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Research on Transmit Power of MISO System Assisted by Active RIS

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Abstract

In this paper, we consider a wireless energy harvesting communication scenario and discusses the problem of optimizing the transmission power of an active reconfigurable intelligent surface (RIS) assisted multiple-input single-output (MISO) simultaneous wireless information and power transfer (SWIPT) system. The main reason for this is the increasing demand for throughput and transmission power performance indicators for wireless communication systems. In addition, the ideas of conservation and environmental protection have prompted the proposal of an active RIS-assisted MISO-SWIPT system. The optimization problem is to establish the minimum base station transmission power under the constraints of the maximum total power of the active RIS, the minimum transmission rate, and the minimum energy collection of the system. The strong coupling between variables is solved by convex relaxation, and the optimization problem is solved by an alternating optimization (AO) algorithm. Simulation results show that the active RIS-assisted MISO-SWIPT system can reduce the transmit power of the base station better than the passive RIS-assisted MISO-SWIPT system.

Keywords

RIS, SWIPT, MISO, transmit power .

1. Introduction

The exponential growth of wireless data services driven by mobile internet and connected devices has led to research on the fifth generation (5G) cellular network[1]. However, with the increasing demand for high data rates, the available spectrum resources are far from enough to support the communication system. With the breakthrough of metamaterial, reconfigurable intelligent surface can help wireless communication systems significantly improve spectral efficiency, which makes RIS a promising candidate for the future 6G[2]. In order to better save energy, simultaneous wireless information and power transfer (SWIPT) has become more and more popular in wireless communication networks, and has attracted the attention of academia and industry [3][4].

In the literature, a multi-user multiple-input single-output (MISO) SWIPT system is proposed in[5], in which the users implemented a PS architecture. The authors investigated the problem of minimum transmit power at the base station (BS) subject to the constraints of minimum Quality of Service of the PS users and minimum EH requirements. In[6], The author considers RIS assisted wireless communication systems and studies minimizing total transmit power under a given minimum data rate requirement. Considering QOS, in this paper we consider the active RIS assisted MISO-SWIPT system applying power splitting receiver for information decoding and energy havesting, the aim is to minimize the total transmit power.

2. System Model

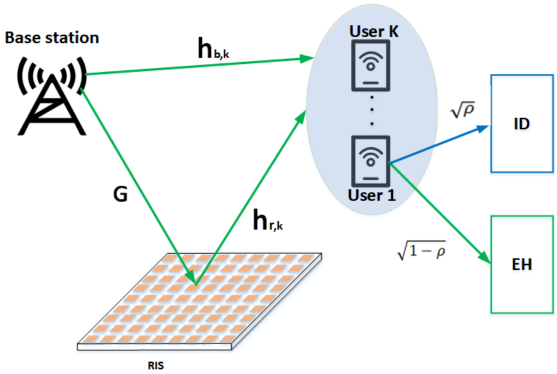

Figure 1: RIS assisted MISO-SWIPT system model

As shown in Figure 1, the downlink system model of active RIS assisted SWIPT with K single antenna users and Mt antenna base stations is established in this chapter. An active RIS with N reflection elements is proposed to improve the reflection link, and at each user, a PS receiver structure is adopted in this chapter, which divides the power of the RF signal sent by the base station to the user. In this process, $\rho \in (0,1)$ is used, The signal in part $\sqrt{\rho}$ is used for information decoding(ID), while the signal in part $\sqrt{1-\rho}$ is used for energy Havesting(EH) . In addition, assuming that all relevant channel state information is known and these channels are quasi static flat fading channels, the amplified reflection signal of an active RIS can be written as $g = Q\Theta x + Q\Theta r + r$, where $r \sim \mathcal{CN}(0_N, \sigma_r^2 I_N)$ is the dynamic noise introduced at the active RIS, r in the second term is the dynamic noise, and **r** in the third term is the static noise, but the static noise is independent of Q, the baseband signal transmitted by the base station can be written as $x = \sum_{i=1}^{K} w_i s_i$, where $w_i \in \mathbb{C}^{M_t \times 1}$ represents the transmission encoding matrix of the kth user, $k = \{1,2,3 \cdots K\}, \forall i \in k$, s_i represents the information carrier signal used for the i-th user, $E|s_i|^2 = 1$, the signal received by the k-th user is represented as

