Secrecy Energy Efficiency in RIS-assisted Networks

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***Abstract*—This paper investigates the secrecy energy efficiency (SEE) performance in the reconfigurable intelligent surface (RIS)-assisted multi-user multiple-input-single-output (MISO) networks. An SEE maximization problem is formulated by optimizing the beamforming vectors and the phase shift coefficients. The considered problem is separated into two subproblems and solved by an alternating optimization based algorithm, where each subproblem is handled by the successive convex approximation (SCA) method. A second order cone programming is designed to initiated the proposed algorithm. Numerical results validate the proposed algorithm, which is shown to be more computational efficient than the benchmark algorithm. Besides, the employment of the RIS is shown to greatly enhance the SEE.**

***Index Terms*—RIS, SEE, MISO, SCA**

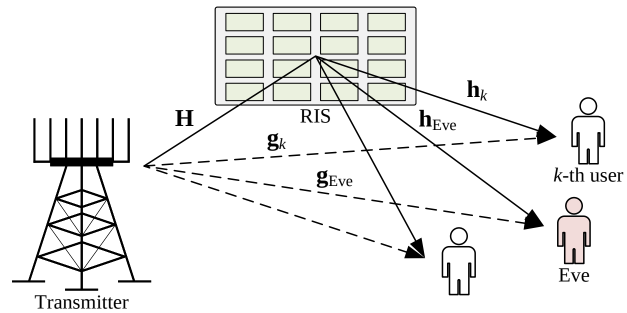

Fig. 1. System model.

I. Introduction

Reconfigurable intelligent surface (RIS) has received increasing interests due to its capability of making the wireless environment programmable and controllable. In particular, RIS is able to provide electromagnetic responses to the amplitudes, phases and polarizations of the incident electromagnetic waves, which mitigates the impact of the obstacles on high-frequency wireless communication. With the abundant spatial degree of freedom provided by the RIS, the information security is also enhanced from the physical-layer security perspective [1]. On the other hand, energy efficiency (EE) has been regarded as an important performance metric to achieve the trade-off between the information transmission and power consumption. By jointly considering the information security and the EE, secrecy EE (SEE) is proposed and defined as the ratio of the secrecy rate to the total power consumption [2].

So far, the secure or energy efficient designs have been studied for several RIS-assisted networks in the literature, see e.g., [3]–[8]. In [3] and [4], the sum secrecy rates were respectively maximized for STAR-RIS networks and RIS-assisted Cell-Free networks. In [5], the RIS was shown to boost the EE compared with traditional relay. In [6], [7] and [8], the EE was investigated for the RIS-assisted nonorthogonal multiple access transmission, the integrated terrestrial-aerial networks and the HetNets, respectively. In [9], an SEE maximization design was investigated for a RIS-assisted multicast network where the inter-user interference was not included.

The SEE for RIS-assisted multiple-input-single-output (MISO) networks has not been reported. Besides, most of the existing algorithms involved semidefinite relaxation (SDR) (e.g., [3], [4]) or Dinkelbach (e.g., [8], [9]) methods. The former method may induce infeasible solution or loss of the optimality and the latter method may require redundant iterations. Especially for generating the training data for machine learning approaches, the computational efficiency and the availability of the optimization algorithm are of high importance. Motivated by this observation, this paper proposed an efficient algorithm to handle the classic SEE maximization problem in a RIS-assisted multi-user MISO network. The main contributions of this paper is summarized as follows. First, an SEE maximization problem is formulated by optimizing the beamforming vectors and the phase shift coefficients. Second, the considered problem is solved in an alternating optimization (AO) manner where the original problem is separated into two subproblems and each subproblem is solved by a successive convex approximation (SCA)-based algorithm which is initiated by solving a second order cone programming (SOCP). Third, numerical results are provided to validate the proposed algorithm, which is shown to be more computational efficient than the benchmark algorithm. Besides, a notable SEE performance gain is achieved due to employing RIS (even without the optimization of phase shift coefficients).

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II. System Model and Problem Formulation

Consider a downlink transmission system as shown in Figure 1, where a N_{T}-antenna transmitter serves K single-antenna users with assistance of a RIS in presence of an eavesdropper (Eve). The RIS consists of N passive reflecting elements. For clarity, we use $k \in \mathcal{K} = \{1, 2, ..., K\}$ to denote the index k-th user and $n \in \mathcal{N} = \{1, 2, ..., N\}$ to denote the n-th reflecting element.

In each time slot, the transmit signal includes K symbols, which is given by

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

where s_k denotes the desired signal of the k-th user and $\mathbf{w}_k \in \mathbb{C}^{N_{\mathrm{T}}}$ denotes the associated beamforming vector. Without loss of generality, it is assumed that $\mathbb{E}\{|s_k|^2\} = 1$. Then, the total power consumption at the transmitter is expressed as

$$P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right) = \mu \sum\nolimits_{i=1}^{K} \|\mathbf{w}_i\|^2 + P_{\mathrm{C}}, \tag{2}$$

where $\mu \in [1, \infty)$ denotes the power amplifier coefficient and P_{C} denotes the constant power consumption.

