Energy-Efficient Resource Allocation for IRS-aided MISO System with SWIPT

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***Abstract*—Combining simultaneous wireless information and power transfer (SWIPT) and intelligent reflecting surface (IRS) is a feasible scheme to enhance the energy efficiency (EE) performance. In this paper, we investigate a multiuser IRS-aided multiple-input single-output (MISO) system with SWIPT. For the purpose of maximizing the EE of the system, we jointly optimize the base station (BS) transmit beamforming vectors, the IRS reflective beamforming vector and the power splitting (PS) ratios, while considering the maximum transmit power budget, the IRS reflection constraints and the quality of service (QoS) requirements containing the minimum data rate and the minimum harvested energy per user. As the proposed EE maximization problem is non-convex and extremely complex, we propose an efficient alternating optimization (AO) algorithm by decoupling the original problem into three subproblems which are tackled iteratively by using the Dinkelbach method. In particular, we apply the successive convex approximation (SCA) as well as the semi-definite relaxation (SDR) techniques to solve the non-convex transmit beamforming and reflective beamforming optimization subproblems. Numerical results confirm the effectiveness of the AO algorithm as well as the benefit of deploying IRS for enhancing the EE performance compared with the benchmark schemes.**

***Index Terms*—Energy efficiency (EE), intelligent reflecting surface (IRS), simultaneous wireless information and power transfer (SWIPT), power splitting (PS).**

I. Introduction

In order to achieve green and sustainable wireless communication, energy efficiency (EE) has become a key indicator in wireless communication systems [1]. Recently, intelligent reflecting surface (IRS) is considered to be one of the effective technologies to support energy-efficient wireless communication, which has received significant attention [2], [3]. By adjusting the phase shifts and the attenuations of the reflecting units, the wireless signal propagation can be collaboratively altered to enhance the desirable signals and suppress the undesirable interfering signals. On the other hand, in order to achieve green and sustainable communication, simultaneous wireless information and power transfer (SWIPT) technology [4] has a wide range of applications due to its ability of transmitting data and supplying power simultaneously.

There have been several significant works on the combination of these two techniques [5]–[8]. The authors in [5] first studied the IRS-aided system with SWIPT to maximize the weighted sum-power of the energy harvesting receivers (EHRs). In [6], the authors minimized the total BS transimit power in an IRS-aided MISO system with SWIPT, in which the imperfect channel state information (CSI) setup was considered. Furthermore, the authors in [7] focused on maximizing the secrecy rate in an IRS-aided MIMO system with SWIPT, where an inexact block coordinate descent (IBCD) method was applied. Besides, the authors in [8] focused on the secrecy rate maximization problem in an IRS-aided system with SWIPT, in which a deep learning (DL)-based scheme was proposed. However, to our best knowledge, the EE maximization problem in an IRS-aided SWIPT system applying the power-splitting (PS) scheme has not been studied yet, thus motivating our works.

In this paper, we aim to maximize the EE of the proposed multiuser IRS-aided MISO system with SWIPT, while satisfying the BS transmit power constraints, the IRS reflection constraint, as well as the QoS conctraints at the users. Furthermore, we propose an AO algorithm to decouple the original EE maximization problem into three subproblems, i.e., transmit beamforming optimization, reflective beamforming optimization and PS ratios optimization. For each subproblem, Dinkelbach method is applied to convert the fractional objective function into a subtractive form. In particular, for the transmit beamforming and reflective beamforming optimization subproblems, we use the successive convex approximation (SCA) as well as the semi-definite relaxation (SDR) techniques to convert the non-convex problems into convex form. Numerical results unveil the effectiveness of the AO algorithm. In addition, the benefit of deploying IRS for enhancing the EE performance can be verified.

II. System Description and Problem Formulation

A. System Description

In this paper, we investigate a multiuser IRS-aided MISO system with SWIPT, which consists of one BS equipped with M transmit antennas, one IRS composed of N passive reflecting units and K single-antenna users. Specially, we denote the set of all users and the set of passive reflecting units as $\mathcal{K} \triangleq \{1, \ldots, K\}$ and $\mathcal{N} \triangleq \{1, \ldots, N\}$. Furthermore, the channel matrix of the BS-IRS link as well as the channel vectors of the IRS-user k link and the BS-user k link are denoted by $\boldsymbol{G} \in \mathbb{C}^{\mathrm{N}\times\mathrm{M}}$, $\boldsymbol{f}_k \in \mathbb{C}^{\mathrm{N}\times 1}$ and $\boldsymbol{h}_k \in \mathbb{C}^{\mathrm{M}\times 1}$, respectively. In addition, s_k and $\boldsymbol{w}_k \in \mathbb{C}^{\mathrm{M}\times 1}$ denote the intended message with unit-power and the corresponding transmit beamforming vector for user k. Accordingly, the transmitted signal can be formulated as

