Beamforming Design for Power Transferring and Secure Communication in RIS-Aided Network

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***Abstract*—In this paper, we consider the weighted sum of transferred power maximization under the secrecy rate (SR) constraints in a secure simultaneous wireless information and power transfer (SWIPT) communication network assisted by reconfigurable intelligent surfaces (RIS). To tackle this challenging problem, we combine the cutting-the-edge successive convex approximation (SCA) and penalty dual decomposition (PDD) methods and have successfully developed a novel iterative solution. Compared to the existing literature, our newly proposed algorithm can apply to the most generic system setting that has arbitrary number of information and/or energy receivers. Numerical results demonstrate the effectiveness of our proposed algorithm and the benefit of RIS deployment.**

***Index Terms*—reconfigurable intelligent surfaces (RIS), SWIPT, successive convex approximation (SCA) method, penalty dual decomposition (PDD) method.**

I. Introduction

Recently, the reconfigurable intelligent surfaces (RIS) has been cast with great attention and has been envisioned as a promising technology to enhance the future wireless communication system [1]. RIS consists of a large number of low-cost, reflecting units, which can reflect the incident electromagnetic (EM) waves and adjust its magnitude and/or phase-shift [2]. Recently, extensive research [3]–[12] has been conducted to investigate utilizing RIS to boost wireless network's performance. The authors in [3] consider maximizing the received power in a RIS-aided multiple-input single-output (MISO) system. [4] demonstrates that the energy efficient (EE) can be greatly improved with the help of RIS. Additionally, RIS has also been widely deployed in simultaneous wireless information and power transfer (SWIPT) system to enlarge the wireless energy transfer range [5]–[8]. For instance, the authors in [5] consider maximizing the weighted sum-power harvested by all energy receivers (ERs) while maintaining the quality-of-service (QoS) of all information receivers (IRs). The paper [6] investigates the weighted sum rate optimization for a multiple-input multiple-output (MIMO) system. The work [7] studies maximization of ERs' receiving power with fairness consideration. The authors in [8] introduce an energy efficiency indicator (EEI) to balance the date rate and harvested energy in a RIS-aided SWIPT system. Besides, RIS can also be exploited to enhance the physical-layer security of wireless communications [9]–[12]. The authors of [9] maximize the secrecy rate (SR) of a RIS-assisted system by developing an alternating algorithm based on the semidefinite relaxation (SDR) method. The paper [10] firstly investigates the imperfect cascaded channels of AP-RIS-eavesdropper in the outage constrained secure IRS-aided communications.

In this paper, we consider a RIS-aided secure SWIPT network, where a multiple-antenna AP serves multiple IRs and ERs via transferring information to the IRs and power to the ERs simultaneously. To ensure secure communication, we consider maximizing the total power harvesting while ensuring all IRs can communicate safely at a guaranteed secure rate. Note that the recent works [11] and [12] are highly relevant to our research. The authors in [11] consider EE maximization in a similar secure communication setting. The paper [12] studies power harvesting maximization in a small-scale system, where only one ER and one IR cooperates. Compared to the existing literature, the contribution of this paper includes:

- To the best of our knowledge, we are the first to consider the secure beamforming problem in an SWIPT network that comprises multiple IRs and multiple ERs simulatenously.
- Compared to the SDR and the dual decomposition methods developed in [12], which can only apply to the very special case of single IR and single ER network, our proposed algorithm, which is based on successive convex approximation (SCA), second-order-cone-programming (SOCP) and penalty dual decomposition (PDD) methods, can apply to the most generic case with any number of IRs and ERs.
- Extensive numerical results verify that the deployment of RIS can great enhance the network's performance.

II. System Model

As shown in Fig.1, a secure SWIPT network assisted by RIS is considered, where an M-antenna AP serves a group of single-antenna IRs and single-antenna ERs simultaneously. The k-th IR and l-th ER are denoted as IR_k and ER_l, respectively. The equivalent baseband channels associated with the

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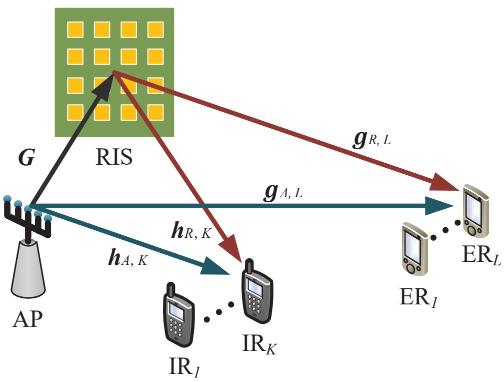

Fig. 1. A secure RIS-aided SWIPT network.

links of AP-RIS, AP-IR$_k$, AP-ER$_l$, RIS-IR$_k$ and RIS-ER$_l$ are denoted as $\boldsymbol{G}\in\mathbb{C}^{N\times M}, \boldsymbol{h}_{A,k}\in\mathbb{C}^{M\times 1}, \boldsymbol{g}_{A,l}\in\mathbb{C}^{M\times 1}, \boldsymbol{h}_{R,k}\in\mathbb{C}^{N\times 1}, \boldsymbol{g}_{R,l}\in\mathbb{C}^{N\times 1}$, respectively, $\forall k\in\mathcal{K}\triangleq\{1,\cdots,K\}$ and $\forall l\in\mathcal{L}\triangleq\{1,\cdots,L\}$. The transmit signal of AP can be represented as:

$$\boldsymbol{x}=\sum\nolimits_{k=1}^{K}\boldsymbol{f}_k s_k, \tag{1}$$

where $\boldsymbol{f}_k\in\mathbb{C}^{M\times 1}$ and $s_k\in\mathbb{C}$ are the transmit beamformer and the information symbol for IR$_k$, respectively. Without loss of generality, we assume that s_k are independent identically distributed random variables with zero mean and unit variance. The transmit beamformers $\{\boldsymbol{f}_k\}$ should comply with average power constraint that is given as

$$\sum\nolimits_{k=1}^{K}\|\boldsymbol{f}_k\|_2^2\leq P_{AP}, \tag{2}$$

where P_{AP} is the maximum transmission power of the AP. Let N be the number of RIS' reflecting units. The reflection coefficients of RIS can be modeled as a complex vector $\boldsymbol{\phi}\triangleq[e^{j\theta_1},\cdots,e^{j\theta_N}]^T$, with θ_n representing the phase shift of the n-th reflecting unit, $\theta_n\in[0,2\pi)$ and $\forall n\in\mathcal{N}\triangleq\{1,\cdots,N\}$. In the following, we alternatively use the diagonal matrix $\boldsymbol{\Phi}=\mathrm{Diag}(\boldsymbol{\phi})$ to equivalently represent the RIS' reflecting coefficients. The received signals at the IR$_k$ and ER$_l$ can be written as