In each time slot, the received signal at the k-th user is given by

$$y_k = \left(\mathbf{g}_k^H + \mathbf{h}_k^H \mathbf{\Phi} \mathbf{H}\right) \sum\nolimits_{i=1}^{K} \mathbf{w}_i s_i + n_k, \tag{3}$$

where $\mathbf{g}_k$, $\mathbf{h}_k$ and $\mathbf{H}$ respectively denote the direct channel between the transmitter and the k-th user, the channel between the RIS and the k-th user and the channel between the transmitter and the RIS. $\mathbf{\Phi} = \mathrm{diag}\{[e^{j\phi_1}, e^{j\phi_2}, ..., e^{j\phi_N}]\}$ denotes the phase shift matrix where $\phi_n \in [0, 2\pi)$ is the phase shift of the n-th unit of the RIS. $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ denotes the additive white Gaussian noises (AWGN) at the k-th user. The received information rate at the k-th user is given by

$$R_k\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) = \log_2\left(1 + \frac{\left|\left(\mathbf{g}_k^H + \mathbf{h}_k^H \mathbf{\Phi} \mathbf{H}\right) \mathbf{w}_k\right|^2}{\sum_{i=1, i\neq k}^{K} \left|\left(\mathbf{g}_k^H + \mathbf{h}_k^H \mathbf{\Phi} \mathbf{H}\right) \mathbf{w}_i\right|^2 + \sigma_k^2}\right). \tag{4}$$

The received signal at the Eve is given by

$$y_{\mathrm{Eve}} = \left(\mathbf{g}_{\mathrm{Eve}}^H + \mathbf{h}_{\mathrm{Eve}}^H \mathbf{\Phi} \mathbf{H}\right) \sum\nolimits_{i=1}^{K} \mathbf{w}_i s_i + n_{\mathrm{Eve}},$$

where $\mathbf{g}_{\mathrm{Eve}}$ and $\mathbf{h}_{\mathrm{Eve}}$ denote the direct channel between the transmitter and the Eve and the channel between the RIS and the Eve, respectively. $n_{\mathrm{Eve}} \sim \mathcal{CN}(0, \sigma_{\mathrm{Eve}}^2)$ denotes the AWGN at the Eve. If the Eve intends to intercept the k-th user, the information leakage rate at the Eve is expressed as

$$R_{\mathrm{Eve},k}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) = \log_2\left(1 + \frac{\left|\left(\mathbf{g}_{\mathrm{Eve}}^H + \mathbf{h}_{\mathrm{Eve}}^H \mathbf{\Phi} \mathbf{H}\right) \mathbf{w}_k\right|^2}{\sum_{i=1, i\neq k}^{K} \left|\left(\mathbf{g}_{\mathrm{Eve}}^H + \mathbf{h}_{\mathrm{Eve}}^H \mathbf{\Phi} \mathbf{H}\right) \mathbf{w}_i\right|^2 + \sigma_{\mathrm{Eve}}^2}\right). \tag{5}$$

The secrecy rate of the k-th user is expressed as

$$R_{\mathrm{Sec},k}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) = \left[R_k\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) - R_{\mathrm{Eve},k}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right)\right]^+.$$

Following [10] and [2], the SEE is defined as the ratio of sum secrecy rates to the total power consumption:

$$\mathrm{SEE}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) = \frac{\sum_{k=1}^{K} R_{\mathrm{Sec},k}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right)}{P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right)}.$$

Our goal is to maximize the SEE of the considered system under constraints of the rate requirement of each user and the power budget of the transmitter. So, the corresponding optimization problem is mathematically expressed as

$$\begin{aligned} \mathbf{P_0}: &\max_{\{\mathbf{w}_i\}, \mathbf{\Phi}} \mathrm{SEE}\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) \\ \text{s.t. } & R_k\left(\{\mathbf{w}_i\}, \mathbf{\Phi}\right) \geq \xi_k, && \text{(6a)} \\ & P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right) \leq P_{\max}, && \text{(6b)} \\ & \phi_n \in [0, 2\pi), \forall i, k \in \mathcal{K}, \forall n \in \mathcal{N} && \text{(6c)} \end{aligned}$$

In constraint (6a), ξ_k denotes the information rate requirement of the k-th user. In constraint (6b), $P_{\max}$ denotes the power budget of the transmitter.

III. The Proposed Solution Approach

Problem P_0 is non-convex. To solve it, an AO-based solution approach is designed with the following detailed possesses.