$$\boldsymbol{x} = \sum_{k=1}^{K} \boldsymbol{w}_k s_k. \tag{1}$$

As for IRS, we denote the reflection amplitude and the phase shift of the n-th reflecting unit as $\phi_n \in [0, 2\pi)$ and $\gamma_n \in [0, 1]$. Accordingly, we denote the reflection-coefficients matrix at the IRS as $\boldsymbol{\Phi} = \text{diag}\left(\gamma_1 e^{j\phi_1}, \ldots, \gamma_N e^{j\phi_N}\right)$, in which $j \triangleq \sqrt{-1}$. In addition, let $\boldsymbol{v} = \left[\gamma_1 e^{j\phi_1}, \ldots, \gamma_N e^{j\phi_N}\right]^H$ represent the reflective beamforming vector, in which $\left|\gamma_n e^{j\phi_n}\right| \leq 1, \forall n \in \mathcal{N}$. Therefore, the combined BS-user k reflective channel can be written as $\boldsymbol{f}_k^H \boldsymbol{\Phi} \boldsymbol{G} = \boldsymbol{v}^H \boldsymbol{\Psi}_k$, where $\boldsymbol{\Psi}_k = \text{diag}\left(\boldsymbol{f}_k^H\right) \boldsymbol{G}$.

We assume that each user employing the PS scheme consists of an energy harvesting (EH) circuit and a conventional information decoding (ID) circuit. Accordingly, the signals transmitted by the BS are divided into two streams for EH and ID respectively. For user k, let $\rho_k (0 < \rho_k < 1)$ denotes the part of the received signals for ID, and the $1 - \rho_k$ part is for EH. Accordingly, by combining reflected signals and the directly transmitted signals, the signal received at user k can be expressed as

$$y_k = \sqrt{\rho_k} \sum_{i=1}^{K} (\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H) \boldsymbol{w}_i s_i + n_k, \tag{2}$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2), \forall k \in \mathcal{K}$ is the additive white Gaussian noise (AWGN).

Furthermore, we treat the interference of the system as noise, and thus the achievable data rate for user k can be written as

$$R_k = \log_2 \left(1 + \frac{\rho_k \left| \left(\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H \right) \boldsymbol{w}_k \right|^2}{\rho_k \sum\limits_{i=1, i \neq k}^{K} \left| \left(\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H \right) \boldsymbol{w}_i \right|^2 + \sigma_k^2} \right). \tag{3}$$

Hence, the total transmission rates can be expressed as

$$R_{total} = \sum_{k=1}^{K} R_k = \sum_{k=1}^{K} \log_2 \left(1 + \frac{\rho_k \left| \left(\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H \right) \boldsymbol{w}_k \right|^2}{\rho_k \sum\limits_{i=1, i \neq k}^{K} \left| \left(\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H \right) \boldsymbol{w}_i \right|^2 + \sigma_k^2} \right). \tag{4}$$

In addition, the energy harvested by user k can be written as

$$e_k = \eta (1 - \rho_k) \sum_{i=1}^{K} \left| (\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H) \boldsymbol{w}_i \right|^2, \tag{5}$$

where η is the energy conversion efficiency. Therefore, we can express the total harvested energy as

$$E = \sum_{k=1}^{K} e_k = \sum_{k=1}^{K} \eta (1 - \rho_k) \sum_{i=1}^{K} \left| (\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H) \boldsymbol{w}_i \right|^2. \tag{6}$$

In general, the harvested energy at all the users can compensate for part of the power consumption in a SWIPT system [9]. As a result, the total power consumption is given by

$$P_{total} = \zeta \sum_{k=1}^{K} \|\boldsymbol{w}_k\|^2 + M P_T + N P_n(b) + P_C - E, \tag{7}$$

where ζ is the reciprocal of the transmit power amplifier drain efficiency, P_T is the power consumption of each transmit antenna, $P_n(b)$ is the power consumption of each reflecting unit of the IRS having b-bit resolution and P_C is the circuit power consumption.