$$y_k = \sum_{i=1}^{K} h_k^H w_i s_i + h_{r,k}^H Q\Theta r + \omega_k \tag{1}$$

where $h_k^H = h_{r,k}^H Q\Theta G + h_{b,k}^H$ is the total channel gain from the base station to user, $h_{r,k}^H \in \mathbb{C}^{N\times 1}$, $h_{b,k}^H \in \mathbb{C}^{M_l \times 1}$ and $G \in \mathbb{C}^{N\times M_t}$ are the channel gains from the RIS to the user link, the channel gains from the base station to the user direct link, and the channel gains from the base station to the active RIS, respectively. $\omega_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the additive Gaussian white noise received at user k, the power consumption of this system also includes the reflected power of the active RIS in the entire system, which can be expressed as

$$P_{RIS} = \sum_{i=1}^{K} \|Q\Theta G w_i\|^2 + \sigma_r^2 \parallel Q\Theta \parallel^2 \tag{2}$$

According to the principle of the PS receiver, the signal used to receive the ID part for the k-th user is represented as

$$y_k^{ID} = \sqrt{\rho_k}\left(\sum_{i=1}^{K} h_k^H w_i s_i + h_{r,k}^H Q\Theta r + \omega_k\right) + n_k \tag{3}$$

where n is the additional noise introduced by the signal processing circuit for the information decoding part at the kth user, so the signal-to-interference plus noise ratio (SINR) at the kth user is represented as

$$SINR_k = \frac{\rho_k |h_k^H w_k|^2}{\rho_k \sum_{\substack{i=1 \\ i\neq k}}^{K} |h_k^H w_i|^2 + \rho_k \sigma_r^2 \|h_{r,k}^H Q\Theta\|^2 + \rho_k \sigma_k^2 + \delta_k^2} \tag{4}$$

According to the principle of PS receiver, for the k-th user, the signal used for the EH part can be represented as

$$y_k^{EH} = \sqrt{1-\rho_k}\left(\sum_{i=1}^{K} \mathbf{h}_k^H \mathbf{w}_i s_i + \mathbf{h}_{r,k}^H \mathbf{Q}\boldsymbol{\Theta}\mathbf{r} + \omega_k\right) + n_k \tag{5}$$

according to formulas (5), it can be inferred that the power available to the kth user can be expressed as

$$P_k^{in} = \zeta_k(1-\rho_k)\left(\sum_{i=1}^{K} \left|\mathbf{h}_k^H \mathbf{w}_i\right|^2 + \sigma_r^2 \left\|\mathbf{h}_{r,k}^H \mathbf{Q}\boldsymbol{\Theta}\right\|^2\right) \tag{6}$$

where ζ_k is the energy conversion efficiency. In the energy collection process of the PS receiver, when the input power continuously increases, the harvested energy does not increase linearly. Through reference [7], we consider a practical parameter nonlinear EH model based on an S-shaped function. Therefore, the energy obtained at the k-th user location is given by the following equation:

$$P_k^{in}(A_k) = a_2 - \frac{1}{a_1}\ln\left(\frac{a_3 - A_k}{A_k}\right) \tag{7}$$

A_k is a traditional logic function, and a_1 and a_2 are constants related to circuit characteristics such as capacitance and resistance, a_3 is a constant which denotes the maximum harvested power at user k,

3. Optimization Of Transmit Power

Our goal is to jointly optimize the active beamforming vector w_k, power spiltting factor ρ_k, active RIS phase shift matrix $\boldsymbol{\Theta}$, and amplification factor sub vector $\mathbf{Q}$ under the constraints of maximum intelligent reflector reflection power, minimum transmission rate of ID receiver at k-th user, and minimum energy collection requirements. The optimization problem can be expressed as

