Power Allocation for IRS-Aided Two-Way Decode-and-Forward Relay Wireless Network

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Abstract—In this paper, an intelligent reflecting surface (IRS)-aided two-way decode-and-forward (DF) relay wireless network is considered, where two users exchange information via IRS and DF relay. To enhance the sum rate performance, three power allocation (PA) strategies are proposed. Firstly, a maximizing sum rate method based on successive convex approximation (Max-SR-SCA) is proposed to jointly optimize the PA factors of user1 ($U_1$), user2 ($U_2$) and relay station (RS). To further improve sum rate performance, a method of maximizing determinant (Max-Det) with a higher sum rate enhancement is presented. Considering the asymmetry of two-way rates caused by channel quality and two users’ demand, maximizing sum rate with rate constraint (Max-SR-RC) is put forward. Simulation results show that the proposed three PA methods not only outperform the equal power allocation (EPA) method, but also the sum rates corresponding to the three PA methods are slightly lower than that of optimal exhaustive search (ES) method. Especially for Max-SR-RC method, its rate gain over EPA is up to 64.7% and its sum rate gap with optimal ES is less than 0.1bits/s/Hz. Furthermore, it is verified that the total power and random shadow variable $X_\sigma$ have a substantial impact on the sum rate.

Index Terms—Intelligent reflecting surface, power allocation, sum rate, two-way decode-and-forward relay.

I. INTRODUCTION

There are many thorny problems in communication networks, such as the propagation loss and multi path fading, which seriously deteriorate the communication performance [1]. With the ability to intelligently adjust the propagation environment, helpful multi path can be created by intelligent reflecting surface (IRS). IRS consists of cost-effective, low-power, and passive reflecting units, which reflect the signal independently to achieve passive beamforming for signal enhancement, spectral and energy efficiency improvement [2]. IRS has been widely applied to different application scenarios, e.g., physical layer security [3], simultaneous wireless information and power transfer [4], [5], mobile edge computing [6], covert communication [7], and UAV communication [8], [9]. In [10] and [11], the authors respectively proposed an IRS-aided wireless communication system. In [10], the active beamformer at the base station, the passive beamformer at the IRS, and the receive filter at the user were jointly designed to minimize the total mean square error (MSE) for signal estimation. For channel estimation, the training sequence of the access point and reflection pattern of the IRS were jointly optimized to minimize MSE in [11]. Moreover, robust channel and secure sum-rate maximization for multiuser MISO downlink systems with self-sustainable IRS were well discussed in [12].

Due to the fact that IRS reflects signal with low-power consumption, which can be regarded as a passive relay. While the conventional relay is an active device with strong signal processing capability to amplify and forward (AF), decode and forward (DF) signal. Its high hardware cost and high-power consumption are inconsistent with our low-energy-consumption communication demand.

How to make full use of the advantages of IRS and relay to serve the wireless communication network is crucial, which has already attracted extensive attention from both academia and industry [13], [14], [15]. In [13], an IRS-aided DF relay network was considered. To optimize the beamforming at relay station (RS) and phase at IRS, three methods of maximizing receive power, i.e., using alternately iterative structure, null-space projection based plus maximum ratio combining (MRC) and IRS element selection based plus MRC, were respectively proposed. [14] presented cooperative relay networks with IRS, where reflection amplitudes changes with the discrete phase. A low-complexity deep reinforcement learning (DRL) scheme was proposed to optimize relay selection and IRS reflection coefficient. In [15], the authors investigated an IRS-aided two-way AF relay network, where phase was solved by signal-to-noise ratio (SNR)-upper-bound-maximization or genetic-SNR-maximization and beamforming was achieved by optimizing beamforming or maximum-ratio beamforming. It demonstrated the proposed algorithms evidently performed better than random phase.

An IRS-assisted DF relay network can be applied to the scenarios where the direct channel between source and destination or source and relay or relay and destination is blocked. All the above literature focused on the optimization of beamforming at RS and phase at IRS, but did not consider power allocation (PA) between users and RS. PA is an efficient way to improve the sum rate, which plays an important role in sum rate. As far as we know, there is little research work on the PA of IRS-aided two-way DF relay network. This motivates us to pay attention to the PA under the total power constraint. Our main contributions are summarized as follows:

1) To improve the sum rate of an IRS-aided two-way DF relay network, a maximizing sum rate method based on successive convex approximation (Max-SR-SCA) is proposed to maximize sum rate by optimizing the power allocation (PA) factors of two users and RS. By utilizing equivalent replacement of PA factor and the first-order Taylor approximation of the product of two PA factors, sub-optimal PA factors of user1 ($U_1$), user2 ($U_2$) and RS are obtained. From the simulation results, the proposed Max-SR-SCA method can harvest higher sum rate than equal power allocation (EPA) method.