The EE of the system is defined as the ratio of the total transmission rates and the total power consumption. Accordingly, the EE of the considered multiuser IRS-aided MISO system with SWIPT can be formulated as

$$\lambda_{EE} \triangleq \frac{R_{total}}{P_{total}}. \tag{8}$$

B. Problem Formulation

Our goal is to maximize the EE of the proposed system by jointly optimizing the transmit beamforming vectors$\{\boldsymbol{w}_k\}$, the reflective beamforming vector $\boldsymbol{v}$ and the PS ratios $\{\rho_k\}$. Mathematically, we can formulate the complete optimization problem as

$$\text{(P1)} \quad \max_{\{\boldsymbol{w}_k\}, \boldsymbol{v}, \{\rho_k\}} \lambda_{EE} \tag{9}$$

$$\text{s.t.} \quad R_k \geq R_{\min}, \forall k \in \mathcal{K}, \tag{10}$$

$$e_k \geq E_{\min}, \forall k \in \mathcal{K}, \tag{11}$$

$$\sum_{k=1}^{K} \|\boldsymbol{w}_k\|^2 \leq P_m, \tag{12}$$

$$|\boldsymbol{v}_n| \leq 1, \forall n \in \mathcal{N}, \tag{13}$$

$$0 < \rho_k < 1, \forall k \in \mathcal{K}. \tag{14}$$

where equation (10) and (11) correspond to the minimum data rate constraint and the minimum harvested energy constraint, in which $R_{\min}$ is the minimum rate requirement and $E_{\min}$ is the minimum harvested energy target per user. Equation (12) guarantees that the transmit power cannot exceed the maximum value P_m. Furthermore, equation (13) and equation (14) correspond to the IRS reflection constraint and the PS ratios constraint respectively. As the variables $\{\boldsymbol{w}_k\}$, $\boldsymbol{v}$ and $\{\rho_k\}$ are coupled intricately, problem (P1) is non-convex, thus becoming intractable.

III. The Proposed AO Algorithm

In this section, an AO algorithm is devdeloped to tackle the complex EE maximization problem by decoupling problem (P1) into three subproblems, and then we slove them alternatively. Specifically, we first optimize the transmit beamforming vectors $\{\boldsymbol{w}_k\}$ to obtain optimal transmit beam pattern design. Subsequently, the reflective beamforming vector $\boldsymbol{v}$ is optimized to obtain optimal channel gain. Finally, we optimize the PS ratio $\{\rho_k\}$ to enhance the EE performance.

A. Transmit Beamforming Optimization

We first optimize the transmit beamforming vectors $\{\boldsymbol{w}_k\}$ with the fixed reflective beamforming vector $\boldsymbol{v}$ and the PS ratios $\{\rho_k\}$. We define $\boldsymbol{a}_k = \boldsymbol{\Psi}_k^H \boldsymbol{v} + \boldsymbol{h}_k$ as the equivalent channel of the BS-user k link, $\forall k \in \mathcal{K}$. Furthermore, we define $\boldsymbol{A}_k = \boldsymbol{a}_k \boldsymbol{a}_k^H$ and $\boldsymbol{W}_k = \boldsymbol{w}_k \boldsymbol{w}_k^H$ with $\boldsymbol{W}_k \succeq \boldsymbol{0}$ and rank($\boldsymbol{W}_k$) ≤ 1. Therefore, R_k and e_k are reformulated as

$$R_k^{'} = \log_2 \left(\frac{\rho_k \sum\limits_{i=1}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2}{\rho_k \sum\limits_{i=1, i \neq k}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2} \right), \tag{15}$$

$$e_k^{'} = \eta (1 - \rho_k) \sum_{i=1}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i). \tag{16}$$

Accordingly, the transmit beamforming optimization problem can be reformulated as

$$\begin{aligned} \text{(P2)} \max_{\{\boldsymbol{W}_k\}} \lambda_{EE}' &\triangleq \frac{R_{total}^{'}}{P_{total}^{'}} \\ &= \frac{\sum\limits_{k=1}^{K} R_k^{'}}{\zeta \sum\limits_{k=1}^{K} \mathrm{Tr}(\boldsymbol{W}_k) + M P_T + N P_n(b) + P_C - \sum\limits_{k=1}^{K} e_k^{'}} \end{aligned} \tag{17}$$

$$\begin{aligned} \text{s.t.} \quad & R_k^{'} \geq R_{\min}, \forall k \in \mathcal{K}, && (18) \\ & e_k^{'} \geq E_{\min}, \forall k \in \mathcal{K}, && (19) \\ & \sum_{k=1}^{K} \mathrm{Tr}(\boldsymbol{W}_k) \leq P_m, && (20) \\ & \boldsymbol{W}_k \succeq \boldsymbol{0}, \forall k \in \mathcal{K}, && (21) \\ & \mathrm{rank}(\boldsymbol{W}_k) \leq 1, \forall k \in \mathcal{K}. && (22) \end{aligned}$$