A. Optimization of $\{\mathbf{w}_i\}$ with given $\tilde{\mathbf{\Phi}}$

With given $\tilde{\mathbf{\Phi}}$, the optimization of $\{\mathbf{w}_i\}$ is via solving the following Problem P_{A}.

$$\begin{aligned} \mathbf{P_A}: &\max_{\{\mathbf{w}_i\}} \mathrm{SEE}\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right) \\ \text{s.t. } & R_k\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right) \geq \xi_k, && \text{(7a)} \\ & \text{(6b)}, \forall i, k \in \mathcal{K}. \end{aligned}$$

Define that

$$\alpha_k = R_k\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right),\ \beta_k = R_{\mathrm{Eve},k}\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right),$$
$$\text{and } t = \sum\nolimits_{k=1}^{K} (\alpha_k - \beta_k)/P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right),$$

Problem P_{A} is expressed as

$$\begin{aligned} \mathbf{P_A^1}: &\max_{\{\mathbf{w}_i, \alpha_i, \beta_i\}, t} t \\ \text{s.t. } & R_k\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right) \geq \alpha_k, && \text{(8a)} \\ & R_{\mathrm{Eve},k}\left(\{\mathbf{w}_i\}, \tilde{\mathbf{\Phi}}\right) \leq \beta_k, && \text{(8b)} \\ & \sum\nolimits_{k=1}^{K} (\alpha_k - \beta_k) \geq t P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right), && \text{(8c)} \\ & \alpha_k \geq \xi_k, && \text{(8d)} \\ & \alpha_k - \beta_k \geq 0, && \text{(8e)} \\ & \text{(6b)}, \forall i, k \in \mathcal{K}. \end{aligned}$$

Constraints (8a) and (8b) are respectively rewritten as

$$\left|\tilde{\mathbf{g}}_k^H \mathbf{w}_k\right|^2 \geq (2^{\alpha_k} - 1)\left(\sum\nolimits_{i=1, i\neq k}^{K} \left|\tilde{\mathbf{g}}_k^H \mathbf{w}_i\right|^2 + \sigma_k^2\right) \tag{9}$$

and

$$\left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_k\right|^2 \leq (2^{\beta_k} - 1)\left(\sum_{i=1, i\neq k}^{K} \left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_i\right|^2 + \sigma_{\mathrm{Eve}}^2\right) \tag{10}$$

where $\tilde{\mathbf{g}}_k^H \triangleq \mathbf{g}_k^H + \mathbf{h}_k^H \tilde{\mathbf{\Phi}} \mathbf{H}$ and $\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \triangleq \mathbf{g}_{\mathrm{Eve}}^H + \mathbf{h}_{\mathrm{Eve}}^H \tilde{\mathbf{\Phi}} \mathbf{H}$. By introducing auxiliary variables $\{a_k, b_k, c_k, d_k, f, g\}$ satisfying that

$$e^{a_k} \geq 2^{\alpha_k} - 1, \tag{11}$$
$$e^{b_k} \geq \sum\nolimits_{i=1, i\neq k}^{K} \left|\tilde{\mathbf{g}}_k^H \mathbf{w}_i\right|^2 + \sigma_k^2, \tag{12}$$
$$e^{c_k} \leq 2^{\beta_k} - 1, \tag{13}$$
$$e^{d_k} \leq \sum\nolimits_{i=1, i\neq k}^{K} \left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_i\right|^2 + \sigma_{\mathrm{Eve}}^2, \tag{14}$$
$$e^{f} \geq t, \tag{15}$$
$$e^{g} \geq P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right), \tag{16}$$
$$\text{and } h_k \leq c_k + d_k, \tag{17}$$

constraints (9), (10) and (8c) are respectively rewritten as

$$\left|\tilde{\mathbf{g}}_k^H \mathbf{w}_k\right|^2 \geq e^{a_k+b_k}, \tag{18}$$

$$\left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_k\right|^2 \leq e^{h_k}, \tag{19}$$

$$\text{and} \sum\nolimits_{\mathrm{k}=1}^{K} \left(\alpha_k - \beta_k\right) \geq e^{f+g}. \tag{20}$$

Then, Problem $\mathrm{P}_{\mathrm{A}}^1$ is equivalent to the following problem:

$$\begin{aligned}\mathbf{P_A^2}: &\max_{\{\mathbf{w}_i,\alpha_i,\beta_i,a_i,b_i,c_i,d_i\},f,g,t} t\\ &\text{s.t. } (6\text{b}),(8\text{d}),(8\text{e}),(11),(12),(13),(14),(15),\\ &\quad (16),(17),(18),(19),(20),\forall i,k \in \mathcal{K}.\end{aligned}$$

Constraints (11), (12), (13), (14), (15), (16), (18) and (19) are non-convex, which however, can be relaxed by the first-order approximation. With feasible $\{\tilde{\mathbf{w}}_k, \tilde{\beta}_k, \tilde{a}_k, \tilde{b}_k, \tilde{f}, \tilde{g}, \tilde{h}_k\}$, the mentioned non-convex constraints are respectively approximated by

$$e^{\tilde{a}_k}\left(1 + a_k - \tilde{a}_k\right) \geq 2^{\alpha_k} - 1, \tag{22}$$

$$e^{\tilde{b}_k}\left(1 + b_k - \tilde{b}_k\right) \geq \sum\nolimits_{i=1,i\neq k}^{K} \left|\tilde{\mathbf{g}}_k^H \mathbf{w}_i\right|^2 + \sigma_k^2, \tag{23}$$

$$2^{\tilde{\beta}_k} + 2^{\tilde{\beta}_k}\ln 2\left(\beta_k - \tilde{\beta}_k\right) \geq e^{c_k} + 1, \tag{24}$$