$$\begin{aligned}
&(\text{P1}): \min_{\mathbf{w}_k,\boldsymbol{\theta},\mathbf{Q},\rho_k} \sum_{k=1}^{K} \|\boldsymbol{w}_k\|_2^2 \\
&\text{s.t. } C_1: \frac{\rho_k\left|\mathbf{h}_k^H \mathbf{w}_k\right|^2}{\rho_k \sum_{k=1}^{K}\left|\mathbf{h}_k^H \mathbf{w}_i\right|^2 + \rho_k \sigma_r^2 \left\|\mathbf{h}_{r,k}^H \mathbf{Q}\boldsymbol{\Theta}\right\|^2 + \rho_k \sigma_k^2 + \delta_k^2} \geq \mu_k^{min} \\
&\quad C_2: \sum_{i=1}^{K} \|\mathbf{Q}\boldsymbol{\Theta}\mathbf{G}\mathbf{w}_i\|^2 + \sigma_r^2 \parallel \mathbf{Q}\boldsymbol{\Theta} \parallel^2 \leq P_{RIS}^{max} \\
&\quad C_3: \zeta_k(1-\rho_k)\left(\sum_{i=1}^{K}\left|\mathbf{h}_k^H \mathbf{w}_i\right|^2 + \sigma_r^2\left\|\mathbf{h}_{r,k}^H \mathbf{Q}\boldsymbol{\Theta}\right\|^2\right) \geq P_k^{in}\left(E_k^{min}\right) \\
&\quad C_4: 0 \leq \rho_k \leq 1
\end{aligned} \tag{8}$$

Since the optimization problem (P1) is non convex and there is still coupling between variables, only through the AO algorithm divide and rule, use the semi definite relaxation technology to optimize the beamforming $\boldsymbol{w}_k$and power division factor$\rho_k$of the base station, and then optimize the active RIS phase shift matrix $\boldsymbol{\Theta}$ and amplification factor $\mathbf{Q}$ based on the penalty function for the given $\boldsymbol{w}_k$ and ρ_k in the case of a given part of output.

3.1. Fixed Θ and Q optimized ρ_k and w_k

For the quadratic problem of beamforming vector$w_k$and power division factor ρ_k, we apply the semidefinite relaxation technique to make $W_k = w_k w_k^H$ and $H_k = h_k h_k^H$, where the matrix $W_k$is semidefinite and satisfies the rank $W_k \leq 1$, then $|\boldsymbol{h}_k|^2 = \text{Tr}\,(\boldsymbol{H}_k)$, $|\boldsymbol{w}_k|^2 = \text{Tr}\,(\boldsymbol{W}_k)$, $\left|\mathbf{h}_k^H \mathbf{w}_k\right|^2 = \text{Tr}\,(\boldsymbol{H}_k \boldsymbol{W}_k)$, we can observe from the optimization problem that the optimization (8) variables $\boldsymbol{\Theta}$ and $\mathbf{Q}$ appear in the form of a product in the constraint. In order to facilitate the processing of the optimization problem, $\boldsymbol{\lambda} = \mathbf{Q}\boldsymbol{\Theta} = \text{diag}\left(q^1 e^{j\theta_1}, \cdots, q^N e^{j\theta_N}\right)$, the optimization problem can be rephrased as

$$\begin{aligned}
(\text{P2}): \min_{\mathbf{W}_k,\rho_k} \quad & \sum_{k=1}^{K} \mathrm{Tr}\,(\mathbf{W}_k) \\
\text{s.t. } C_1 \quad & : \frac{\mathrm{Tr}\,(\mathbf{H}_k\mathbf{W}_k)}{\mu_k^{\min}} - \sum_{i=1,i\neq k}^{K} \mathrm{Tr}\,(\mathbf{H}_k\mathbf{W}_i) \geq \sigma_r^2 \left\|\mathbf{h}_{r,k}^{H}\mathbf{Q}\boldsymbol{\Theta}\right\|^2 + \sigma_k^* \\
C_2 \quad & : \sum_{i=1}^{K} \mathrm{Tr}\,(\boldsymbol{\lambda}\mathbf{G}\mathbf{W}_i G^H \boldsymbol{\lambda}^H) + \sigma_r^2 \parallel \boldsymbol{\lambda} \parallel^2 \leq P_{RIS}^{\max} \\
C_3 \quad & : \zeta_k(1-\rho_k)\left(\sum_{i=1}^{K} \mathrm{Tr}\,(\mathbf{H}_k\mathbf{W}_i) + \sigma_r^2 \left\|\mathbf{h}_{r,k}^{H}\boldsymbol{\lambda}\right\|^2\right) \geq P_k^{in}\left(E_k^{\min}\right) \\
C_4 \quad & : 0 \leq \rho_k \leq 1, \mathbf{W}_k \succeq 0, \mathbf{W}_k \succeq 0, \mathrm{Rank}\,(\mathbf{W}_k) \leq 1
\end{aligned} \tag{9}$$