$$y_{I,k}=(\boldsymbol{h}_{A,k}^H+\boldsymbol{h}_{R,k}^H\boldsymbol{\Phi}\boldsymbol{G})\sum\nolimits_{i=1}^{K}\boldsymbol{f}_i s_i+n_{I,k},\ \forall k, \tag{3}$$

$$y_{E,l}=(\boldsymbol{g}_{A,l}^H+\boldsymbol{g}_{R,l}^H\boldsymbol{\Phi}\boldsymbol{G})\sum\nolimits_{i=1}^{K}\boldsymbol{f}_i s_i+n_{E,l},\ \forall l, \tag{4}$$

respectively, where $n_{I,k}\sim\mathcal{CN}(0,\sigma_{I,k}^2)$ and $n_{E,l}\sim\mathcal{CN}(0,\sigma_{E,l}^2)$ are the complex additive white Gaussian noise (AWGN) at the IR$_k$ and ER$_l$, respectively. The signal of signal-to-interference-plus-noise ratio (SINR) of IR$_k$ is given by

$$\gamma_k^{IR}=\frac{|\boldsymbol{h}_k^H\boldsymbol{f}_k|^2}{\sum_{i\neq k}^{K}|\boldsymbol{h}_k^H\boldsymbol{f}_i|^2+\sigma_{I,k}^2},\ \forall k, \tag{5}$$

where $\boldsymbol{h}_k^H\triangleq\boldsymbol{h}_{A,k}^H+\boldsymbol{h}_{R,k}^H\boldsymbol{\Phi}\boldsymbol{G}$. Considering the fact that the electromagnetic waves harvested by the ERs carry information of IRs, there exists a possibility that the IRs' privacy could be eavesdropped by the ERs. Therefore, the received SINR at ER$_l$ for intercepting the information of IR$_k$ can be given by

$$\gamma_{k,l}^{ER}=\frac{|\boldsymbol{g}_l^H\boldsymbol{f}_k|^2}{\sum_{i\neq k}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2+\sigma_{E,l}^2},\ \forall k,l, \tag{6}$$

where $\boldsymbol{g}_l^H\triangleq\boldsymbol{g}_{A,l}^H+\boldsymbol{g}_{R,l}^H\boldsymbol{\Phi}\boldsymbol{G}$. According to [13], the achieved SR at IR$_k$ is defined as

$$R_{SR_k}=\left[\log(1+\gamma_k^{IR})-\max_{\forall l\in\mathcal{L}}\log(1+\gamma_{k,l}^{ER})\right]^+,\ \forall k, \tag{7}$$

where $[x]^+\triangleq\max\{x,0\}$.

In this paper, we adopt a linear energy harvesting model and neglect the power of received noise [14]. The weighted sum of ERs' harvested power is given by

$$P_E=\sum\nolimits_{l=1}^{L}\sum\nolimits_{k=1}^{K}\zeta_l\omega_l(|(\boldsymbol{g}_{A,l}^H+\boldsymbol{g}_{R,l}^H\boldsymbol{\Phi}\boldsymbol{G})\boldsymbol{f}_k|^2), \tag{8}$$

where ζ_l and ω_l are denoted as the efficiency of power harvesting and the priority weight for ER$_l$, respectively.

III. Problem Formulation and Proposed Algorithm

In this section, we maximize the weighted sum of the harvested power of all ERs while assuring the secure transmission rate associated with all IRs remain above predefined level via jointly optimizing the transmit beamformers $\{\boldsymbol{f}_k\}$ and phase shifts $\boldsymbol{\Phi}$. The optimization problem is formulated as

$$(\mathrm{P1}):\max_{\{\boldsymbol{f}_k\},\boldsymbol{\Phi}}\ P_E \tag{9a}$$

$$\text{s.t.}\ \sum\nolimits_{k=1}^{K}\|\boldsymbol{f}_k\|_2^2\leq P_{AP}, \tag{9b}$$

$$R_{SR_k}\geq R_{tar_k},\ \forall k, \tag{9c}$$

$$|\boldsymbol{\phi}_n|=1,\ \forall n. \tag{9d}$$

where $R_{tar_k}>0$ denotes the target SR level of IR$_k$.

Considering the definition of R_{SR_k}, the constraint (9c) is equivalent to the following inequality

$$\log(1+\gamma_k^{IR})-\log(1+\gamma_{k,l}^{ER})\geq R_{tar_k},\ \forall k,l. \tag{10}$$

Therefore the problem (P1) can be rewritten as

$$(\mathrm{P2}):\max_{\{\boldsymbol{f}_k\},\boldsymbol{\Phi}}\ P_E \tag{11a}$$

$$\text{s.t.}\ \sum\nolimits_{k=1}^{K}\|\boldsymbol{f}_k\|_2^2\leq P_{AP}, \tag{11b}$$

$$\log(1+\gamma_k^{IR})-\log(1+\gamma_{k,l}^{ER})\geq R_{tar_k},\ \forall k,l, \tag{11c}$$

$$|\boldsymbol{\phi}_n|=1,\ \forall n. \tag{11d}$$

The problem (P2) is challenging due to its highly non-convex objective and constraints. To make the SR constraints more tractable, the secrecy rate in (11c) can be equivalently written as

$$\begin{aligned}&\log(1+\gamma_k^{IR})-\log(1+\gamma_{k,l}^{ER}) \qquad (12)\\&=\underbrace{\log\left(1+|\boldsymbol{h}_k^H\boldsymbol{f}_k|^2(\sum\nolimits_{i\neq k}^{K}|\boldsymbol{h}_k^H\boldsymbol{f}_i|^2+\sigma_{I,k}^2)^{-1}\right)}_{A_{1_k}}\\&\underbrace{-\log\left(1+\sum\nolimits_{i=1}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2}\right)}_{A_{2_{k,l}}}+\underbrace{\log\left(1+\sum\nolimits_{i\neq k}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2}\right)}_{A_{3_{k,l}}}.\end{aligned}$$

Then we introduce the following *Lemma* that are proved in [15] to equivalently transform $\{A_{1_k}\}$ and $\{A_{2_{k,l}}\}$.

Lemma 1. *Define a $m\times m$ matrix function*

$$\boldsymbol{E}(\boldsymbol{U},\boldsymbol{V})\triangleq(\boldsymbol{I}-\boldsymbol{U}^H\boldsymbol{H}\boldsymbol{V})(\boldsymbol{I}-\boldsymbol{U}^H\boldsymbol{H}\boldsymbol{V})^H+\boldsymbol{U}^H\boldsymbol{N}\boldsymbol{U}, \tag{13}$$

where $\boldsymbol{N}$ is any positive definite matrix. The following three facts hold true.