$$\begin{aligned}&\sum\nolimits_{i=1,i\neq k}^{K}\left(2\mathrm{Re}\left\{\tilde{\mathbf{w}}_i^H \tilde{\mathbf{g}}_{\mathrm{Eve}}\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_i\right\} - \left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \tilde{\mathbf{w}}_i\right|^2\right) + \\ &\quad \sigma_{\mathrm{Eve}}^2 \geq e^{d_k},\end{aligned} \tag{25}$$

$$e^{\tilde{f}}\left(1 + f - \tilde{f}\right) \geq t, \tag{26}$$

$$e^{\tilde{g}}\left(1 + g - \tilde{g}\right) \geq P_{\mathrm{T}}\left(\{\mathbf{w}_i\}\right), \tag{27}$$

$$2\mathrm{Re}\left\{\tilde{\mathbf{w}}_k^H \tilde{\mathbf{g}}_k \tilde{\mathbf{g}}_k^H \mathbf{w}_k\right\} - \left|\tilde{\mathbf{g}}_k^H \tilde{\mathbf{w}}_k\right|^2 \geq e^{a_k+b_k}, \tag{28}$$

$$\text{and } e^{\tilde{h}_k}\left(1 + h_k - \tilde{h}_k\right) \geq \left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \mathbf{w}_k\right|^2. \tag{29}$$

Problem $\mathrm{P}_{\mathrm{A}}^2$ is approximated by the following convex Problem $\mathrm{P}_{\mathrm{A}}^3$.

$$\begin{aligned}\mathbf{P_A^3}: &\max_{\{\mathbf{w}_i,\alpha_i,\beta_i,a_i,b_i,c_i,d_i,h_i\},f,g,t} t\\ &\text{s.t. } (6\text{b}),(8\text{d}),(8\text{e}),(17),(20),(22),(23),(24),(25),\\ &\quad (26),(27),(28),(29),\forall i,k \in \mathcal{K}.\end{aligned}$$

Note that the approximation from Problem P_{A} to Problem $\mathrm{P}_{\mathrm{A}}^3$ only involves the first-order approximation. To improve the approximation precession, the SCA method is employed and the proposed algorithm is summarized in Algorithm 1. As analyzed in [11], a stationary-point result is guaranteed by the SCA method.

$$\begin{cases}\tilde{\beta}_k = R_{\mathrm{Eve},k}\left(\{\tilde{\mathbf{w}}_i\}, \tilde{\mathbf{\Phi}}\right)\\ \tilde{a}_k = \ln\left(2^{R_k\left(\{\tilde{\mathbf{w}}_i\},\tilde{\mathbf{\Phi}}\right)} - 1\right)\\ \tilde{b}_k = \ln\left(\sum_{i=1,i\neq k}^{K}\left|\tilde{\mathbf{g}}_k^H \tilde{\mathbf{w}}_i\right|^2 + \sigma_k^2\right)\\ \tilde{f} = \ln\left(\mathrm{SEE}\left(\{\tilde{\mathbf{w}}_i\}, \tilde{\mathbf{\Phi}}\right)\right)\\ \tilde{g} = \ln\left(P_{\mathrm{T}}\left(\{\tilde{\mathbf{w}}_i\}\right)\right)\\ \tilde{h}_k = \ln\left(\left|\tilde{\mathbf{g}}_{\mathrm{Eve}}^H \tilde{\mathbf{w}}_k\right|^2\right)\end{cases} \tag{31}$$

To obtain an initial point (in step 2 of Algorithm 1), a feasibility problem is constructed as follows.

Algorithm 1: The proposed algorithm for Problem P_{A}

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1 Given $\tilde{\mathbf{\Phi}}$;
2 Initialize $\{\tilde{\mathbf{w}}_i, \tilde{\beta}_i, \tilde{a}_i, \tilde{b}_i, \tilde{f}, \tilde{g}, \tilde{h}_i\}$ being feasible to Problem $\mathrm{P}_{\mathrm{A}}^2$;
3 **while** *the stopping criterion is not met* **do**
4   Solve Problem $\mathrm{P}_{\mathrm{A}}^3$ to obtain the optimal solution $\{\mathbf{w}_i^\star\}$;
5   Update $\tilde{\mathbf{w}}_i = \mathbf{w}_i^\star$ ($\forall i \in \mathcal{K}$);
6   Update $\{\tilde{\beta}_i, \tilde{a}_i, \tilde{b}_i, \tilde{f}, \tilde{g}, \tilde{h}_i\}$ by (31) with $\{\tilde{\mathbf{w}}_i\}$;

$$\begin{aligned}\mathbf{P_I}: &\mathrm{Find}\,\{\mathbf{w}_i\}\\ &\text{s.t. } (6\text{b}),(7\text{a}),\forall i,k \in \mathcal{K}.\end{aligned}$$

Denote $\gamma_k \triangleq (2^{\xi_k} - 1)$, constraint (7a) is re-expressed as

$$\left(1 + \frac{1}{\gamma_k}\right)\left|\tilde{\mathbf{g}}_k^H \mathbf{w}_k\right|^2 \geq \sum\nolimits_{i=1}^{K}\left|\tilde{\mathbf{g}}_k^H \mathbf{w}_i\right|^2 + \sigma_k^2$$