Where $\sigma_k^* = \sigma_k^2 + \frac{\delta_k^2}{\rho_k}$, the optimization problem (P2) is a standard semi definite programming problem, and the left side of the constraint is affine, which is a convex problem. W_k^* obtains the optimal solution through eigenvalue decomposition, which can be effectively solved through CVX software.

3.2. Fixed Θ and Q optimized ρ_k and w_k

In designing the active RIS precoding matrix, in order to facilitate the processing of optimization problem, $\varphi = \mathrm{diag}\left(q^1 e^{j\theta_1}, \cdots, q^N e^{j\theta_N}\right)^H$, $h_{b,k}^H w_k = g_{k,k}$, $h_{r,k}^H \lambda G w_k = \varphi^H f_{k,k}$ are defined, where $\boldsymbol{f}_{k,k} = \mathrm{diag}\left(\mathbf{h}_{r,k}^H\right)\mathbf{G}\mathbf{w}_k$, $\mathbf{T}_k = \mathrm{diag}\,(\mathbf{G}\mathbf{w}_k)\left(\mathrm{diag}\,(\mathbf{G}\mathbf{w}_k)\right)^H$, $\mathbf{S}_k = \mathrm{diag}\left(\mathbf{h}_{r,k}^H\right)\mathrm{diag}\left(\mathbf{h}_{r,k}\right)$. Transform the SDR relaxation optimization problem into a convex problem. Introducing $\boldsymbol{v} = [\boldsymbol{\varphi}^T \quad 1]^T \in \mathbb{C}^{(N+1)\times 1}$ and $\mathbf{U}_{k,i} = \left[\boldsymbol{f}_{k,i}\boldsymbol{f}_{k,i}{}^H, \boldsymbol{f}_{k,i}\mathbf{g}_{k,i}{}^H; \boldsymbol{f}_{k,i}{}^H\mathbf{g}_{k,i}, 0\right]$. Further, we define $\mathbf{V} := \mathbf{v}\mathbf{v}^H \in \mathbb{C}^{(N+1)\times(N+1)}$, optimization problems (8) are relaxed to

$$\begin{aligned}
(\text{P3}): \text{Find } \boldsymbol{V} & \\
\text{s.t. } C_1 \quad & : \frac{\mathrm{Tr}\,(\mathbf{U}_{k,k}\mathbf{V})|g_{k,k}|^2}{\mu_k^{\min}} - \sum_{\substack{i=1\\ i\neq k}}^{K} \mathrm{Tr}\left(\mathbf{U}_{k,i}\mathbf{V}\right) - \sigma_r^2 \mathrm{Tr}\left(\tilde{\mathbf{S}}_k\mathbf{V}\right) \geq \sigma_k^* \\
C_2 \quad & : \sum_{i=1}^{K} \mathrm{Tr}\left(\tilde{\mathbf{T}}_k\mathbf{V}\right) + \sigma_r^2 \mathrm{Tr}\,(\mathbf{V}) \leq P_{RIS}^{\max} \\
C_3 \quad & : \zeta_k(1-\rho_k)\left(\sum_{i=1}^{K} \mathrm{Tr}\left(\mathbf{U}_{k,i}\mathbf{V}\right) + \left|\boldsymbol{g}_{k,i}\right|^2 + \sigma_r^2 \mathrm{Tr}\left(\tilde{\mathbf{S}}_k\mathbf{V}\right)\right) \geq P_k^{in}\left(E_k^{\min}\right) \\
C_4 \quad & : \mathbf{V} \succeq 0
\end{aligned} \tag{10}$$