1) For any positive definite matrix $\boldsymbol{E} \in \mathbb{C}^{m\times m}$, we have

$$-\text{logdet}(\boldsymbol{E}) = \max_{\boldsymbol{W}\succ\boldsymbol{0}} \text{logdet}(\boldsymbol{W}) - \text{Tr}(\boldsymbol{W}\boldsymbol{E}) + m, \quad (14)$$

with the optimal $\boldsymbol{W}$ in (13) given by $\boldsymbol{W}^\star = \boldsymbol{E}^{-1}$.

2) For any positive definite matrix $\boldsymbol{W}$, we have

$$\boldsymbol{U}^\star \triangleq \arg\min_{\boldsymbol{U}} \text{Tr}(\boldsymbol{W}\boldsymbol{E}(\boldsymbol{U},\boldsymbol{V})) = (\boldsymbol{N} + \boldsymbol{H}\boldsymbol{V}\boldsymbol{V}^H\boldsymbol{H}^H)^{-1}\boldsymbol{H}\boldsymbol{V}, \quad (15)$$

and

$$\boldsymbol{E}(\boldsymbol{U}^\star,\boldsymbol{V}) = (\boldsymbol{I} + \boldsymbol{V}^H\boldsymbol{H}^H\boldsymbol{N}^{-1}\boldsymbol{H}\boldsymbol{V})^{-1}. \quad (16)$$

3) We have

$$\text{logdet}(\boldsymbol{I}+\boldsymbol{H}\boldsymbol{V}\boldsymbol{V}^H\boldsymbol{H}^H\boldsymbol{N}^{-1}) = \max_{\boldsymbol{W}\succ\boldsymbol{0},\boldsymbol{U}} \text{logdet}(\boldsymbol{W}) - \text{Tr}(\boldsymbol{W}\boldsymbol{E}(\boldsymbol{U},\boldsymbol{V})) + m. \quad (17)$$

By applying *Lemma* 1 and introducing the auxiliary variables $\{u_k\}$, $\{w_{I_k}\}$ and $\{w_{E_{k,l}}\}$, we can transform the terms $\{A_{1_k}\}$ and $\{A_{2_{k,l}}\}$. Firstly, we define

$$e_k=|1-u_k^*\boldsymbol{h}_k^H\boldsymbol{f}_k|^2+|u_k|^2\left(\sum\nolimits_{i\neq k}^{K}|\boldsymbol{h}_k^H\boldsymbol{f}_i|^2+\sigma_{I,k}^2\right),\ \forall k. \quad (18)$$

Based on Fact 3), we can equivalently transform A_{1_k} as follows:

$$A_{1_k} = \max_{w_{I_k}>0,u_k} \log(w_{I_k}) - w_{I_k}e_k + 1,\ \forall k. \quad (19)$$

Furthermore, by Fact 1), we have

$$A_{2_{k,l}} = \max_{w_{E_{k,l}}>0} \log(w_{E_{k,l}}) - w_{E_{k,l}}\left(1+\sum\nolimits_{i=1}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2}\right)+1,\ \forall k,l. \quad (20)$$

Since $\{A_{3_{k,l}}\}$ cannot be solved directly, we convert $\{A_{3_{k,l}}\}$ by introducing slack variables $\{t_{k,l}\}$. Therefore, (12) is equivalent to

$$\bar{w}_{k,l}-w_{I_k}e_k-w_{E_{k,l}}\bar{e}_{k,l}+\log(t_{k,l}) \geq R_{tar_k},\ \forall k,l, \quad (21)$$

$$t_{k,l} \leq 1+\sum\nolimits_{i\neq k}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2},\ \forall k,l, \quad (22)$$

where $\bar{w}_{k,l}$ and $\bar{e}_{k,l}$ are respectively defined as

$$\bar{w}_{k,l} \triangleq \log(w_{I_k}) + \log(w_{E_{k,l}}) + 2, \quad (23)$$

$$\bar{e}_{k,l} \triangleq 1+\sum\nolimits_{i\neq k}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2}. \quad (24)$$

Then the problem (P2) is equivalently expressed as

$$\text{(P3)}: \max_{\{\boldsymbol{f}_k\},\boldsymbol{\Phi},\{u_k\},\{w_{I_k}\},\{w_{E_{k,l}}\},\{t_{k,l}\}} P_E \quad (25a)$$

$$\text{s.t.} \sum\nolimits_{k=1}^{K}\|\boldsymbol{f}_k\|_2^2 \leq P_{AP}, \quad (25b)$$

$$\bar{w}_{k,l}-w_{I_k}e_k-w_{E_{k,l}}\bar{e}_{k,l}+\log(t_{k,l})\geq R_{tar_k},\ \forall k,l, \quad (25c)$$

$$t_{k,l} \leq 1+\sum\nolimits_{i\neq k}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2},\ \forall k,l, \quad (25d)$$

$$|\boldsymbol{\phi}_n| = 1,\ \forall n. \quad (25e)$$

In the next, we adopt block coordinate descent (BCD) method to tackle the above problem.

A. Optimizing auxiliary variables

Via invoking *Lemma* 1, it can be verified that the update of the variables $\{u_k\}$, $\{w_{I_k}\}$ and $\{w_{E_{k,l}}\}$ have closed form solutions that are given as follows

$$u_k^\star = \boldsymbol{h}_k^H\boldsymbol{f}_k\left(\sum\nolimits_{i=1}^{K}|\boldsymbol{h}_k^H\boldsymbol{f}_i|^2+\sigma_{I,k}^2\right)^{-1},\ \forall k, \quad (26)$$

$$w_{I_k}^\star=\left(1-\boldsymbol{f}_k^H\boldsymbol{h}_k\left(\sum\nolimits_{i=1}^{K}|\boldsymbol{h}_k^H\boldsymbol{f}_i|^2+\sigma_{I,k}^2\right)^{-1}\boldsymbol{h}_k^H\boldsymbol{f}_k\right)^{-1},\ \forall k, \quad (27)$$

$$w_{E_{k,l}}^\star = \left(1+\sum\nolimits_{i=1}^{K}|\boldsymbol{g}_l^H\boldsymbol{f}_i|^2\sigma_{E,l}^{-2}\right)^{-1},\ \forall k,l. \quad (28)$$