2) To make a higher sum rate enhancement, two high-performance PA strategies, namely maximizing determinant (Max-Det) and maximizing sum rate with rate constraint (Max-SR-RC), are presented. For each subcase between the rate of $U_1$-RS-$U_2$ link and $U_2$-RS-$U_1$ link ($R_{12} + R_{21}$) and the rate of multiple access channel ($R_{MAC}$) in Max-Det method, by using inequality

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transformation, non-convex problem are converted to convex for sub-optimal PA factors. In Max-SR-RC method, the asymmetry between $R_{12}$ and $R_{21}$ is taken into account. Simulation results show that the proposed two methods can obtain higher sum rate than Max-SR-SCA method. Especially for Max-SR-RC method, its sum rate is approximate to that of optimal exhaustive search (ES) method.

The remainder of this paper is organized as follows. In Section II, an IRS-aided two-way DF relay network is described. In Section III, three PA schemes for better sum rate are demonstrated. Simulation results are presented in Section IV, and conclusions are drawn in Section V.

**Notation:** Scalars, vectors and matrices are represented by letters of lower case, bold lower case, and bold upper case. \((\cdot)^T\) and \((\cdot)^H\) stand for transpose and conjugate transpose, respectively. \(\mathbb{E}\{\cdot\}\) and \(\|\cdot\|\) denote expectation operation and 2-norm, respectively. The sign \(\mathbf{I}_M\) is the \(M \times M\) identity matrix. \(\text{det}(\cdot)\) and \(e(\cdot)\) represent determinant and matrix index.

## II. SYSTEM MODEL

As shown in Fig. 1, we consider an IRS-aided two-way relay network. The network comprises a half-duplex two-way DF RS with \(M\) transmit antennas, an IRS with \(N\) reflecting elements, and two single-antenna users. Two users are respectively denoted by \(U_1\) and \(U_2\), which mutually exchange information with the help of IRS and RS. Due to path loss, the power of signals reflected by the IRS twice or more are such weak that they can be ignored. In the first time slot, the received signal at RS can be expressed as

\[
y_r = \sqrt{\beta_1} P (h_{1r} + H_{1r} \Theta_1 h_{1i}) x_1 + \sqrt{\beta_2} P (h_{2r} + H_{r} \Theta_2 h_{2i}) x_2 + n_r,
\]

where \(x_1\) and \(x_2\) are the independent transmit signal from \(U_1\) and \(U_2\), respectively. \(P\) is the total transmission power and limited. \(\beta_1\) and \(\beta_2\) are the power allocation parameters of \(U_1\) and \(U_2\). \(\mathbb{E}\{x_1^2\} = 1\) and \(\mathbb{E}\{x_2^2\} = 1\). Without loss of generality, we assume a Rayleigh fading environment [16]. Let \(h_{1r} \in \mathbb{C}^{M \times 1}\), \(H_{1r} \in \mathbb{C}^{M \times N}\) and \(h_{1i} \in \mathbb{C}^{N \times 1}\) represent the channels from \(U_1\) to RS, from IRS to RS, and from \(U_1\) to IRS, \(h_{2r} \in \mathbb{C}^{M \times 1}\) and \(H_{2r} \in \mathbb{C}^{M \times N}\) represent the channels from \(U_2\) to RS and from IRS to RS. \(\Theta_1\) is the diagonal reflection-coefficient matrix of IRS, which is denoted as \(\Theta_1 = \text{diag}(e^{j\theta_{11}}, \ldots, e^{j\theta_{1N}}), \theta_{1i} \in (0, 2\pi)\) is the phase shift of the \(i\)th element. \(n_r \in \mathbb{C}^{M \times 1}\) is the additive white Gaussian noise (AWGN) with distribution \(n_r \sim \mathcal{C}\mathcal{N}(0, \sigma_r^2 \mathbf{I}_M)\). Considering \(x_2\) as unknown interference, RS first decodes \(x_1\) to \(\tilde{x}_2\).

Then the contribution of \(x_1\) can be eliminated from (1), and \(x_2\) can be decoded to \(\tilde{x}_2\).