Without loss of feasibility, the following extra constraints to Problem P_{I} can be added.

$$\mathrm{Re}\left\{\tilde{\mathbf{g}}_k^H \mathbf{w}_k\right\} \geq 0, \mathrm{Im}\left\{\tilde{\mathbf{g}}_k^H \mathbf{w}_k\right\} = 0 \tag{33}$$

Then, Problem P_{I} is cast as the following convex SOCP:

$$\begin{aligned}\mathbf{P_I^1}: &\mathrm{Find}\,\{\mathbf{w}_i\}\\ &\text{s.t. } \sqrt{\left(1 + \frac{1}{\gamma_k}\right)}\tilde{\mathbf{g}}_k^H \mathbf{w}_k \geq \left\|\mathbf{\Omega}_k \mathbf{f} + \mathbf{b}_k\right\| \qquad (34\text{a})\\ &\quad (6\text{b}),(33),\forall i,k \in \mathcal{K}.\end{aligned}$$

where

$$\begin{aligned}&\mathbf{f} \triangleq \left[\mathbf{w}_1^H, \mathbf{w}_2^H, ..., \mathbf{w}_K^H\right]^H \in \mathbb{C}^{KN_{\mathrm{T}}},\\ &\mathbf{b}_k \triangleq \left[\mathbf{0}_K^T, \sigma_k^2\right]^T \in \mathbb{C}^{K+1},\\ &\text{and } \mathbf{\Omega}_k \triangleq \begin{bmatrix}\mathrm{diag}\left(\tilde{\mathbf{g}}_k^H, \tilde{\mathbf{g}}_k^H, ..., \tilde{\mathbf{g}}_k^H\right)\\ \mathbf{0}_{KN_{\mathrm{T}}}^T\end{bmatrix} \in \mathbb{C}^{(K+1)\times KN_{\mathrm{T}}}.\end{aligned}$$

By solving Problem $\mathrm{P}_{\mathrm{I}}^1$ to obtain feasible $\{\tilde{\mathbf{w}}_i\}$ to Problem P_{A} , $\{\tilde{\beta}_i, \tilde{a}_i, \tilde{b}_i, \tilde{f}, \tilde{g}, \tilde{h}_i\}$ is calculated by (31) with $\{\tilde{\mathbf{w}}_i\}$.

B. Optimization of $\mathbf{\Phi}$ with given $\{\tilde{\mathbf{w}}_i\}$

Define a variable vector

$$\boldsymbol{\psi} = [\psi_1, ..., \psi_N]^T = [e^{j\phi_1}, ..., e^{j\phi_N}]^T \in \mathbb{C}^{N\times 1},$$

where $|\psi_n| = 1$ due to $\phi_n \in [0, 2\pi)$, $\forall n \in \mathcal{N}$. It holds that

$$\mathbf{h}_k^H \mathbf{\Phi}\mathbf{H}\mathbf{w}_i = \underbrace{\mathbf{h}_k^H \mathrm{diag}\left(\mathbf{H}\mathbf{w}_i\right)}_{\triangleq \boldsymbol{\kappa}_{ki}}\boldsymbol{\psi},$$

$$\text{and } \mathbf{h}_{\mathrm{Eve}}^H \mathbf{\Phi}\mathbf{H}\mathbf{w}_i = \underbrace{\mathbf{h}_{\mathrm{Eve}}^H \mathrm{diag}\left(\mathbf{H}\mathbf{w}_i\right)}_{\triangleq \boldsymbol{\kappa}_{\mathrm{Eve},i}}\boldsymbol{\psi}.$$

With given $\{\tilde{\mathbf{w}}_i\}$, the optimization of $\tilde{\mathbf{\Phi}}$ is via solving the following Problem P_{B}.

$$\mathbf{P_B}: \max_{\boldsymbol{\psi}} \sum\nolimits_{k=1}^{K} R_{\mathrm{Sec},k}\left(\{\tilde{\mathbf{w}}_i\}, \mathrm{diag}\left(\boldsymbol{\psi}\right)\right)$$

$$\text{s.t. } R_k\left(\{\tilde{\mathbf{w}}_i\}, \mathrm{diag}(\boldsymbol{\psi})\right) \geq \xi_k, \tag{35a}$$

$$|\psi_n| = 1, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}. \tag{35b}$$

Introduce auxiliary variables $\{x_k, y_k, z_k, v_k, w_k\}$ satisfying that

$$\begin{aligned}
&e^{x_k} \geq 2^{\alpha_k} - 1,\ e^{y_k} \geq \sum\nolimits_{i=1, i\neq k}^{K} \left|\mathbf{g}_k^H \tilde{\mathbf{w}}_i + \boldsymbol{\kappa}_{ki}\boldsymbol{\psi}\right|^2 + \sigma_i^2,\\
&e^{z_k} \leq 2^{\beta_k} - 1,\\
&e^{v_k} \leq \sum\nolimits_{i=1, i\neq k}^{K} \left|\mathbf{g}_{\mathrm{Eve}}^H \tilde{\mathbf{w}}_i + \boldsymbol{\kappa}_{\mathrm{Eve},i}\boldsymbol{\psi}\right|^2 + \sigma_{\mathrm{Eve}}^2,\\
&\text{and } w_k \leq z_k + v_k.
\end{aligned}$$