B. Optimizing $\boldsymbol{f}$

In this subsection, we present the method to update $\{\boldsymbol{f}_k\}$. With other variables being fixed, the update of $\{\boldsymbol{f}_k\}$ and $\{t_{k,l}\}$ are reduced to solving the following problem

$$\text{(P4)}: \max_{\{\boldsymbol{f}_k\},\{t_{k,l}\}} \sum\nolimits_{k=1}^{K}\boldsymbol{f}_k^H\boldsymbol{A}\boldsymbol{f}_k \quad (29a)$$

$$\text{s.t.} \sum\nolimits_{k=1}^{K}\boldsymbol{f}_k^H\boldsymbol{f}_k \leq P_{AP}, \quad (29b)$$

$$\sum\nolimits_{i=1}^{K}\boldsymbol{f}_i^H\boldsymbol{B}_{k,l}\boldsymbol{f}_i-2\text{Re}\{\boldsymbol{b}_k\boldsymbol{f}_k\}+b_{k,l}-\log(t_{k,l})\leq 0,\forall k,l, \quad (29c)$$

$$t_{k,l} \leq 1+\sum\nolimits_{i\neq k}^{K}\boldsymbol{f}_i^H\boldsymbol{g}_l\boldsymbol{g}_l^H\boldsymbol{f}_i\sigma_{E,l}^{-2},\ \forall k,l, \quad (29d)$$

with the parameters in problem (P4) being defined as follows:

$$\boldsymbol{A} \triangleq \sum\nolimits_{l=1}^{L}\boldsymbol{g}_l\boldsymbol{g}_l^H,\ \boldsymbol{b}_k \triangleq w_{I_k}u_k^*\boldsymbol{h}_k^H,\ \forall k, \quad (30)$$
$$\boldsymbol{B}_{k,l} \triangleq (w_{I_k}|u_k|^2\boldsymbol{h}_k\boldsymbol{h}_k^H + w_{E_{k,l}}\sigma_{E,l}^{-2}\boldsymbol{g}_l\boldsymbol{g}_l^H),\ \forall k,l,$$
$$b_{k,l} \triangleq w_{I_k}(1+|u_k|^2\sigma_{I,k}^2)+w_{E_{k,l}}-\bar{w}_{k,l}+R_{tar_k},\ \forall k,l.$$

The problem (P4) is non-convex since it is maximizing a convex fucntion. Inspired by the cutting-the-edge majorization-minimization (MM) framework [16], we replace the original convex objective (29a) and the nonconvex constraint (29d) by their linearizations, respectively, which are given as

$$\text{(P5)}: \max_{\{\boldsymbol{f}_k\},\{t_{k,l}\}}\sum\nolimits_{k=1}^{K}\left\{2\text{Re}\{\hat{\boldsymbol{f}}_k^H\boldsymbol{A}(\boldsymbol{f}_k-\hat{\boldsymbol{f}}_k)\}+\hat{\boldsymbol{f}}_k^H\boldsymbol{A}\hat{\boldsymbol{f}}_k\right\} \quad (31a)$$

$$\text{s.t.} \sum\nolimits_{k=1}^{K}\boldsymbol{f}_k^H\boldsymbol{f}_k \leq P_{\text{AP}}, \quad (31b)$$

$$\sum\nolimits_{i=1}^{K}\boldsymbol{f}_i^H\boldsymbol{B}_{k,l}\boldsymbol{f}_i-2\text{Re}\{\boldsymbol{b}_k\boldsymbol{f}_k\}+b_{k,l}-\log(t_{k,l})\leq 0,\forall k,l, \quad (31c)$$

$$t_{k,l}\leq 1+\sum\nolimits_{i\neq k}^{K}\left\{2\text{Re}\{\hat{\boldsymbol{f}}_i^H\boldsymbol{g}_l\boldsymbol{g}_l^H(\boldsymbol{f}_i-\hat{\boldsymbol{f}}_i)\}+\hat{\boldsymbol{f}}_i^H\boldsymbol{g}_l\boldsymbol{g}_l^H\hat{\boldsymbol{f}}_i\right\}\sigma_{E,l}^{-2}, \quad (31d)$$

where $\{\hat{\boldsymbol{f}}_k\}$ are feasible solutions obtained in the last iteration. The problem (P5) is convex and can be solved by CVX [17].

C. Optimizing $\boldsymbol{\Phi}$

When other variables are given, $\boldsymbol{\Phi}$ and $\{t_{k,l}\}$ should be updated via solving the following problem

$$\text{(P6)}: \min_{\boldsymbol{\phi},\{t_{k,l}\}} -\{\boldsymbol{\phi}^H\boldsymbol{Q}^T\boldsymbol{\phi}+2\text{Re}\{\boldsymbol{q}^T\boldsymbol{\phi}\}+q\} \quad (32a)$$

$$\text{s.t.}\ \boldsymbol{\phi}^H\boldsymbol{S}_{k,l}\boldsymbol{\phi}+2\text{Re}\{\boldsymbol{s}_{k,l}\boldsymbol{\phi}\}+s_{k,l}-\log(t_{k,l})\leq 0,\ \forall k,l, \quad (32b)$$

$$t_{k,l} \leq \boldsymbol{\phi}^H\boldsymbol{Z}_{k,l}^T\boldsymbol{\phi}+2\text{Re}\{\boldsymbol{z}_{k,l}^T\boldsymbol{\phi}\}+z_{k,l},\ \forall k,l, \quad (32c)$$

$$|\boldsymbol{\phi}_n| = 1,\ \forall n, \quad (32d)$$

where the parameters of problem (P6) are defined as

$$\boldsymbol{R}_{g,l}\triangleq\text{Diag}(\boldsymbol{g}_{R,l}^H)\boldsymbol{G},\ \boldsymbol{R}_{h,k}\triangleq\text{Diag}(\boldsymbol{h}_{R,k}^H)\boldsymbol{G},\ \boldsymbol{F}\triangleq\sum\nolimits_{k=1}^{K}\boldsymbol{f}_k\boldsymbol{f}_k^H, \quad (33)$$
$$\boldsymbol{Q}\triangleq\sum\nolimits_{l=1}^{L}\boldsymbol{R}_{g,l}\boldsymbol{F}\boldsymbol{R}_{g,l}^H,\ \boldsymbol{q}\triangleq\sum\nolimits_{l=1}^{L}\boldsymbol{R}_{g,l}\boldsymbol{F}\boldsymbol{g}_{A,l},\ q\triangleq\sum\nolimits_{l=1}^{L}\boldsymbol{g}_{A,l}^H\boldsymbol{F}\boldsymbol{g}_{A,l}.$$

Besides, $s_{k,l}$, $\boldsymbol{s}_{k,l}$, $\boldsymbol{S}_{k,l}$, $z_{k,l}$, $\boldsymbol{z}_{k,l}$ and $\boldsymbol{Z}_{k,l}$ are given in (34), shown at the top of next page.