Next, we apply Dinkelbach method [10] to convert the objective function (17) into a subtractive fuction. Furthermore, we introduce a parameter q and reformulate the objective function of problem (P2) as

$$H(q) = \max_{\{\boldsymbol{W}_k\}} R_{total}^{'} - q P_{total}^{'} \tag{23}$$

Nevertheless, fuction (23) is still non-convex. To efficiently solve the problem, we introduce new variables as follows

$$e^{p_k} = \rho_k \sum_{i=1}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2, \forall k \in \mathcal{K}, \tag{24}$$

$$e^{q_k} = \rho_k \sum_{i=1, i \neq k}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2, \forall k \in \mathcal{K}. \tag{25}$$

Then, we have

$$R_{total}^{'} = \sum_{k=1}^{K} (p_k - q_k) \log_2(e). \tag{26}$$

Accordingly, we can further reformulate problem (P2) as

$$\text{(P2.1)} \max_{\{\boldsymbol{W}_k\}, \{p_k\}, \{q_k\}} \sum_{k=1}^{K} (p_k - q_k) \log_2(e) - q P_{total}^{'} \tag{27}$$

$$\begin{aligned} \text{s.t.} \quad & \rho_k \sum_{i=1}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2 \geq e^{p_k}, \forall k \in \mathcal{K}, && (28) \\ & \rho_k \sum_{i=1, i \neq k}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2 \leq e^{q_k}, \forall k \in \mathcal{K}, && (29) \\ & (p_k - q_k) \log_2(e) \geq R_{\min}, \forall k \in \mathcal{K}, && (30) \\ & (19), (20), (21), (22). \end{aligned}$$

However, problem (P2.1) still cannot be directly solved owing to the non-convex constraint (29). Here we apply the SCA technique to tackle this issue. The first-order Taylor expansion of e^{q_k} at $\{\bar{q}_k\}$ is $e^{\bar{q}_k} + e^{\bar{q}_k}(q_k - \bar{q}_k), \forall k \in \mathcal{K}$, where $\bar{q}_k$ is feasible to the problem (P2.1). Thus, constraint (29) can be rewritten as

$$\rho_k \sum_{i=1, i \neq k}^{K} \mathrm{Tr}(\boldsymbol{A}_k \boldsymbol{W}_i) + \sigma_k^2 \leq e^{\bar{q}_k} + e^{\bar{q}_k}(q_k - \bar{q}_k), \forall k \in \mathcal{K}. \tag{31}$$

Furthermore, we apply SDR technique to relax the non-convex rank-one constraint (22), thus reformulating problem (P2.1) as

$$\text{(P2.2)} \max_{\{\boldsymbol{W}_k\}, \{p_k\}, \{q_k\}} \sum_{k=1}^{K} (p_k - q_k) \log_2(e) - q P_{total}^{'} \tag{32}$$

$$\text{s.t.} \quad (19), (20), (21), (28), (30), (31).$$

For a fixed parameter q, it is obvious that the problem (P2.2) is strictly concave in $\{\boldsymbol{W}_k\}, \{p_k\}, \{q_k\}$, $\forall k \in \mathcal{K}$, and thus we can iteratively update $\bar{q}_k$ to solve it efficiently by using the standard convex optimization methods [11] and obtain the optimal solution $\{\boldsymbol{W}_k^*\}$. Moreover, we can prove that $\{\boldsymbol{W}_k^*\}$ sastifies constraint (22) [12]. Therefore, we can obtain the optimal transmit beamforming vectors $\{\boldsymbol{w}_k^*\}$ by eigenvalue decomposition.

B. Reflective Beamforming Optimization

Similar to section III-A, we apply the SCA and SDR techniques as well as Dinkelbach method to optimize the reflective beamforming vector $\boldsymbol{v}$ with the fixed transmit beamforming vectors $\{\boldsymbol{w}_k\}$ and the PS ratios $\{\rho_k\}$. Therefore, we define $\boldsymbol{c}_{k,i} = \boldsymbol{\Psi}_k \boldsymbol{w}_i$ and $d_{k,i} = \boldsymbol{h}_k^H \boldsymbol{w}_i, \forall k \in \mathcal{K}, i \in \mathcal{K}$. Then, we have

$$\left| \left(\boldsymbol{v}^H \boldsymbol{\Psi}_k + \boldsymbol{h}_k^H \right) \boldsymbol{w}_i \right|^2 = \boldsymbol{v}^H \boldsymbol{C}_{k,i} \boldsymbol{v} + 2\mathrm{Re} \left\{ \boldsymbol{v}^H \boldsymbol{u}_{k,i} \right\} + |d_{k,i}|^2, \tag{33}$$