In the second time slot, superposition coding is considered to combine the decode messages. The transmit signal from RS is given by

\[
x_t = u_{12} \tilde{x}_2 + u_{11} \tilde{x}_1,
\]

where \(u_{11} \in \mathbb{C}^{M \times 1}\) and \(u_{12} \in \mathbb{C}^{M \times 1}\) are the transmit beamforming vector for \(U_1\) and \(U_2\). If \(|u_{11}|^2 = 1\) and \(|u_{12}|^2 = 1\). Since each user has perfect knowledge of the signal they send, after each user subtracts the self-interference from the received signal, the equivalent received signal at \(U_1\) and \(U_2\) are

\[
y_1 = \sqrt{\beta_1} P (h_{1r}^H + h_{1r}^H \Theta_2 H_{1r}^H) u_{11} \tilde{x}_2 + n_1,
\]

\[
y_2 = \sqrt{\beta_2} P (h_{2r}^H + h_{2r}^H \Theta_2 H_{2r}^H) u_{12} \tilde{x}_1 + n_2,
\]

where \(\mathbb{E}\{\tilde{x}_2^2\} = 1\) and \(\mathbb{E}\{\tilde{x}_1^2\} = 1\). \(\beta_1\) is the power allocation parameter of RS, the diagonal reflection-coefficient matrix of IRS is represented as \(\Theta_2 = \text{diag}(e^{j\theta_{21}}, \ldots, e^{j\theta_{2N}}), \theta_{2i} \in (0, 2\pi)\) is the phase shift of the \(i\)th element. \(n_1\) and \(n_2\) are the AWGN with distribution \(n_1 \sim \mathcal{C}\mathcal{N}(0, \sigma_1^2)\) and \(n_2 \sim \mathcal{C}\mathcal{N}(0, \sigma_2^2)\), respectively. It is assumed that all the channel state informations are available, and \(\sigma_1^2 = \sigma_2^2 = \sigma^2\). The achievable rate of \(U_1\)-RS-\(U_2\) link can be expressed as

\[
R_{12} = \min\{R_{11r}, R_{12r}\},
\]

where \(R_{11r}\) and \(R_{12r}\) are the rates of \(U_1\)-RS and RS-\(U_2\) link, respectively,

\[
R_{11r} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_1 P ||h_{1r} + H_{1r} \Theta_1 h_{1i}||^2}{\sigma^2}\right),
\]

\[
R_{12r} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_2 P ||h_{2r} + H_{2r} \Theta_2 h_{2i}||^2}{\sigma^2}\right).
\]

Similarly, the achievable rate of \(U_2\)-RS-\(U_1\) link can be represented as follows

\[
R_{21} = \min\{R_{21r}, R_{21i}\},
\]

where \(R_{21r}\) and \(R_{21i}\) are the rates of \(U_2\)-RS and RS-\(U_1\) link, respectively,

\[
R_{21r} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_2 P ||h_{2r} + H_{2r} \Theta_1 h_{2i}||^2}{\sigma^2}\right),
\]

\[
R_{21i} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_1 P ||h_{1r} + H_{1r} \Theta_2 h_{1i}||^2}{\sigma^2}\right).
\]

The achievable multiple access channel rate of \(U_1\)-RS and \(U_2\)-RS can be represented as follows

\[
R_{MAC} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_1 P ||h_{1r} + H_{1r} \Theta_1 h_{1i}||^2}{\sigma^2} + \frac{\beta_2 P ||h_{2r} + H_{2r} \Theta_1 h_{2i}||^2}{\sigma^2}\right).
\]

Therefore, the achievable sum rate of the proposed system is defined as follows

\[
R = \min\{R_{12} + R_{21}, R_{MAC}\} = \min\{\min\{R_{11r}, R_{12r}\} + \min\{R_{21r}, R_{21i}\}, R_{MAC}\}.
\]
III. PROPOSED THREE PA METHODS

Aiming at maximizing $R$, the optimization problem is casted as

$$\max \beta_1, \beta_2, \beta_3, u_{1r}, u_{2r}, \Theta_1, \Theta_2 \min \{R_{1r} + R_{2r}, R_{MAC}\}$$
(13a)

s.t. $0 < \beta_1, \beta_2, \beta_3 < 1, \beta_1 + \beta_2 + \beta_3 = 1$,  
(13b)
\[
\|u_{1r}^H\|_2^2 = 1, \|u_{2r}^H\|_2^2 = 1,
\]
(13c)
\[
\Theta_1(i, i) = 1, \Theta_2(i, i) = 1, \forall i = 1, \ldots, N.
\]
(13d)