The problem (P6), minimizes a nonconvex objective function. Hence, following similar arguments as before, we adopt

$$z_{k,l} \triangleq 1+\sum_{i\neq k}^{K} \boldsymbol{g}_{A,l}^H \boldsymbol{f}_i \boldsymbol{f}_i^H \boldsymbol{g}_{A,l}\sigma_{E,l}^{-2},\ \boldsymbol{z}_{k,l} \triangleq \sum_{i\neq k}^{K} \boldsymbol{R}_{g,l}\boldsymbol{f}_i\boldsymbol{f}_i^H \boldsymbol{g}_{A,l}\sigma_{E,l}^{-2},\ \boldsymbol{Z}_{k,l} \triangleq \sum_{i\neq k}^{K} \boldsymbol{R}_{g,l}\boldsymbol{f}_i\boldsymbol{f}_i^H \boldsymbol{R}_{g,l}^H\sigma_{E,l}^{-2},\ \forall k,l, \tag{34}$$
$$s_{k,l} \triangleq -\bar{w}_{k,l}+w_{I_k}(1-2\mathrm{Re}\{u_k\boldsymbol{f}_k^H\boldsymbol{h}_{A,k}\}+|u_k|^2(\boldsymbol{h}_{A,k}^H\boldsymbol{F}\boldsymbol{h}_{A,k}+\sigma_{I,k}^2))+w_{E_{k,l}}(1+\boldsymbol{g}_{A,l}^H\boldsymbol{F}\boldsymbol{g}_{A,l}\sigma_{E,l}^{-2})+R_{tar_k},$$
$$\boldsymbol{s}_{k,l} \triangleq w_{I_k}|u_k|^2(\boldsymbol{R}_{h,k}\boldsymbol{F}\boldsymbol{h}_{A,k})^T - w_{I_k}u_k^*(\boldsymbol{R}_{h,k}\boldsymbol{f}_k)^T + w_{E_{k,l}}(\boldsymbol{R}_{g,l}\boldsymbol{F}\boldsymbol{g}_{A,l}\sigma_{E,l}^{-2})^T,$$
$$\boldsymbol{S}_{k,l} \triangleq w_{I_k}|u_k|^2(\boldsymbol{R}_{h,k}\boldsymbol{F}\boldsymbol{R}_{h,k}^H)^T + w_{E_{k,l}}(\boldsymbol{R}_{g,l}\boldsymbol{F}\boldsymbol{R}_{g,l}^H\sigma_{E,l}^{-2})^T,\ \forall k,l.$$

SCA method to convexify the problem as follows:

$$(\mathrm{P7}):\ \min_{\boldsymbol{\phi},\{t_{k,l}\}}\ -2\mathrm{Re}\{(\boldsymbol{q}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T)\boldsymbol{\phi}\}+(\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T\hat{\boldsymbol{\phi}})^*-q \tag{35a}$$
$$\text{s.t. } \boldsymbol{\phi}^H\boldsymbol{S}_{k,l}\boldsymbol{\phi}+2\mathrm{Re}\{\boldsymbol{s}_{k,l}\boldsymbol{\phi}\}+s_{k,l}-\log(t_{k,l})\le 0,\ \forall k,l, \tag{35b}$$
$$t_{k,l}\le 2\mathrm{Re}\{(\boldsymbol{z}_{k,l}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T)\boldsymbol{\phi}\}-(\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T\hat{\boldsymbol{\phi}})^*+z_{k,l},\ \forall k,l, \tag{35c}$$
$$|\boldsymbol{\phi}_n|=1,\ \forall n. \tag{35d}$$

where $\hat{\boldsymbol{\phi}}$ is any feasible solution obtained previously. Note that problem (P7) is still non-convex due to the nonlinear equality constraint (35d). To attack this problem, we adopt PDD method [18], [19] and [20] to solve it. Firstly, we introduce an auxiliary variable $\boldsymbol{\psi}$ as follows:

$$(\mathrm{P8}):\ \min_{\boldsymbol{\phi},\{t_{k,l}\}}\ -2\mathrm{Re}\{(\boldsymbol{q}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T)\boldsymbol{\phi}\}+(\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T\hat{\boldsymbol{\phi}})^*-q \tag{36a}$$
$$\text{s.t. } \boldsymbol{\phi}^H\boldsymbol{S}_{k,l}\boldsymbol{\phi}+2\mathrm{Re}\{\boldsymbol{s}_{k,l}\boldsymbol{\phi}\}+s_{k,l}-\log(t_{k,l})\le 0,\forall k,l, \tag{36b}$$
$$t_{k,l}\le 2\mathrm{Re}\{(\boldsymbol{z}_{k,l}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T)\boldsymbol{\phi}\}-(\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T\hat{\boldsymbol{\phi}})^*+z_{k,l},\ \forall k,l, \tag{36c}$$
$$\boldsymbol{\phi}=\boldsymbol{\psi},\ |\boldsymbol{\psi}_n|=1,\ |\boldsymbol{\phi}_n|\le 1,\ \forall n. \tag{36d}$$

Next, via penalizing the equality constraint, we obtain the augmented Lagrangian problem of (P8) as follows:

$$(\mathrm{P9}):\ \min_{\boldsymbol{\phi},\boldsymbol{\psi},\boldsymbol{\lambda},\{t_{k,l}\}}\ -2\mathrm{Re}\{(\boldsymbol{q}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T)\boldsymbol{\phi}\}+\frac{1}{2\rho}\|\boldsymbol{\phi}-\boldsymbol{\psi}\|_2^2 + \mathrm{Re}\{\boldsymbol{\lambda}^H(\boldsymbol{\phi}-\boldsymbol{\psi})\}+(\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T\hat{\boldsymbol{\phi}})^*-q \tag{37a}$$
$$\text{s.t. } \boldsymbol{\phi}^H\boldsymbol{S}_{k,l}\boldsymbol{\phi}+2\mathrm{Re}\{\boldsymbol{s}_{k,l}\boldsymbol{\phi}\}+s_{k,l}-\log(t_{k,l})\le 0,\forall k,l, \tag{37b}$$
$$t_{k,l}\le 2\mathrm{Re}\{(\boldsymbol{z}_{k,l}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T)\boldsymbol{\phi}\}-(\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T\hat{\boldsymbol{\phi}})^*+z_{k,l},\ \forall k,l, \tag{37c}$$
$$|\boldsymbol{\psi}_n|=1,\ |\boldsymbol{\phi}_n|\le 1,\ \forall n. \tag{37d}$$

According to [18] and [19], the PDD method is a two-layer iterative procedure, with its inner layer alternatively updating $\boldsymbol{\phi}$ and $\boldsymbol{\psi}$ by BCD method and its outer layer selectively updating the dual variable $\boldsymbol{\lambda}$ or the penalty coefficient ρ. The PDD method is specified subsequently.