where $\boldsymbol{C}_{k,i} = \boldsymbol{c}_{k,i}\boldsymbol{c}_{k,i}^H$, $\boldsymbol{u}_{k,i} = \boldsymbol{c}_{k,i}d_{k,i}^H$. Moreover, we define $\boldsymbol{R}_{k,i} = \begin{bmatrix} \boldsymbol{C}_{k,i} & \boldsymbol{u}_{k,i} \\ \boldsymbol{u}_{k,i}^H & 0 \end{bmatrix}$ and $\bar{\boldsymbol{v}} = \begin{bmatrix} \boldsymbol{v} \\ 1 \end{bmatrix}$. Then we have

$$\left|\left(\boldsymbol{v}^H\boldsymbol{\Psi}_k + \boldsymbol{h}_k^H\right)\boldsymbol{w}_i\right|^2 = \bar{\boldsymbol{v}}^H\boldsymbol{R}_{k,i}\bar{\boldsymbol{v}} + |d_{k,i}|^2. \tag{34}$$

Furthermore, we define $\boldsymbol{V} = \bar{\boldsymbol{v}}\bar{\boldsymbol{v}}^H$. Therefore, R_k and e_k can be reformulated as:

$$R_k'' = \log_2\left(\frac{\rho_k\sum\limits_{i=1}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2}{\rho_k\sum\limits_{i=1,i\neq k}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2}\right), \tag{35}$$

$$e_k'' = \eta(1-\rho_k)\sum_{i=1}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2). \tag{36}$$

Then we apply Dinkelbach method and use SDR technique to reformulate problem (P1) as problem (P3),

$$\text{(P3)}\max_{\{\boldsymbol{V}\}}\lambda_{EE}'' \triangleq R_{total}'' - qP_{total}''$$
$$= \sum_{k=1}^{K}R_k'' - q(\zeta\sum_{k=1}^{K}\|\boldsymbol{w}_k\|^2 + MP_T + NP_n(b) + P_C - e_k'') \tag{37}$$

$$\text{s.t.}\quad R_k'' \geq R_{\min}, \forall k \in \mathcal{K}, \tag{38}$$
$$e_k'' \geq E_{\min}, \forall k \in \mathcal{K}, \tag{39}$$
$$\boldsymbol{V}_{n,n} \leq 1, \forall n \in \mathcal{N}, \tag{40}$$
$$\boldsymbol{V}_{N+1,N+1} = 1, \tag{41}$$
$$\boldsymbol{V} \succeq \boldsymbol{0}, \tag{42}$$
$$\mathrm{rank}(\boldsymbol{V}) \leq 1. \tag{43}$$

Similar to section III-A, we introduce new variables as follows

$$e^{s_k} = \rho_k\sum_{i=1}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2, \forall k \in \mathcal{K}, \tag{44}$$

$$e^{t_k} = \rho_k\sum_{i=1,i\neq k}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2, \forall k \in \mathcal{K}. \tag{45}$$

The first-order Taylor expansion of e^{t_k} at $\bar{t}_k$ is $e^{\bar{t}_k} + e^{\bar{t}_k}(t_k - \bar{t}_k)$, where $\bar{t}_k$ is feasible to the problem (P3). By using SCA technique and relaxing the non-convex constraint (43), we can further reformulate problem (P3) as

$$\text{(P3.1)}\max_{\{\boldsymbol{V}\},\{s_k\},\{t_k\}}\sum_{k=1}^{K}(s_k - t_k)\log_2(e) - qP_{total}'' \tag{46}$$

$$\text{s.t.}\quad \rho_k\sum_{i=1}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2 \geq e^{s_k}, \forall k \in \mathcal{K}, \tag{47}$$

$$\rho_k\sum_{i=1,i\neq k}^{K}(\mathrm{Tr}\left(\boldsymbol{R}_{k,i}\boldsymbol{V}\right) + |d_{k,i}|^2) + \sigma_k^2 \leq e^{\bar{t}_k} + e^{\bar{t}_k}(t_k - \bar{t}_k), \forall k \in \mathcal{K}, \tag{48}$$

$$(s_k - t_k)\log_2(e) \geq R_{\min}, \forall k \in \mathcal{K}, \tag{49}$$
$$(39), (40), (41), (42).$$

For a fixed parameter q, it is obvious that the problem (P3.1) is strictly concave in $\boldsymbol{V}, \{s_k\}, \{t_k\}, \forall k \in \mathcal{K}$, and thus we can iteratively update $\{\bar{t}_k\}$ to obtain the optimal solution to problem (P3.1) denoted by $\boldsymbol{V}^*$. Particularly, if $\mathrm{rank}\left(\boldsymbol{V}^*\right) \leq 1$, we can apply the eigenvalue decomposition to obtain reflecting vector $\boldsymbol{v}^*$. Nevertheless, if $\mathrm{rank}\left(\boldsymbol{V}^*\right) > 1$, then the Gaussian randomization procedure [13] need to be applied to obtain the solution that satisfies constraint (43).