The alternative iteration process can be performed among $\beta_1, \beta_2, \beta_3$, $u_{1r}, u_{2r}, \Theta_1$ and $\Theta_2$ until the convergence criterion is satisfied, while maximum $R$ is obtained. However, here we mainly focus on the PA problem. It is assumed that $u_{1r}, u_{2r}, \Theta_1$ and $\Theta_2$ are fixed when $\beta_1, \beta_2$ and $\beta_3$ are optimized during each iteration. The above problem can be transformed to

$$\max_{\beta_1, \beta_2, \beta_3} \min \{\min\{R_{1r}, R_{2r}\} + \min\{R_{2r}, R_{1r}\}, R_{MAC}\}$$
(14a)

s.t. $0 < \beta_1, \beta_2, \beta_3 < 1, \beta_1 + \beta_2 + \beta_3 = 1$.
(14b)

To solve the optimization problem, three PA schemes are proposed, which are Max-SR-SCA, Max-Det and Max-SR-RC, respectively, and the related details are as follow.

A. Proposed Max-SR-SCA

For convenience, let us define $\gamma_1 = (h_{1r}^H + h_{1r}^H \Theta_1 h_{1r}) u_{1r}^2$ and $\gamma_2 = (h_{2r}^H + h_{2r}^H \Theta_2 h_{2r}) u_{2r}^2$. Therefore, we have

$$R_{1r} = \frac{\log_2(1 + \gamma_1 \beta_1 P)}{2}, R_{2r} = \frac{\log_2(1 + \gamma_2 \beta_2 P)}{2},$$
(15)

$$R_{2r} = \frac{\log_2(1 + \gamma_2 \beta_2 P)}{2}, R_{1r} = \frac{\log_2(1 + \gamma_1 \beta_1 P)}{2},$$
(16)

$$R_{MAC} = \frac{1}{2} \log_2(1 + \gamma_1 \beta_1 P + \gamma_2 \beta_2 P).$$
(17)

The system sum rate $R$ is expanded as follows

$$R = \min\{R_{1r} + R_{2r}, R_{1r} + R_{2r}, R_{1r} + R_{2r}, R_{2r} + R_{2r}, R_{1r} + R_{1r}, R_{MAC}\}.$$  
(18)

Clearly, $R_{1r} + R_{2r} > R_{MAC}$, so the case of $R_{1r} + R_{2r}$ is excluded directly. The above reduction is to cut

$$R = \min\{R_{1r} + R_{2r}, R_{1r} + R_{2r}, R_{2r} + R_{2r}, R_{2r} + R_{1r}, R_{1r} + R_{1r}, R_{MAC}\}.$$  
(19)

the optimization problem is further recasted as

$$\max_{\beta_1, \beta_2, \beta_3, R} R$$
(20a)

s.t. $0 < \beta_1, \beta_2, \beta_3 < 1, \beta_1 + \beta_2 + \beta_3 = 1$,  
(20b)
\[
R \leq R_{1r} + R_{2r}, R \leq R_{2r} + R_{1r},
\]
(20c)
\[
R \leq R_{1r} + R_{1r}, R \leq R_{MAC},
\]
(20d)

where $R_{1r} + R_{2r} = \frac{1}{2} \log_2(1 + \gamma_1 \beta_1 P)(1 + \gamma_2 \beta_2 P)$, $R_{2r} + R_{2r} = \frac{1}{2} \log_2(1 + \gamma_2 \beta_2 P)(1 + \gamma_1 \beta_1 P)$ and $R_{1r} + R_{1r} = \frac{1}{2} \log_2(1 + \gamma_1 \beta_1 P)(1 + \gamma_2 \beta_2 P)$. Due to the fact that $R \leq R_{1r} + R_{1r}, R \leq R_{2r} + R_{2r}, R \leq R_{MAC}$, and $R \leq R_{1r} + R_{2r}$ are non-convex. Inserting

$\beta_1 = 1 - \beta_1 - \beta_2$ back into $R_{1r} + R_{2r}$ yields the following inequality

$$2^R \leq 1 + \gamma_1 P + (\beta_1 P - \gamma_1 \beta_1 P + 2 \gamma_1 \beta_2 P)^2$$

$$- \gamma_1 \beta_1 P - \gamma_1 \beta_2 P + \gamma_1 \beta_2 P^2.$$  
(21)