In the inner layer, when $\boldsymbol{\psi}$ is fixed, the problem with respect to $\boldsymbol{\phi}$ and $\{t_{k,l}\}$ can be rewritten as

$$(\mathrm{P10}):\ \min_{\boldsymbol{\phi},\{t_{k,l}\}}\ -2\mathrm{Re}\{(\boldsymbol{q}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T)\boldsymbol{\phi}\}+\frac{1}{2\rho}\|\boldsymbol{\phi}-\boldsymbol{\psi}\|_2^2 + \mathrm{Re}\{\boldsymbol{\lambda}^H(\boldsymbol{\phi}-\boldsymbol{\psi})\}+(\hat{\boldsymbol{\phi}}^H\boldsymbol{Q}^T\hat{\boldsymbol{\phi}})^*-q \tag{38a}$$
$$\text{s.t. } \boldsymbol{\phi}^H\boldsymbol{S}_{k,l}\boldsymbol{\phi}+2\mathrm{Re}\{\boldsymbol{s}_{k,l}\boldsymbol{\phi}\}+s_{k,l}-\log(t_{k,l})\le 0,\forall k,l, \tag{38b}$$
$$t_{k,l}\le 2\mathrm{Re}\{(\boldsymbol{z}_{k,l}^T+\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T)\boldsymbol{\phi}\}-(\hat{\boldsymbol{\phi}}^H\boldsymbol{Z}_{k,l}^T\hat{\boldsymbol{\phi}})^*+z_{k,l},\ \forall k,l, \tag{38c}$$
$$|\boldsymbol{\phi}_n|\le 1,\ \forall n. \tag{38d}$$

which is a convex problem and can be numerically solved.

When $\boldsymbol{\phi}$ is fixed, $\boldsymbol{\psi}$ should be updated via solving the following problem

$$(\mathrm{P11}):\ \min_{\boldsymbol{\psi}}\ \frac{1}{2\rho}\|\boldsymbol{\phi}-\boldsymbol{\psi}\|_2^2+\mathrm{Re}\{\boldsymbol{\lambda}^H(\boldsymbol{\phi}-\boldsymbol{\psi})\} \tag{39a}$$
$$\text{s.t. } |\boldsymbol{\psi}_n|=1,\ \forall n. \tag{39b}$$

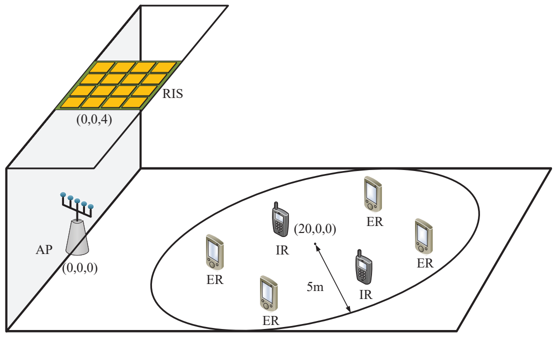

Fig. 2. The experiment scenario model.

Note that the quadratic term with respect to $\boldsymbol{\psi}$ in the objective function is constant, i.e., $\frac{1}{2\rho}\|\boldsymbol{\psi}\|_2^2=\frac{N}{2\rho}$ since $\boldsymbol{\psi}$ has unit modulus entries. Therefore, problem (P11) is reduced to the following problem

$$(\mathrm{P12}):\ \max_{|\boldsymbol{\psi}|=\boldsymbol{1}_N}\ \mathrm{Re}\{(\boldsymbol{\phi}+\rho\boldsymbol{\lambda})^H\boldsymbol{\psi}\}. \tag{40}$$

Note that the optimal solution of problem (P12) can be obtained when the phases of the elements of $\boldsymbol{\psi}$ are all aligned with those of $(\rho^{-1}\boldsymbol{\phi}+\boldsymbol{\lambda})$, which is given as

$$\boldsymbol{\psi}^\star=\exp(j\cdot\angle(\boldsymbol{\phi}+\rho\boldsymbol{\lambda})^H\boldsymbol{\psi}). \tag{41}$$

After the inner loop achieves convergence, the outer layer will choose to update the dual variable $\boldsymbol{\lambda}$ or the penalty coefficient ρ by judging whether the equality $\boldsymbol{\phi}=\boldsymbol{\psi}$ approximately holds or not. The above two cases are as follows:

1) when the equality $\boldsymbol{\phi}=\boldsymbol{\psi}$ approximately holds, the outer layer will select to update $\boldsymbol{\lambda}$ in a gradient ascent manner [21], which is given by
$$\boldsymbol{\lambda}:=\boldsymbol{\lambda}+\rho^{-1}(\boldsymbol{\phi}-\boldsymbol{\psi}); \tag{42}$$
2) when the equality constraint $\boldsymbol{\phi}=\boldsymbol{\psi}$ is far from "being true", the outer layer will force the equality $\boldsymbol{\phi}=\boldsymbol{\psi}$ to be approximately achieved in the subsequent iterations via increasing the penalty parameter ρ^{-1} as follows:
$$\rho^{-1}:=c^{-1}\cdot\rho^{-1}, \tag{43}$$
where c is a predetermined constant which is in the range of $(0,1)$.

The PDD-based method is summarized in Algorithm 1. The proposed algorithm is summarized in Algorithm 2.

IV. Numerical Results

In this section, we evaluate the performance of our proposed algorithm by numerical results. The experiment network containing 2 single-antenna IRs and a group of single-antenna ERs

Algorithm 1 PDD Method to Solve (P9)

initialize $\boldsymbol{\phi}^{(0)}$, $\boldsymbol{\psi}^{(0)}$, $\boldsymbol{\lambda}^{(0)}$, $\rho^{(0)}$ and $k=1$;
repeat
  set $\boldsymbol{\phi}^{(k-1,0)} := \boldsymbol{\phi}^{(k-1)}$, $\boldsymbol{\psi}^{(k-1,0)} := \boldsymbol{\psi}^{(k-1)}$, $t=0$;
  repeat
    update $\boldsymbol{\phi}^{(k-1,t+1)}$ by solving (P10);
    update $\boldsymbol{\psi}^{(k-1,t+1)}$ by (41);
    $t++$;
  until *convergence*
  set $\boldsymbol{\phi}^{(k)} := \boldsymbol{\phi}^{(k-1,\infty)}$, $\boldsymbol{\psi}^{(k)} := \boldsymbol{\psi}^{(k-1,\infty)}$;
  if $\|\boldsymbol{\phi}^{(k)} - \boldsymbol{\psi}^{(k)}\|_\infty \le \eta_k$ **then**
    $\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)} + \frac{1}{\rho^{(k)}}(\boldsymbol{\phi}^{(k)} - \boldsymbol{\psi}^{(k)})$, $\rho^{(k+1)} := \rho^{(k)}$;
  else
    $\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)}$, $1/\rho^{(k+1)} := 1/(c \cdot \rho^{(k)})$;
  end if
  $k++$;
until $\|\boldsymbol{\phi}^{(k)} - \boldsymbol{\psi}^{(k)}\|_2$ is sufficiently small