C. PS Ratios Optimization

By applying Dinkelbach method to problem (P1) and fixing the transmit beamforming vectors $\{\boldsymbol{w}_k\}$ and the reflective beamforming vector $\boldsymbol{v}$, the PS ratios optimization problem can be formulated as

$$\text{(P4)}\max_{\{\rho_k\}}\quad \mathcal{R}(\boldsymbol{\rho}) = R_{total} - qP_{total} \tag{50}$$
$$\text{s.t.}\quad R_k \geq R_{\min}, \forall k \in \mathcal{K}, \tag{51}$$
$$e_k \geq E_{\min}, \forall k \in \mathcal{K}, \tag{52}$$
$$0 < \rho_k < 1, \forall k \in \mathcal{K}. \tag{53}$$

Here we rewrite the objective function as

$$\mathcal{R}(\boldsymbol{\rho}) = \sum_{k=1}^{K}\mathcal{R}_k, \tag{54}$$

where

$$\mathcal{R}_k = R_k - q\zeta\|\boldsymbol{w}_k\|^2 - \frac{q}{K}(MP_T + NP_n(b) + P_C) + qe_k. \tag{55}$$

For a fixed parameter q, we can prove that the objective function (50) is strictly concave in $\rho_k, \forall k \in \mathcal{K}$ and $\frac{d^2\mathcal{R}(\boldsymbol{\rho})}{d\rho_i d\rho_j} = 0, \forall i \neq j$, which means the PS ratio of each user is independent of each other. Hence, we can divide problem (P4) into K non-interfering subproblems. Generally, the subproblems of problem (P4) can be formulated as

$$\text{(P4.1)}\quad \max_{\{\rho_k\}}\quad \mathcal{R}_k(\rho_k) \tag{56}$$
$$\text{s.t.}\quad (51), (52), (53).$$

According to the constraints (51)-(53), ρ_k should be limited as

$$\rho_k^{\min} \leq \rho_k \leq \rho_k^{\max} \tag{57}$$

where $\rho_k^{\min} = \frac{(2^{R_{\min}}-1)\sigma_k^2}{\left|\left(\boldsymbol{v}^H\boldsymbol{\Psi}_k + \boldsymbol{h}_k^H\right)\boldsymbol{w}_k\right|^2 - (2^{R_{\min}}-1)\sum\limits_{i=1,i\neq k}^{K}\left|\left(\boldsymbol{v}^H\boldsymbol{\Psi}_k + \boldsymbol{h}_k^H\right)\boldsymbol{w}_i\right|^2}$ > 0 ensures that the minimum data rate constraint of user k can be satisfied, and $\rho_k^{\max} = 1 - \frac{E_{\min}}{\eta\sum\limits_{i=1}^{K}\left|\left(\boldsymbol{v}^H\boldsymbol{\Psi}_k + \boldsymbol{h}_k^H\right)\boldsymbol{w}_i\right|^2} < 1$ ensures the minimum harvested energy constraint of user k can be satisfied. Furthermore, since $\frac{d^2\mathcal{R}(\boldsymbol{\rho})}{d\rho_k^2} < 0, \forall k \in \mathcal{K}$, $\mathcal{R}_k$ is strictly concave in ρ_k. Therefore, we can solve the equation $\frac{d\mathcal{R}(\rho_k)}{d\rho_k} = 0$ and obtain a unique root denoted by