Since $\beta_1, \beta_2 \leq \frac{1}{2}(\beta_1^2 + \beta_2^2)$, the lower-bound of $-\beta_1 \beta_2$ is $-\frac{1}{4}(\beta_1^2 + \beta_2^2)$, which further yields

$$2^R \leq 1 + \gamma_1 P + (\beta_1 P - \gamma_1 \beta_1 P + 2 \gamma_1 \beta_2 P)^2$$

$$- \gamma_1 \beta_2 P + \gamma_1 \beta_2 P^2,$$
(22)

which is a convex constraint. In the same manner, $R_{1r} + R_{2r}$ can be rewritten as

$$2^R \leq 1 + \gamma_1 P + (\beta_1 P - \gamma_1 \beta_1 P + 2 \gamma_1 \beta_2 P)^2$$

$$- \gamma_1 \beta_2 P + \gamma_1 \beta_2 P^2.$$  
(23)

Similarly, $R_{2r} + R_{2r}$ can be written in the following form

$$2^R \leq 1 + \gamma_1 P + (\gamma_2 P - \gamma_1 \gamma_2 P^2,$$
(24)

which is still a non-convex constraint. $\gamma_2 \gamma_2 P^2$ is a convex function, SCA can be applied to obtain its low bound, which is expressed by the first-order Taylor expansion. The first-order Taylor approximation of $\gamma_2 \gamma_2 P^2$ at feasible point $\beta_3$ is given by

$$\gamma_2 \gamma_2 P^2 \leq 2 \gamma_2 \beta_2 P^2,$$  
(25)

Combining (24) and (25), $R_{1r} + R_{2r}$ further can be converted to

$$2^R \leq 1 + \gamma_1 \gamma_2 P^2 + 2 \gamma_2 \beta_2 P^2(\beta_3 - \beta_3),$$
(26)

Therefore, the optimization problem is further reformulated as

$$\max_{\gamma_1, \gamma_2, \gamma_3, R} R$$
(27a)

s.t. $0 < \beta_1, \beta_2, \beta_3 < 1, \beta_1 + \beta_2 + \beta_3 = 1$,  
(27b)
\[
R \leq R_{MAC}, (22), (23), (26),
\]
(27c)

which is a convex optimization problem and can be solved efficiently via CVX. The total computational complexity is $O(\sqrt{3}(56 + 8M^2 + 4M N + 8M)\log(1/\epsilon))$, where $\epsilon$ represents the computation accuracy. Its highest order is $M N^2$ float-point operations (FLOPs).

B. Proposed Max-Det

In the Section III-A, Max-SR-SCA is proposed to obtain the sum rate and the corresponding PA factors. To further achieve a higher sum rate, a high-performance Max-Det method is proposed. Let us define $A = (h_{1r} + H_{2r} \Theta_1 h_{1r}) h_{1r} + (H_{2r} + H_{1r} \Theta_2 h_{2r}) h_{2r}, \chi = \|u_{1r}^H + H_{2r}^H \Theta_2 u_{2r}\|_2^2$ and $\tau = \|h_{1r}^H + h_{2r}^H \Theta_2 H_{2r}^H u_{1r}\|_2^2$. Due to $e^{h(A)} = \det(e^A)$ and $e^{h(B)} = \det(e^B)$, $R_{1r}, R_{2r}, R_{1r}, R_{1r}$ and $R_{MAC}$ can be also expressed as follow

$$R_{1r} = \log_2 \frac{1 + \beta_1 P \sin(A)}{\sigma^2}, R_{2r} = \log_2 \frac{1 + \beta_2 P \sin(B)}{\sigma^2},$$
(28)

$$R_{2r} = \log_2 \frac{1 + \beta_2 P \sin(B)}{\sigma^2}, R_{1r} = \log_2 \frac{1 + \beta_1 P \sin(A)}{\sigma^2},$$
(29)

$$R_{MAC} = \frac{1}{2} \log_2 \left(1 + \beta_1 P \sin(A) + \beta_2 P \sin(B)\right).$$  
(30)
There are two cases to be discussed in the comparison between $R_{12} + R_{31}$ and $R_{MAC}$, and each case has several subcases.

