At the receiver, the maximum a posteriori (MAP) detector is employed. The BLER performance of the precoder designed in [31] is also provided. As observed in Fig. 5, the precoders based on finite-alphabet inputs exhibit better performance. For example, at BLER $= 10^{-2}$, the performance gains are about 9 dB for BPSK inputs with $L = 3$ and 7 dB for QPSK inputs with $L = 2$, respectively. Therefore, the precoders proposed in this paper not only achieve larger mutual information, but also offer lower BLER than the precoder designed in [31] when input signals are replaced by finite-alphabet inputs. Comparing the SDR based and search based precoders, we can observe that the BLER performance of the former is a bit better than that of the latter.

Figs. 6 and 7 provide the simulation results under a more realistic channel model, where the channel gains are modeled as i.i.d. zero-mean complex Gaussian random variables [42], [43]. Specifically, when $L = 2$, the covariances of channel gains are given by $\sigma^2_{h_1} = \sigma^2_{g_1} = 4$ and $\sigma^2_{h_2} = \sigma^2_{g_2} = 1$, $i = 1, 2$, respectively; when $L = 3$, the covariances

![FIGURE 4. Mutual information versus SNR for SWIPT-enabled relay system with QPSK inputs and $L = 2$.](image)

![FIGURE 5. BLER versus SNR for SWIPT-enabled relay system.](image)

![FIGURE 6. Average mutual information versus SNR for SWIPT-enabled relay system with BPSK inputs and $L = 3$.](image)
of channel gains are given by $\sigma^2_{h_i^1} = \sigma^2_{g_i^1} = 4$, $\sigma^2_{h_i^2} = \sigma^2_{g_i^2} = 1$, and $\sigma^2_{h_i^3} = \sigma^2_{g_i^3} = 1$, $i = 1, 2$, respectively. Other simulation parameters are the same as previously given. For each channel realization, the mutual information with finite-alphabet inputs is obtained by using the algorithms based on SDR and search, respectively. The average mutual information is calculated over 1000 channel realizations. Fig. 6 shows average mutual information versus SNR, where $L$ is set to be 3 and BPSK modulation is employed. The average mutual information with precoder developed in [31] is also provided in the Gaussian and finite-alphabet input cases. As shown in this figure, over more realistic channels, the proposed algorithms still exhibit almost the same excellent performance, both of which are superior to the precoder developed in [31] when the inputs are finite-alphabet signals.

Fig. 7 shows average BLER versus SNR, where average BLER is also calculated over 1000 channel realizations. The results for two settings, i.e., BPSK with $L = 3$ and QPSK with $L = 2$, are presented. It is easy to find that the SDR based algorithm offers better performance than the search based algorithm, especially with $L = 2$. BPSK with $L = 3$ and QPSK with $L = 2$, respectively. Other simulation parameters are the same as previously given. For each channel realization, the effective channel $H$ is also a diagonal matrix. Let $\Omega = H^H H$, and then $\Omega$ is a diagonal PSD matrix. Let $\Omega = \text{diag}(\omega_1, \omega_2, \ldots, \omega_L)$. Then the $l$-th diagonal entry $\omega_l$ is given by

$$\omega_l = \eta (1 - \rho) \mu_l \left( \sum_{i=1}^{N} g_{l,i} \right)^2 \left( \sum_{i=1}^{N} g_{l,i}^* \right)^* \tag{44}$$

where $\mu_l = \frac{1}{\sqrt{N + \eta (1 - \rho) \sum_{i=1}^{N} g_{i}^* (g_{i}^*)^*}}$. Let $d_{mk} = P_{mk} = [d_1, d_2, \ldots, d_L]^T$, then we have

$$C_{mk}^H C_{mk} = e_{mk}^H P_{mk} H^H H P_{mk} e_{mk} = d_{mk}^H \Omega d_{mk} = \sum_{l=1}^{L} \omega_l d_l d_l^* \tag{46}$$

where $d_l$ denotes the $l$-th entry of the vector $d_{mk}$.

Now, optimization problem (15) can be rewritten as

$$\min_{F, \rho} \frac{1}{M^L} \sum_{m=1}^{M^L} \sum_{k=1}^{M^L} \log \exp \left( \frac{-d_{mk}^H \Omega d_{mk}}{2 \sigma^2} \right) \tag{47a}$$

subject to $\text{Tr} (P P^H) \leq L \tag{47b}$

$$\rho_{\min} \leq \rho \leq \rho_{\max} \tag{47c}$$

Maximizing objective function (47a) is equivalent to maximizing each term in (47a). In other words, optimization problem (47) can be transformed into a set of $M^{2L}$ optimization problems with different $m$ and $k$, each of them is given by

$$\max_{\rho, d_l} d_{mk}^H \Omega d_{mk} = \sum_{l=1}^{L} \omega_l d_l d_l^* \tag{48a}$$

subject to $\text{Tr} (P P^H) \leq L \tag{48b}$

$$\rho_{\min} \leq \rho \leq \rho_{\max} \tag{48c}$$

It is easy to find that $d_l d_l^*$ have relation only to $P$. Therefore, when the precoder $P$ is given, which means that $d_l$ is
fixed, problem (48) is equivalent to an optimization problem with respect to \( \omega_l \):

\[
\max_{\rho} \sum_{l=1}^{L} \omega_l d_l^* d_l \quad \text{s.t.} \quad \rho_{\min} \leq \rho \leq \rho_{\max}.
\]  

(49a)

Since \( d_l^* d_l \) and \( \omega_l \) are both non-negative, problem (49) is finally transformed into \( L \) optimization problems, where the \( l \)-th one is given by

\[
\max_{\rho} \omega_l \rho \
\text{s.t.} \quad \rho_{\min} \leq \rho \leq \rho_{\max}.
\]  

(50a)

According to (44), we know \( \omega_l \) is a monotonously decreasing function with respect to \( \rho \). So, to achieve the maximum value of \( \omega_l \), the optimal PS ratio \( \rho_{\text{opt}} \) satisfies

\[ \rho_{\text{opt}} = \rho_{\min}. \]  

(51)

The proof is completed. \( \square \)

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