Optimization problem (P3) is a feasibility problem, but optimization problems usually produce solutions with a rank higher than 1. We use penalty terms to handle the rank one constraint, and the equivalent form can be written as $\parallel \mathbf{v} \parallel_* - \parallel \mathbf{v} \parallel_2 \leq 0$, where $\parallel \mathbf{v} \parallel_2$ represents the spectral norm.When the matrix $\boldsymbol{V}$ is rank equality,the optimization problem can be represented as

$$\min_{\mathbf{V}} \frac{1}{2\tau}(\parallel \mathbf{V} \parallel_* - \parallel \mathbf{V} \parallel_2), \ \text{ s.t. } C_1 - C_4 \tag{11}$$

Where τ is the penalty factor. Since the objective function is the difference between two convex function, the optimization problem is nonconvex. Next, the continuous convex approximation technique is used to approximate $\boldsymbol{\Psi}(\mathbf{V}) = \parallel \mathbf{V} \parallel_2$with first-order Taylor expansion, which is the lower bound of the whole world. Since the first-order Taylor expansion is

$$\boldsymbol{\Psi}(\mathbf{V}) \geq \boldsymbol{\Psi}\left(\mathbf{V}^i\right) + \mathrm{Tr}\left(\nabla_{\mathbf{V}}^H \boldsymbol{\Psi}\left(\mathbf{V}^i\right)\left(\mathbf{V} - \mathbf{V}^i\right)\right) \triangleq \tilde{\boldsymbol{\Psi}}(\mathbf{V}) \tag{12}$$

Where $\nabla_{\mathbf{V}}\|\mathbf{V}^i\|_2 = \nabla_{\mathbf{V}}\boldsymbol{\beta}_i^H\mathbf{V}^i\boldsymbol{\beta}_i = \nabla_{\mathbf{V}}\mathrm{Tr}\left(\mathbf{V}^i\boldsymbol{\beta}_i\boldsymbol{\beta}_i^H\right) = \boldsymbol{\beta}_i\boldsymbol{\beta}_i^H$, $\boldsymbol{\beta}_i$ is the eigenvector corresponding to the maximum eigenvalue of $\mathbf{V}^i$. In order to achieve optimization of SINR and energy collection margin, relaxation variables SINR residual ϖ_k and EH residual ∇_k are introduced. The new optimization problem can be described as

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$$\begin{aligned} &\min_{\mathbf{V}} \frac{1}{2\tau}\left(\| \mathbf{V} \|_* - \tilde{\Psi}(\mathbf{V})\right) - \sum_{k=1}^{K}(\alpha\varpi_k + \vartheta\nabla_k) \\ &\text{s.t. } C_1 \text{-} C_4 \\ &\qquad \varpi_k, \nabla_k \geq 0, \forall k \end{aligned} \tag{13}$$

By using $\mu_k^{\min} + \varpi_k$ instead of $\mu_k^{\min}$ and $P_k^{in}(E_k^{\min}) + \nabla_k$ instead of $P_k^{in}(E_k^{\min})$, modified constraints are obtained, and α and ϑ are constants, indicating that the optimization problem (13) is convergent. The main process is presented in Algorithm 1.

Algorithm 1: Alternating Optimization Algorithm

1: Initialization $\mathbf{V}^{(0)}$, set maximum number of iterations n_{max}=10 and the maximum error tolerance ϵ=

2: **repeat**

3: Solve problem(p2) for a given $\mathbf{V}^{(n)}$and obtain $\{\mathbf{W}_k^{(n)}, \rho_k^{(n)}\}$.

4: Solve problem(P5) for given $\{\mathbf{W}_k^{(n)}, \rho_k^{(n)}\}$ and obtain $\mathbf{V}^{(n+1)}$.

5: Set $n \leftarrow n+1$

6: until $\frac{\left|p_1^{(n)} - p_1^{(n-1)}\right|}{p_1^{(n-1)}} \geq \epsilon$, return $\{\mathbf{V}^{(*)}\}$

7: end.