Case A: When $R_{12} + R_{32} \geq R_{MAC}$.

subcase 1: $R_{12} = R_{12r}$ (i.e. $R_{12r} \leq R_{12}$), $R_{31} = R_{31r}$ (i.e. $R_{31r} < R_{31}$) and $R_{12} + R_{31} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right)$. The corresponding convex optimization problem is

$$\max_{\beta_1, \beta_2} \beta_1 P \ln |e| + \beta_2 P \ln |e|$$

subject to

$$0 < \beta_1, \beta_2, \beta_1 < 1, \beta_1 + \beta_2 + \beta_3 = 1,$$

$$\beta_1 \ln |e| < \beta_3 \ln \frac{|e|}{\tau},$$

$$1 + \beta_1 P \ln |e| + \beta_2 P \ln |e| \leq \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right).$$

Case B: When $R_{12} + R_{31} < R_{MAC}$.

Similarly, there are three situations that need to be discussed.

subcase 1: $R_{12} + R_{31} = \frac{1}{2} \log_2 \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right)$, introducing a variable $\gamma$, the corresponding optimization problem is

$$\max_{\beta_1, \beta_2, \gamma} \gamma$$

subject to

$$0 < \beta_1, \beta_2, \beta_1 < 1, \beta_1 + \beta_2 + \beta_3 = 1,$$

$$\beta_1 \ln |e| < \beta_2 \ln |e| \frac{\gamma}{\tau},$$

$$\gamma \leq \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right),$$

$$\gamma \leq \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right).$$

The low bound $a$ of $\left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right)$ is given. According to [18], its up bound $d$ is

$$\frac{1}{2} \left(1 + \frac{\beta_1 P \ln |e|}{\sigma^2} \right) \left(1 + \frac{\beta_2 P \ln |e|}{\sigma^2} \right) \left(\sigma^2 + \beta_1 P \ln |e| \sigma^2 + \beta_2 P \ln |e| \right)^2.$$
where $\rho$ is a variable, $c$ and $f$ are the low and up bound of $(1 + \frac{\beta_1 P_x}{\sigma}) (1 + \frac{\beta_3 P_x}{\sigma})$, and $f = \frac{1}{2} (1 + \frac{2\beta_3 P_x}{\sigma}) \left( \frac{\sigma^2 + \beta_3 P_x}{\sigma^2 + \beta_3 P_x} \right)^{2 \gamma} + \frac{(\sigma^2 + \beta_3 P_x)^{2 \gamma}}{\sigma^2 + \beta_3 P_x}$. The above convex optimization problems can be solved by CVX. Compare the sum rates corresponding to the above subcases, and the maximum value is considered as the system sum rate. Meanwhile, power factors $\beta_1$, $\beta_2$ and $\beta_3$ are obtained. Its computational complexity is $O(\lceil 37\sqrt{6} + 129\sqrt{7} + 147\sqrt{8} + (\sqrt{6} + 3\sqrt{7} + 3\sqrt{8})(8M N^2 + 4M N + 8M) \rceil\ln(1/\varepsilon))$ FLOPs, which is higher than that of Max-SR-SCA method.

C. Proposed Max-SR-RC

In fact, there exist asymmetries of two-way channel quality and two users’ demand in the IRS-aided two-way DF relay network, thereby the asymmetry between $R_{12}$ and $R_{21}$ is generated. In this subsection, we make an investigation of PA in the case of $R_{12} = \mu R_{21}$, which is called Max-SR-RC method. The optimization problem is given by

$$\begin{align*}
\max_{\beta_1, \beta_2, \beta_3} & \quad R \\
\text{s.t.} & \quad 0 < \beta_1, \beta_2, \beta_3 < 1, \beta_1 + \beta_2 + \beta_3 = 1, \quad 0 < \mu, \quad R_{12} = \mu R_{21},
\end{align*}$$

(39a)

(39b)

(39c)

where $\mu$ is a constant. Substituting (39c) into the object function and expanding it, the above problem can be rewritten as

$$\begin{align*}
\max_{\beta_1, \beta_2, \beta_3} & \quad \min \left\{ \frac{1}{2} \log_2 (1 + \gamma \beta_1 P + \gamma \beta_2 P), \frac{1}{2} \log_2 (1 + \gamma \beta_2 P + \gamma \beta_3 P) \right\} \\
\text{s.t.} & \quad 0 < \mu, \quad (39b),
\end{align*}$$

(40a)

(40b)