Algorithm 2 Proposed Algorithm

initialize $i=0$;
randomly generate feasible $\{\boldsymbol{f}_k^{(0)}\}$ and $\boldsymbol{\phi}^{(0)}$;
repeat
  update $\{u_k\}$, $\{w_{I_k}\}$ and $\{w_{E_{k,l}}\}$ by (26), (27) and (28);
  set $\boldsymbol{f}_k^{(i,0)} := \boldsymbol{f}_k^{(i)}$, $\forall k$, $m=0$;
  repeat
    update $\{\boldsymbol{f}_k^{(i,m+1)}\}$ by solving (P5);
    $m++$;
  until *convergence*
  set $\boldsymbol{f}_k^{(i+1)} := \boldsymbol{f}_k^{(i,\infty)}$, $\forall k$;
  update $\boldsymbol{\phi}^{(i+1)}$ by invoking Alg.1;
  $i++$;
until $\left|\frac{P_E(\{\boldsymbol{f}_k^{(i+1)}\},\boldsymbol{\phi}^{(i+1)}) - P_E(\{\boldsymbol{f}_k^{(i)}\},\boldsymbol{\phi}^{(i)})}{P_E(\{\boldsymbol{f}_k^{(i)}\},\boldsymbol{\phi}^{(i)})}\right| \le \varepsilon$

is shown in Fig. 2. The number of ERs L, AP's antennas M and RIS' reflecting elements N vary from 2 to 4, 2 to 6 and 50 to 150, respectively. In the experiment, the AP and the RIS are located at $(0,0,0)$m and $(0,0,4)$m, respectively. The IRs and ERs are randomly distributed within a circle with the radius of 5m and its center located at $(20,0,0)$m. Therefore, The IRs and ERs are randomly distributed 15m to 25m from the AP, respectively. We assume that an uniform linear array (ULA) at the AP and an uniform rectangular array (URA) at the RIS. Since the AP, the RIS, the IRs and the ERs are closed to each other, the fading channel is assumed to be Rician fading with a Rician factor of 4. The reference path loss is 30dB per 1m. The path loss exponents of direct channel and RIS-related channel are set as $\alpha_d = 3.5$ and $\alpha_r = 3$, respectively. The antenna gain of the AP, IRs and ERs are 0dBi and that of each reflecting element at the RIS is 5dBi. The all IRs have common target SR level with $R_{th} = R_{tar_k}, \forall k$. Other parameters setting are $P_{AP} = 27$dBm, $\sigma_{I,k}^2 = \sigma_{E,l}^2 = -90$dBm, $c = 0.85$, $\zeta_l = 0.5$ and $\omega_l = 1$, $\forall k$, l.

Fig.3 illustrates the effectiveness of PDD method in updating $\boldsymbol{\phi}$. As suggested by the figure, under various settings, PDD method generally converges within 50 iterations with the constraint $\boldsymbol{\phi} = \boldsymbol{\psi}$ being finally well satisfied.

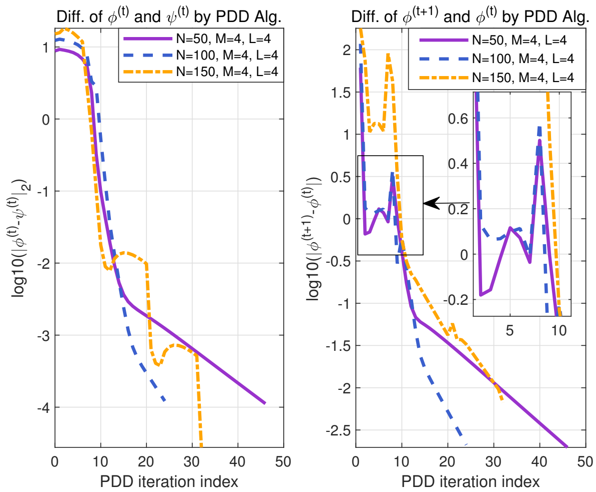

Fig. 3. Convrg. of PDD outer layer, where $R_{th} = 1$bps/Hz.

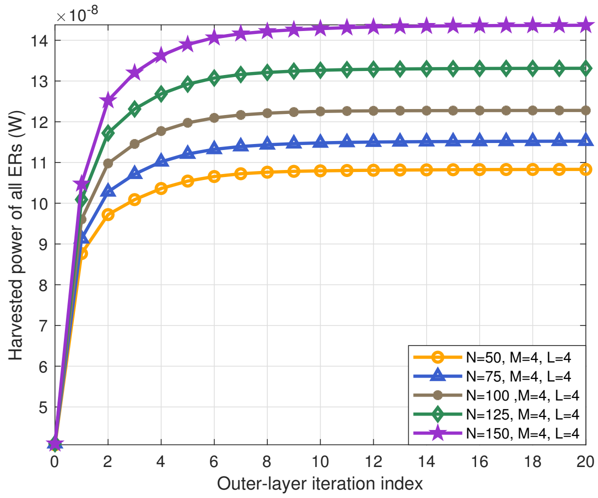

Fig. 4. Convrg. of our proposed algorithm, where $R_{th} = 1$bps/Hz.

In the later experiments, 50 channel realizations are generated. Fig. 4 demonstrates the convergence behavior of our proposed PDD based solutions with different numbers of RIS' reflecting elements. The proposed algorithm usually converges within about 20 iterations. After convergence, our proposed algorithm achieves significant harvested power improvements compared to the initial phases. Besides, increasing the number of RIS' units accordingly improves the harvested power at all ERs.

Fig. 5 illustrates the harvested power of all ERs versus the target SR level R_{th}. In our experiment, it is observed that the harvested power of all ERs decreases as R_{th} increases. Compared to both no RIS and random RIS schemes, the harvested power can be significantly enlarged by deploying the RIS.

In Fig. 6, we compare the harvested power of all schemes

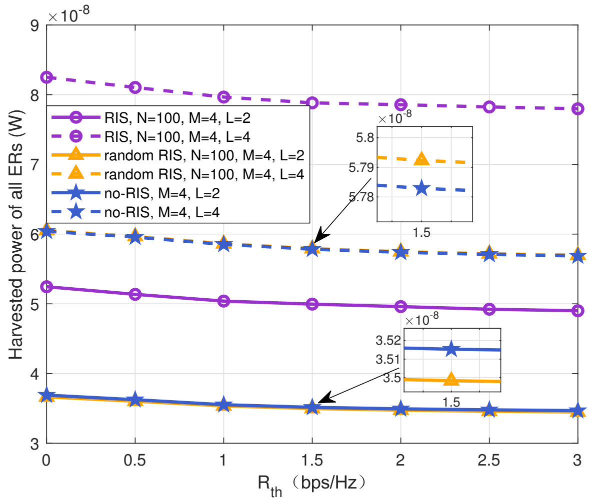

Fig. 5. Harvested power of all ERs versus R_{th}.