By employing the first-order approximation, Problem $\mathrm{P_B}$ is approximated by the following convex Problem $\mathrm{P_B^1}$.

$$\begin{aligned}
\mathbf{P_B^1}:& \max_{\{\alpha_i,\beta_i,x_i,y_i,z_i,v_i,w_i\},\boldsymbol{\psi}} \sum\nolimits_{k=1}^{K} (\alpha_k - \beta_k) + \\
& p\sum\nolimits_{n=1}^{N} \left(\left|\tilde{\psi}_n\right|^2 + 2\mathrm{Re}\left\{\tilde{\psi}_n'\left(\psi_n - \tilde{\psi}_n\right)\right\} - 1\right)
\end{aligned}$$

$$\text{s.t. } \alpha_k \geq \xi_k, \tag{36a}$$

$$2\mathrm{Re}\left\{\left(\mathbf{g}_k^H \tilde{\mathbf{w}}_k + \boldsymbol{\kappa}_{kk}\tilde{\boldsymbol{\psi}}\right)^H \boldsymbol{\kappa}_{kk}\left(\boldsymbol{\psi} - \tilde{\boldsymbol{\psi}}\right)\right\} + \left|\mathbf{g}_k^H \tilde{\mathbf{w}}_k + \boldsymbol{\kappa}_{kk}\tilde{\boldsymbol{\psi}}\right|^2 \geq e^{x_k + y_k}, \tag{36b}$$

$$e^{\tilde{x}_k}\left(1 + x_k - \tilde{x}_k\right) \geq 2^{\alpha_k} - 1, \tag{36c}$$

$$e^{\tilde{y}_k}\left(1 + y_k - \tilde{y}_k\right) \geq \sum\nolimits_{i=1, i\neq k}^{K} \left|\mathbf{g}_k^H \tilde{\mathbf{w}}_i + \boldsymbol{\kappa}_{ki}\boldsymbol{\psi}\right|^2 + \sigma_i^2, \tag{36d}$$

$$e^{\tilde{w}_k}\left(1 + w_k - \tilde{w}_k\right) \geq \left|\mathbf{g}_{\mathrm{Eve}}^H \tilde{\mathbf{w}}_k + \boldsymbol{\kappa}_{\mathrm{Eve},k}\boldsymbol{\psi}\right|^2, \tag{36e}$$

$$z_k + v_k \geq w_k, \tag{36f}$$

$$2^{\tilde{\beta}_k} + 2^{\tilde{\beta}_k}\ln 2\left(\beta_k - \tilde{\beta}_k\right) \geq e^{z_k} + 1, \tag{36g}$$

$$(37), \|\boldsymbol{\psi}\|_\infty \leq 1, \forall i, k \in \mathcal{K}, \forall n \in \mathcal{N},$$

where $\tilde{\boldsymbol{\psi}}$ is feasible to Problem $\mathrm{P_B}$ and $\{\tilde{\beta}_k, \tilde{x}_k, \tilde{y}_k, \tilde{w}_k\}$ is calculated by (38) with the given $\tilde{\boldsymbol{\psi}}$. p is a positive constant to enforce the penalty part[1], i.e., $\sum_{n=1}^{N}(|\psi_n|^2 - 1)$, to 0 with the optimal solution to Problem $\mathrm{P_B^1}$.

$$\begin{cases}
\tilde{\beta}_k = R_{\mathrm{Eve},k}\left(\{\tilde{\mathbf{w}}_i\}, \mathrm{diag}\left(\tilde{\boldsymbol{\psi}}\right)\right)\\
\tilde{x}_k = \ln\left(2^{R_k\left(\{\tilde{\mathbf{w}}_i\}, \mathrm{diag}\left(\tilde{\boldsymbol{\psi}}\right)\right)} - 1\right)\\
\tilde{y}_k = \ln\left(\sum_{i=1, i\neq k}^{K}\left|\mathbf{g}_k^H \tilde{\mathbf{w}}_i + \boldsymbol{\kappa}_{ki}\tilde{\boldsymbol{\psi}}\right|^2 + \sigma_i^2\right)\\
\tilde{w}_k = \ln\left(\left|\mathbf{g}_{\mathrm{Eve}}^H \tilde{\mathbf{w}}_k + \boldsymbol{\kappa}_{\mathrm{Eve},k}\tilde{\boldsymbol{\psi}}\right|^2\right)
\end{cases} \tag{38}$$

To improve the approximation precession due to the first-order approximation, the SCA method is employed and the proposed algorithm is summarized in Algorithm 2. Note that Algorithm 2 can also be initiated by solving Problem $\mathrm{P_I^1}$.