Since it is similar to Max-SR method, the above problem can be further transformed as

$$\begin{align*}
\max_{\beta_1, \beta_2, \beta_3, R} & \quad R \\
\text{s.t.} & \quad 2^{2R} \leq 1 + \gamma \beta_1 P, 2^{2R} \leq 1 + \gamma \beta_2 P, \\
& \quad 2^{2R} \leq 1 + \gamma \beta_2 P + \gamma \beta_3 P,
\end{align*}$$

(41a)

(41b)

(41c)

which is also a convex optimization problem. Similarly, PA factors $\beta_1$, $\beta_2$, $\beta_3$ and sum rate $R$ can be obtained, which contains shadow fading. The complexity is $O(4\sqrt{7}(44 + 6M N^2 + 3M N + 6M) \ln(1/\varepsilon))$, which is lower than the other two methods.

IV. SIMULATION AND NUMERICAL RESULTS

In this section, numerical simulations are performed to evaluate and compare the sum rate performance between the proposed three methods and EPA method. Moreover, it is assumed that $U_1$, $U_2$, IRS and RS are located in three-dimensional (3D) space, the positions of $U_1$, $U_2$, IRS and RS are given as (0, 0, 0), (0, 100 m, 0), (−10 m, 50, 20 m) and (10 m, 50, 10 m), respectively. We take a more realistic environment into account, and assume that all channels follow large-scale fading, which contains shadow fading. The path loss model is $PL(d) = PL_0 - 10\log_{10}(\frac{d^\lambda}{d_0^\lambda}) - X_s$, where $PL_0 = -20\log_{10}(\frac{4\pi d_0}{\lambda})$ is the path loss at the reference distance $d_0$, $\lambda$ is wavelength, $\alpha$ is the path loss exponent, and $X_s$ is a Gaussian random shadow variable with distribution $X_s \sim \mathcal{N}(0, \sigma^2)$. The path loss exponents associated with IRS are 2.1, those of $U_1$-RS and $U_2$-RS links are 2.3. The remaining system parameters are set as follows: $f_c = 1.5$ GHz, $\sigma^2 = -80$ dBm. ES method is consider as the optimal method, its sum rate performance is used as a performance upper bound. While the sum rate performance of EPA method is regarded as a performance lower bound.

Fig. 2 illustrates the achievable sum rate of Max-SR-RC method versus $\mu$ with different total power: $P = \{0$ dBm, 10 dBm, 20 dBm, 30 dBm$\}$. It can be seen that as $\mu$ increases, the sum rate performance gradually increases. Until $\mu \geq 3$, the achievable sum rate tends to be stable. For convenience, $\mu$ is defined as 3.

Fig. 3 plots the curves of achievable sum rate versus total power with $M = 4$, $N = 16$ and $\sigma = 3$ dB. It can be clearly seen that the proposed Max-SR-SCA, Max-Det and Max-SR-RC perform better than EPA method. Furthermore, among the proposed three methods, the sum rate performance of Max-SR-RC method is most closest to that of ES method in all total power region, followed by Max-Det method and Max-SR-SCA method. For instance, when total power is equal to 30 dBm, the sum rate performance gaps between the best method Max-SR-RC, the worst method Max-SR-SCA and ES method are respectively 0.1bits/Hz and 0.3bits/Hz.

Fig. 4 illustrates the curves of achievable sum rate versus $\sigma$ with total power $= 30$ dBm, $M = 4$ and $N = 16$. It can be observed that as $\sigma$ increases, a larger shadowing fading is formed, which results in a rapid degradation of the sum rate performance. In the meanwhile, the sum rate performance gaps between the proposed three methods and ES method gradually narrow. However, the sum rate performance gains of the proposed three methods over EPA method become more
obvious. For example, when $\sigma$ is 4.5 dB, the best method Max-SR-RC can harvest up to 64.7% sum rate gain over EPA method, the worst method Max-SR-SCA has a 35.1% rate gain over EPA method.

V. CONCLUSION

In this paper, in order to improve the achievable sum rate of an IRS-aided two-way DF relay wireless network, three high-performance PA schemes, namely Max-SR-SCA, Max-Det and Max-SR-RC, were proposed. Simulation results showed that the proposed three methods can harvest better rate gain over EPA method in terms of sum rate performance. Among the proposed three methods, the sum rate performance of the best method Max-SR-RC is most closest to that of ES method. Additionally, the rate increases with total power, while decreases with $\sigma$.

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