4. Simulation Results

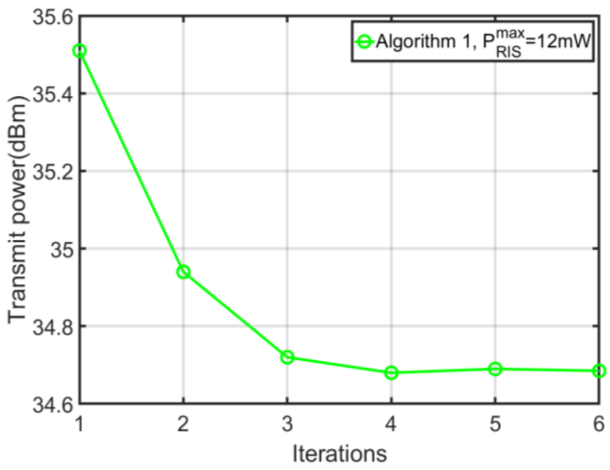

Figure 2:convergence of AO algorithm

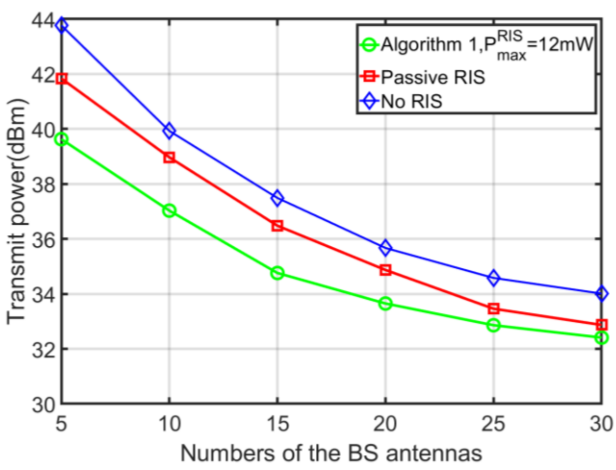

Figure 3:transmission power under different number of BS antennas

For simulations, a two-dimensional coordinate system is used to set the positions of users, BS, and active RIS. All users are randomly distributed within a circle with a radius of 2.5m centered on (3.6 m, 8.5 m), the base station is located at (3.8 m, 0 m), the active is located at(0 m, 9 m), we consider the system as shown in Figure2 and Figure3 with parameters K = 4, $\mu_k^{\min} = 10$dB, $\zeta_k = 1$, $E_k^{\min} = -20$dBm, $\tau = 5 \times 10^{-5}$, $\epsilon = 4$, $\delta_k^2 = -50$dBm, $\sigma_r^2 = -70$dBm, $\sigma_k^2 = -70$dBm, the nonlinear EH parameters are set to $a_1 = 6400$, $a_2 = 0.003$, $a_3 = 0.02$. Given the reflection power $P_{RIS}^{max} = 12$dBW at the active RIS, the number of antennas in the base station is M_t=15, and the reflection element at the active RIS is N=20, the study investigates the transmission power of the system during the iteration process of the proposed algorithm, as shown in Figures2. The curve tends to be stable after four iterations and eventually converges.

As shown in Figure3, the number of antennas with different transmission power compared to the base station is plotted. Given the constraints of the active RIS with a reflection element N=20 and the maximum reflection power at the active RIS with $\mathrm{P}_{\mathrm{RIS}}^{\max} = 12\mathrm{dBW}$, as the number of antennas M_t continues to increase, it is clear that the performance of the MISO-SWIPT system assisted by the source RIS is still superior to that of the passive RIS assisted MISO-SWIPT system and the system without RIS assistance.

5. Conclusion

This article proposes an architecture for an active RIS assisted MISO-SWIPT system, deduces and establishes an optimization problem for minimizing transmission power. Due to the coupling of optimization variables involved in the optimization problem, the optimization problem is non convex. We propose using an alternating optimization algorithm to decompose the optimization problem into two sub problems. We use methods such as semi definite relaxation, continuous convex approximation, and penalty function to transform the optimization sub problem into a standard convex optimization problem. The convergence of the proposed algorithm and the performance of the proposed architecture are verified in simulation result.

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