[1]To balance the trade-off between computational efficiecny and the computational accuracy, a dynamic p is adopted as $\ell \times \sum_{k=1}^{K} R_{\mathrm{Sec},k}(\{\tilde{\mathbf{w}}_i\}, \mathrm{diag}(\tilde{\boldsymbol{\psi}}))$ with $\ell \in (0, 0.5)$.

Algorithm 2: The proposed algorithm for Problem $\mathrm{P_B}$

1 Given $\{\tilde{\mathbf{w}}_i\}$;
2 Initialize $\tilde{\boldsymbol{\psi}}$ being feasible to Problem $\mathrm{P_B}$ and $\{\tilde{\beta}_i, \tilde{x}_i, \tilde{y}_i, \tilde{w}_i\}$ via (38);
3 **while** *the stopping criterion is not met* **do**
4 Solve Problem $\mathrm{P_B^1}$ to obtain the optimal solution $\boldsymbol{\psi}^\star$;
5 Update $\tilde{\boldsymbol{\psi}} = \boldsymbol{\psi}^\star$;
6 Update $\{\tilde{\beta}_i, \tilde{x}_i, \tilde{y}_i, \tilde{w}_i\}$ via (38) ;

Algorithm 3: The proposed algorithm for Problem $\mathrm{P_0}$.

1 **while** *the stop criterion is not met* **do**
2 Obtain $\{\tilde{\mathbf{w}}_i\}$ via Algorithm 1 with given $\tilde{\boldsymbol{\Phi}}$;
3 Obtain $\tilde{\boldsymbol{\psi}}$ via Algorithm 2 with given $\{\tilde{\mathbf{w}}_i\}$ and update $\tilde{\boldsymbol{\Phi}} = \mathrm{diag}(\tilde{\boldsymbol{\psi}})$;

C. The Proposed Solution Approach

A near-optimal result[2] of Problem $\mathrm{P_0}$ can be derived by iteratively running Algorithm 1 and Algorithm 2, which is summarized as Algorithm 3.

IV. Numerical results

This section provides the numerical results to evaluate the proposed algorithm with the following simulation setting. A transmitter with $N_\mathrm{T} = 8$ antennas, a RIS with $N = 8$ reflecting elements, and $K = 4$ users are considered. The path loss to noise ratio of each link is set as 10dB. The small-scale fading is assumed to be Rician fading with a Rician factor being 4. The power budget $P_{\max}$, the constant power consumption P_C and the power amplifier efficiency factor μ are set as 30dBm, 20dBm and 1, respectively. The information requirement ξ_k of each user is set as 1bit/s/Hz. The involved convex formulations are solved using the convex solver `SDPT3` under Mathworks MATLAB R2022b and running on a computer with Core-i7-12700 CPU and 16GB RAM.

Figure 2 shows the non-decreasing and the convergence behaviors of the proposed Algorithm 1, Algorithm 2 and Algorithm 3, respectively. In Algorithm 3, the optimal solution obtained by Algorithm 1/Algorithm 2 is a feasible solution to Problem $\mathrm{P_B}$/Problem $\mathrm{P_A}$. Therefore, by iteratively running Algorithm 1 and Algorithm 2, the SEE is monotonically increased. It is also observed that the achievable SEE by Algorithm 3 is greater than that of Algorithm 1 and Algorithm 2, which validates the efficiency of Algorithm 1 and Algorithm 2 in the optimization of $\{\mathbf{w}_i\}$ and $\{\boldsymbol{\Phi}\}$, respectively. Table I and Table II compares the running time of the optimization of $\{\mathbf{w}_i\}$ between Algorithm 1 and a benchmark algorithm with $N_\mathrm{T} = 8$ and $N_\mathrm{T} = 16$, respectively, where the benchmark algorithm is based on Dinkelbach and SDR methods. The proposed algorithm is shown to be more computationally efficient than the benchmark one and the performance gain

[2]The AO-based algorithm does not guarantee a stationary-point solution. Nevertheless, when the AO-based algorithm converges after plenty of iterations, the derived result tends to be near-optimal.

$$\sum_{i=1,i\neq k}^{K}\left(2\mathrm{Re}\left\{\left(\mathbf{g}_{\mathrm{Eve}}^{H}\tilde{\mathbf{w}}_i+\boldsymbol{\kappa}_{\mathrm{Eve},i}\tilde{\boldsymbol{\psi}}\right)^{H}\boldsymbol{\kappa}_{\mathrm{Eve},i}\left(\boldsymbol{\psi}-\tilde{\boldsymbol{\psi}}\right)\right\}+\left|\mathbf{g}_{\mathrm{Eve}}^{H}\tilde{\mathbf{w}}_i+\boldsymbol{\kappa}_{\mathrm{Eve},i}\tilde{\boldsymbol{\psi}}\right|^{2}\right)+\sigma_{\mathrm{Eve}}^{2}\geq e^{v_k} \tag{37}$$

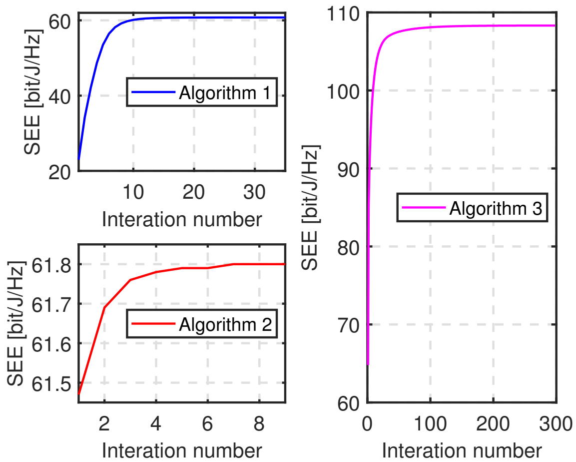

Fig. 2. Convergence behavior of the proposed algorithms.