TABLE I
ALTERNATING OPTIMIZATION ALGORITHM

INITIALIZE: $\{\boldsymbol{w}_k\}^{(n)}, \boldsymbol{v}^{(n)}, \{\rho_k\}^{(n)}$ and $q^{(n)}$.
REPEAT:
Set m=0, $q^{(m)} = q^{(n)}$ and $\{\boldsymbol{w}_k\}^{(m)} = \{\boldsymbol{w}_k\}^{(n)}$.
REPEAT:
For given $\boldsymbol{v}^{(n)}, \{\rho_k\}^{(n)}$ and $q^{(m)}$, iteratively solve problem (P2.2) and obtain the solution $\{\boldsymbol{w}_k\}^{(m+1)}$.
Calculate $q^{(m+1)} = \lambda_{EE}^{(m+1)}$, set $m = m + 1$.
UNTIL converge, set $\{\boldsymbol{w}_k\}^{(n+1)} = \{\boldsymbol{w}_k\}^{(m)}$.
Set $q^{(0)} = \lambda_{EE}^{(m)}$, $m = 0$ and $\boldsymbol{v}^{(m)} = \boldsymbol{v}^{(n)}$.
REPEAT:
For given $\{\boldsymbol{w}_k\}^{(n+1)}, \{\rho_k\}^{(n)}$ and $q^{(m)}$, iteratively solve problem (P3.1) and obtain the solution $\boldsymbol{v}^{(m+1)}$.
Calculate $q^{(m+1)} = \lambda_{EE}^{(m+1)}$, set $m = m + 1$.
UNTIL converge, set $\boldsymbol{v}^{(n+1)} = \boldsymbol{v}^{(m)}$.
Set $q^{(0)} = \lambda_{EE}^{(m)}$, $m = 0$ and $\{\rho_k\}^{(m)} = \{\rho_k\}^{(n)}$.
REPEAT:
For given $\{\boldsymbol{w}_k\}^{(n+1)}, \boldsymbol{v}^{(n+1)}$ and $q^{(m)}$, solve problem (P4.1) and obtain the solution $\{\rho_k\}^{(m+1)}$.
Calculate $q^{(m+1)} = \lambda_{EE}^{(m+1)}$, set $m = m + 1$.
UNTIL converge, set $\{\rho_k\}^{(n+1)} = \{\rho_k\}^{(m)}$.
Set $q^{(n+1)} = \lambda_{EE}^{(m)}$ and $n = n + 1$.
UNTIL converge.

$\hat{\rho}_k$ to maximize $\mathcal{R}_k$. In general, the optimal PS ratio of user k can be obtained as follows

$$\rho_k^* = \begin{cases} \rho_k^{\min}, & \hat{\rho}_k < \rho_k^{\min} \\ \hat{\rho}_k, & \rho_k^{\min} \le \hat{\rho}_k \le \rho_k^{\max} \\ \rho_k^{\max}, & \hat{\rho}_k > \rho_k^{\max} \end{cases} \quad (58)$$

Consequently, we can obtain the optimal solution $\{\rho_k^*\}$ of problem (P4) by separately solving the K non-interfering subproblems.

Based on the previous derivations and analyses, the AO algorithm proposed to slove the original problem (P1) can be summarized in TABLE I.

IV. NUMERICAL RESULT AND DISSUTION

In this section, we provide numerical results to validate the effectiveness of the AO algorithm in a downlink MISO IRS-aided SWIPT system with one BS located at (0,0), one IRS located at (5m, 0) and $K = 3$ users located at (5m, -1m), (5m, 1m), (6m, 0), respectively. Furthermore, the distance-dependent path loss model [14] can be formulated as $P_L = D_0(\frac{d}{d_r})^{-\alpha}$, where the path-loss exponents α of the BS-IRS, IRS-user and BS-user links are set to be 2, 2.5 and 3.6, respectively. In addition, the reference path loss at $d_r = 1$m is $D_0 = -30$dB. Referring to [15], the BS-user link follows Rayleigh fading, and the IRS-aided links follow Rician fading. Furthermore, the IRS and BS are both assumed to be equipped with several uniform linear array (ULA) antenna elements. Other simulation parameters are as follows: $M = 3, N = 16, \sigma_k^2 = -40$dbm, $P_m = 40$dbm, $R_{min} = 1.1$ bps/Hz, $E_{min} = 1$uw, $P_T = 0.1$w, $P_n(b) = 0.01$w, $P_C = 2$w, $\zeta = 1.2$, $\eta = 0.6$. For the purpose of demonstrating the superiority of the AO algorithm, we propose

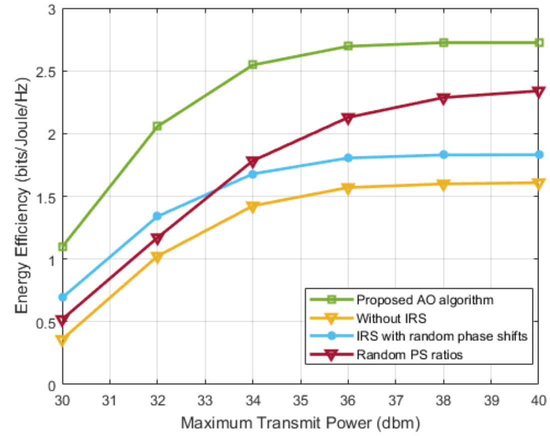

Fig. 1. EE versus maximum transmit power of the BS.