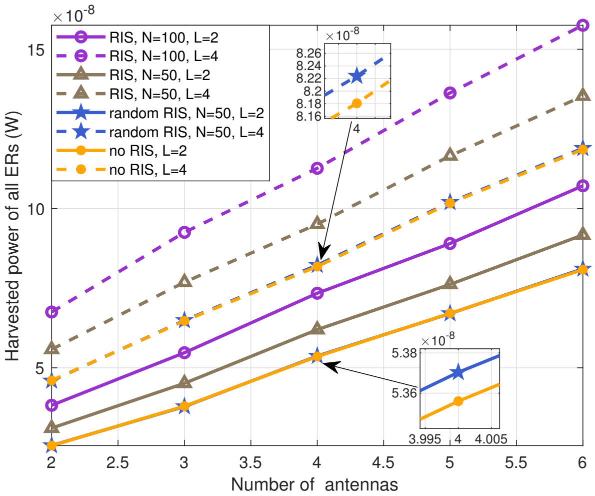

Fig. 6. Harvested power of all ERs versus M, where $R_{th} = 0.1$bps/Hz.

versus M. It can be observed that by increasing the number of AP's antennas, the harvested power of all ERs increases monotonically in all schemes, and our proposed algorithm significantly outperforms both the no RIS and the random RIS schemes. Additionally, increasing the number of RIS' reflecting elements and ERs accordingly improves the harvested power, respectively.

V. Conclusions

In this paper, we investigate the power maximization problem in a RIS-aided multi-ER communication network with SR constraints. To tackle this challenging problem, an iterative solution was proposed based on the SCA method and PDD method, which converges well and can apply to more generic settings compared to the existing literature. Numerical results verify that, with the RIS deployment, the harvested power has significant improve and outperforms the no RIS and the random RIS schemes.

References

[1] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106-112, Jan. 2020.

[2] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE Access*, vol. 7, pp. 116 753-116 773, 2019.

[3] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5394-5409, Nov. 2019.

[4] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Trans. Wireless Commun.*, vol. 18, no. 8, pp. 4157-4170, Aug. 2019.

[5] Q. Wu and R. Zhang, "Weighted sum power maximization for intelligent reflecting surface aided SWIPT," *IEEE Wireless Commun. Lett.*, vol. 9, no. 5, pp. 586-590, May 2020.

[6] C. Pan, H. Ren, K. Wang, M. Elkashlan, A. Nallanathan, J. Wang, and L. Hanzo, "Intelligent reflecting surface aided MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 8, pp. 1719-1734, Aug. 2020.

[7] Y. Tang, G. Ma, H. Xie, J. Xu, and X. Han, "Joint transmit and reflective beamforming design for IRS-assisted multiuser MISO SWIPT systems," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Dublin, Ireland, Jun. 2020, pp. 1-6.

[8] S. Zargari, A. Khalili and R. Zhang, "Energy efficiency maximization via joint active and passive beamforming design for multiuser MISO IRS-aided SWIPT," *IEEE Wireless Commun. Lett.*, vol. 10, no. 3, pp. 557-561, Mar. 2021.

[9] M. Cui, G. Zhang, and R. Zhang, "Secure wireless communication via intelligent reflecting surface," *IEEE Wireless Commun. Lett.*, vol. 8, no. 5, pp. 1410-1414, Oct. 2019.

[10] S. Hong, C. Pan, H. Ren, K. Wang, K. K. Chai, and A. Nallanathan, "Robust transmission design for intelligent reflecting surface-aided secure communication systems with imperfect cascaded CSI," *IEEE Trans. Wireless Commun.*, vol. 20, no. 4, pp. 2487-2501, Apr. 2021.

[11] J. Liu, K. Xiong, Y. Lu, D. W. K. Ng, Z. Zhong, and Z. Han, "Energy efficiency in secure IRS-aided SWIPT," *IEEE Wireless Commun. Lett.*, vol. 9, no. 11, pp. 1884-1888, Nov. 2020.

[12] W. Shi, X. Zhou, L. Jia, Y. Wu, F. Shu, and J. Wang, "Enhanced secure wireless information and power transfer via intelligent reflecting surface," *IEEE Commun. Lett.*, vol. 25, no. 4, pp. 1084-1088, Apr. 2021.

[13] F. Shu, X. Wu, J. Hu, J. Li, R. Chen, and J. Wang, "Secure and precise wireless transmission for random-subcarrier-selection-based directional modulation transmit antenna array," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 4, pp. 890-904, Apr. 2018.

[14] S. Zargari, A. Khalili, Q. Wu, M. Robat Mili and D. W. K. Ng, "Max-min fair energy-efficient beamforming design for intelligent reflecting surface-aided SWIPT systems with non-linear energy harvesting model," *IEEE Trans. Veh. Technol.*, vol. 70, no. 6, pp. 5848-5864, Jun. 2021.

[15] Q. Shi, M. Razaviyayn, Z. Q. Luo, and C. He, "An iteratively weighted mmse approach to distributed sum-utility maximization for a mimo interfering broadcast channel," *IEEE Trans. Signal Process.*, vol. 59, no. 9, pp. 4331-4340, May 2011.

[16] Y. Sun, P. Babu, and D. P. Palomar, "Majorization-minimization algorithms in signal processing, communications, and machine learning," *IEEE Trans. Signal Process.*, vol. 65, no. 3, pp. 794-816, Feb. 2017.

[17] M. Grant and S. Boyd, *CVX: Matlab software for disciplined convex programming, version 2.1*, http://cvxr.com/cvx, Mar. 2014.

[18] Q. Shi and M. Hong, "Penalty dual decomposition method for nonsmooth nonconvex optimization-Part I: Algorithms and convergence analysis," *IEEE Trans. Signal Process.*, vol. 68, pp. 4108-4122, Jun. 2020.

[19] Q. Shi and M. Hong, "Penalty dual decomposition method for nonsmooth nonconvex optimization-Part II: Applications," *IEEE Trans. Signal Process.*, vol. 68, pp. 4242-4257, Jun. 2020.

[20] Y. Liu, J. Zhao, M. Li, and Q. Wu, "Intelligent reflecting surface aided MISO uplink communication network: Feasibility and power minimization for perfect and imperfect CSI," *IEEE Trans. Commun.*, vol. 69, no. 3, pp. 1975-1989, Mar. 2021.

[21] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. and Trends in Machine Learning*, vol. 3, no. 1, pp. 1-122, 2011.