TABLE I
AVERAGE RUNNING TIMES (S) OF THE OPTIMIZATION OF $\{\mathbf{w}_i\}$ WITH $N_T = 8$ AND $N = 8$ FOR DIFFERENT VALUES OF K.

K	2	4	6	8
Algorithm 1 (Proposed)	34.3	50.8	82.3	128.8
Benchmark	50.6	110.5	187.1	282.3

TABLE II
AVERAGE RUNNING TIMES (S) OF THE OPTIMIZATION OF $\{\mathbf{w}_i\}$ WITH $N_{\mathrm{T}} = 16$ AND $N = 8$ FOR DIFFERENT VALUES OF K.

K	2	4	6	8
Algorithm 1 (Proposed)	43.1	73.4	86.3	134.0
Benchmark	149.6	256.8	328.1	650.6

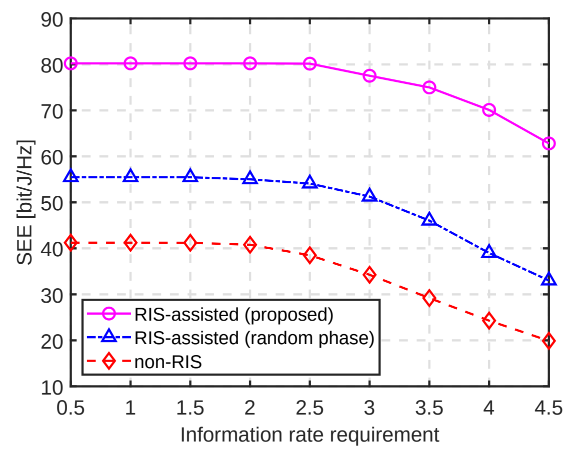

Fig. 3. SEE versus information rate requirement ξ_k.

goes larger with larger N_{T} or K. The reason is that the proposed algorithm involves one-layer iteration while the benchmark one includes dual-layer iteration. Besides, due to not adopting SDR, the computation time for running Gaussian randomization is further saved.

Figure 3 shows the SEE versus the information rate requirement. For comparison, the RIS-assisted design with random $\mathbf{\Phi}$ and the non-RIS design with only optimization of $\{\mathbf{w}_i\}$ are also simulated. It is observed that the SEE first keeps unchanged and then decreases with the increment of the information rate requirement. Compared with the non-RIS design, a notable SEE performance gain is achieved due to employing RIS even without the optimization of $\mathbf{\Phi}$. Besides, the effectiveness of the optimization of $\mathbf{\Phi}$ of the proposed algorithm is validated, since the proposed design outperforms the RIS-assisted design with random $\mathbf{\Phi}$.

Figure 4 shows the SEE derived by different (N, N_T) pairs. It is observed that the increment of the number of antennas/reflecting elements contributes the improvement of the SEE. The reason is that with more spatial degree of freedom, both the inter-user interference and the information leakage are mitigated, which enhances the information transmission. As it is cost-efficient to increase the number of reflecting elements, the advantage of employing RIS is emphasised.

V. CONCLUSION

This paper studied an AO-based algorithm to maximize the SEE in RIS-assisted multi-user MISO networks. The beamforming vectors and the phase shift coefficients were respectively optimized by two SCA-based algorithms and an SOCP was designed to initiate the proposed algorithm. Numerical results validated the convergence behavior and the computational efficiency of the proposed algorithm. Besides, the RIS was shown to greatly enhance the SEE.

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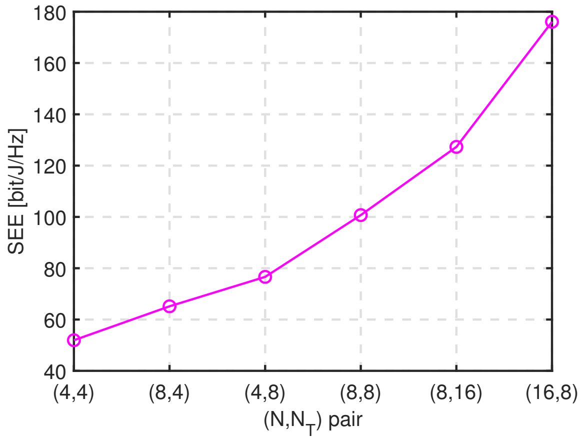

Fig. 4. SEE versus (N, N_{T}) pair.

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