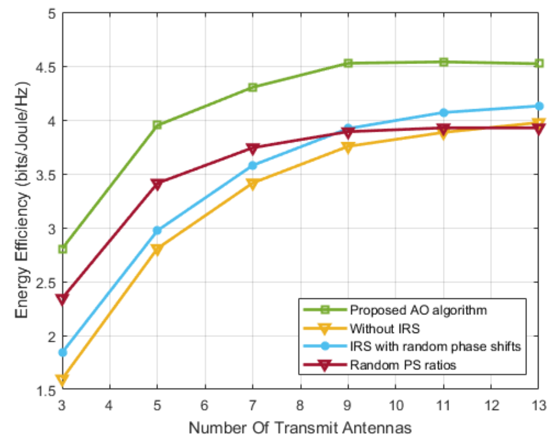

Fig. 2. EE versus the number of transmit antennas.

three benchmark schemes for comparison: 1) Conventional system without IRS [16], 2) Proposed system with random IRS phase shifts, 3) Proposed system with random PS ratios.

Fist of all, we investigate the EE performance versus maximum transmit power of the BS. As we can see in Fig. 1, for all the schemes, EE fist increases and then reaches an asymptotic value as P_m increases. This is because with a large value of P_m, the exceed power transmitted by BS has no effect on EE, which means the balance between the total power consumption and the total transmission rate is obtained. Obviously, the proposed AO algorithm is observed to achieve higher EE as compared to the other three benchmark schemes due to its capability of utilizing the transmit power effectively. In other words, by optimizing reflective beamforming and the PS ratios, the proposed AO algorithm can make the signal transmission environment more favorable, thus outperforming the three benchmark schemes. In particular, the EE of the IRS-aided system is nearly 70% larger than the one without IRS when $P_m \geq 38$ dBm, which indiates the benefit of deploying IRS for enhancing the EE performance.

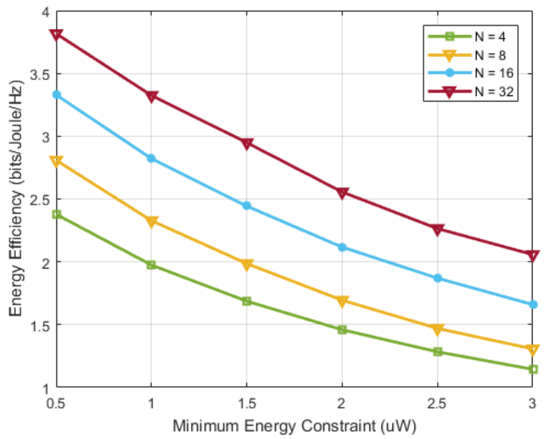

Fig. 3. EE versus minimum energy constraint per user.

In the next simulation, we gradually increase the number of transmit antennas to investigate its effect on EE. It can be observed in Fig. 2, EE increases rapidly when the number of antennas is relatively small. This is because as M increases, higher spatial diversity gain and beamforming gain can be obtained, thus yielding higher transmission rates and harvested energy. However, with a relatively large number of antennas, the increase in EE becomes slower. The proposed algorithm and the three benchmark schemes have a similar increasing trend. This is because although the transmission rates increase, the energy consumption of the additional transmit antennas will make the slope of these four curves gradually decrease. In the end, the total transmission rate and the total power consumption can be balanced.

Finally, we investage the effect of the number of reflecting units at the IRS in the EE performance versus minimum energy constraints. As we can see in Fig. 3, EE gradually decreases as E_{min} increases for N from 4 to 32. This is becauese for a large value of E_{min}, the PS ratios need to decrease to meet the harvested energy demand. In other words, more power needed to be allocated to EH, thus leading to a decline in the achievable transmission rate. In addition, comparing the four curves in Fig. 3, we can know that as the number of reflectiving units increases, the value of EE increases as well. This is because with a larger number of N, the design of the reflective beamforming vectors for EE maximization can become more flexible. That is to say, the users can obtain stronger passive beamforming gain, which leads to a higher transmission rate. On the other hand, even if N increases, the power consumed by the additional reflecting units is relatively low. With a higher total transmission rate and a lightly boosted total energy consumption, the EE performance is improved significantly.

V. Conclusion

In this paper, we maximize the EE of a multiuser IRS-aided MISO system with SWIPT, while sastifing the BS transmit power constraints, the IRS reflection constraint, and the QoS conctraints of each user. As the optimization variables, i.e., the transmit beamforming vectors, the reflective beamforming vector and the PS ratios are intricately coupled, the original problem is extremely complex and non-convex. To effectively solve the problem, we propose an AO algorithm to decouple the original problem into three subproblems. Accordingly, we apply Dinkelbach method as well as SDR and SCA techniques to solve the subproblems. Finally, compared with the three benchmarks, the effectiveness of the AO algorithm and the benefit of deploying IRS can be validated by numerical results.

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