An SCA and Relaxation Based Energy Efficiency Optimization for Multi-User RIS-Assisted NOMA Networks

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Abstract—Reconfigurable intelligent surface (RIS) assisted non-orthogonal multiple access (NOMA) transmission can effectively improve the energy/spectrum efficiency in wireless networks. This paper designs a low-complexity scheme to achieve the balanced tradeoff between the sum-rate and power consumption in a RIS-assisted NOMA system, which can be measured by energy efficiency. To solve the formulated problem effectively, the original non-convex problem is first decomposed into two subproblems, i.e., beamforming optimization and phase shift optimization. Alternating optimization is proposed to solve these two subproblems iteratively. In particular, successive convex approximation (SCA) is utilized to convert the non-convex constraints to convex ones. The provided simulation results demonstrate that the proposed scheme can achieve superior performance on energy efficiency compared to the random phase shifts and orthogonal multiple access (OMA) schemes.

Index Terms—5G, Convex Optimization, RIS, MISO, NOMA.

I. INTRODUCTION

Recently, the fifth-generation (5G) wireless network has been widely deployed throughout the world. The application value of 5G has gradually attracted attention in academia, industry and even medicine [1]. Non-orthogonal multiple access (NOMA) is a promising technology in beyond 5G system (B5G) due to its high spectrum efficiency [2]. NOMA allows more wireless communication devices to be connected to the networks. Reconfigurable intelligent surface (RIS) has also been considered as a potential and innovative technology in B5G networks. A RIS consists of a large number of passive reflecting elements, and a RIS controller is connected to both the base station (BS) and a RIS [3]. These elements in the RIS are able to smartly tune the phase shifts of the incident signals in order to realize the 3D reflected beamforming [3], [4]. Besides, the RIS is a low power consumption device and it is convenient to be equipped.

In order to achieve the tradeoff between the data rate and power consumption [5], energy efficiency has been introduced and defined as a ratio between the total data rate and power consumption [6], [7]. Recently, some research works have demonstrated the feasibility of energy efficiency optimization for the two-user case in RIS-assisted NOMA systems [8], [9]. Different from the existing work which focused on the two-user case in [9], this paper considers the multi-user case and designs an algorithm to maximize energy efficiency in a downlink multiple input single output (MISO) RIS-assisted NOMA network. Meanwhile, the direct link from the BS to the users is considered. From the aspect of the proposed optimization methodology, we decouple the original problem to the beamforming and phase shift suboptimal problems and then solve them alternately [10]. By applying successive convex approximation (SCA), the energy efficiency will converge to a local optimal value [11], [12]. Besides, different from the semidefinite relaxation (SDR) method for the phase shift optimization in [9], in this paper, we apply SCA to optimize phase shifts of the RIS. In simulation, we compare the energy efficiency of the proposed scheme with the benchmark schemes using random phase shifts and OMA and investigate the impact of the number of reflecting elements of RIS, internal circuit power, power amplifier coefficient and transmitting power budget on the performance of RIS-NOMA.

II. SYSTEM MODEL

In this paper, we consider a quasi-static downlink MISO RIS-NOMA network with one BS and multiple single-antenna users. The BS is equipped with $M$ antennas and the number of users is $K$, and the RIS consists of $N$ passive reflecting elements to assist the transmission from the BS to the users. Besides, assume that the BS can communicate with the users through both the RIS and direct link from the BS to the users in this model. Define $\mathbf{G} \in \mathbb{C}^{N \times M}$ and $\mathbf{h}_{k,d}^H \in \mathbb{C}^{1 \times N}$ as the channel gains from the BS to the RIS and the RIS to the users, respectively. The direct channel gain from the BS to the users is denoted by $h_{k,i}^H \in \mathbb{C}^{1 \times M}$, where $k$ denotes the index of the $k$th user where $k = 1, \ldots, K$. We define $\Theta = \text{diag}(e^{j\theta_1}, \ldots, e^{j\theta_N})$ as the phase reflection matrix, where $\theta_k \in [0, 2\pi]$ is the reflection phase shift in this system. Consider the channel gain of the $K$ users are $\mathbf{h}_1^H, \ldots, \mathbf{h}_K^H$, where $\mathbf{h}_k^H = h_{k,i}^H \Theta \mathbf{G} + \mathbf{h}_{k,d}^H$. Therefore, the received signal at the $k$th user can be written as follow:

$$y_k = \mathbf{h}_k^H \left( \sum_{i=1}^{K} \mathbf{w}_i s_i \right) + n_k,$$

where $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ is the beamforming vector from the BS to the $k$th user, and $n_k \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN), where $\sigma^2$ is the variance of the noise. In the downlink RIS-assisted NOMA system, the performance of successive interference cancellation (SIC) is highly affected by the decoding order, which indicates that when decoding $U_k$’s signal, the interference from the users whose signals have been decoded before could be cancelled. In fact, the decoding order depends on the users’ capability. In this paper, assume $U_k$’s signal is decoded before $U_j$’s signal, for $k < j$. The signal-interference-plus-noise ratio (SINR) of $U_k$’s signal decoded at $U_i$ ($k = 1, \ldots, K$ and $i = 1, \ldots, K$, $k \leq i$) can be expressed as followed:

$$\text{SINR}_{k,i} = \frac{\left| \mathbf{h}_k^H \mathbf{w}_k \right|^2}{\sum_{l=k+1}^{K} \left| \mathbf{h}_l^H \mathbf{w}_l \right|^2 + \sigma^2}.$$  

In this network, the condition that SIC can be carried out is that the $k$th user’s signal can be decoded by the $i$th user successfully ($k \leq i \leq K$). We first define $\text{SINR}_k$ as the achievable SINR for $U_k$’s signal and $\text{SINR}_{k,i}$ is the SINR for $U_k$’s signal to be decoded by the $i$th user. The $\text{SINR}_k$ is defined as followed:

$$\text{SINR}_k = \min\{\text{SINR}_{k,i}\}.$$  

Note that (3) can guarantee that all the signal for $U_k$ can be successfully decoded at $U_i$ because $\text{SINR}_k$ is the minimal of $\text{SINR}_{k,i}$ as shown in (3). Therefore, the SIC can be implemented successfully as well.
All the interference from the other users can be removed when decoding $U_k$’s signal because the $k^{th}$ user’s signal is decoded at the last stage of SIC. Therefore, the SINR of $U_k$ is

$$\text{SINR}_k = \frac{|h_{k,H}^H w_k|^2}{\sigma^2}. \quad (4)$$

Thus, the achieved data rate of the $k^{th}$ user is

$$R_k = \log_2(1 + \text{SINR}_k). \quad (5)$$

### III. PROBLEM FORMULATION

This work is aimed to maximize the system energy efficiency which is the ratio between sum-rate and total power consumption in a RIS-NOMA system. In particular, define the internal circuit power consumption of the BS as $P_c$ and set a parameter $\eta \in [0, 1]$ to denote the power amplifier coefficient at the BS. Thus, the energy efficiency problem addressed in this paper can be formulated as followed:

$$\max_{\mathbf{w}_1, \ldots, \mathbf{w}_K} \eta \sum_{k=1}^{K} R_k$$

s.t. \hspace{1em} \frac{1}{\eta} \sum_{k=1}^{K} \|w_k\|^2 + P_c \geq \alpha \rho, \quad (6a)$$

$$R_k \geq R_{k,\text{min}}, k = 1, \ldots, K, \quad (6b)$$

$$\sum_{k=1}^{K} \|w_k\|^2 \leq P_{\text{max}}, \quad (6c)$$

$$\theta_n \in [0, 2\pi], n = 1, \ldots, N. \quad (6d)$$

Firstly, (6b) indicates that each user’s data rate has to be no less than a minimal data rate $R_{k,\text{min}}$, $k = 1, \ldots, K$ to satisfy the quality of service (QoS) requirement. Constraint (6c) shows that the total power budget of beamforming at the BS for users is not supposed to be larger than a maximum threshold $P_{\text{max}}$. (6d) demonstrates that the angle of each reflecting element should be in the range of $[0, 2\pi]$. However, (P6) is a non-convex problem due to the fact that $R_k$ is not convex with respect to $\mathbf{w}$ and $\Theta$. QoS requirement (6b) is also not convex, making this problem more complicated.

### IV. PROPOSED OPTIMIZATION METHODOLOGY

In this section, we mainly design a low-complexity algorithm which can effectively obtain a suboptimal solution of (P6). From the problem formulation, it can be seen that there are two types of variables, namely beamforming vectors and the phase shifts in this optimization problem. Due to the fact that the vector $w_k$ is a complex-valued vector, the complexity of the problem could be greatly increased if solving the optimization problem with $w$ and $\Theta$ directly. Therefore, in this paper, an optimization scheme is proposed by alternately solving beamforming and phase shift optimization problems. In the process of addressing the non-convex functions and constraints in the beamforming and phase shift optimization problems, some slack variables are introduced to relax these non-convex functions. Moreover, SCA is utilized in the algorithm design to obtain the suboptimal solution of the energy efficiency.

#### A. Beamforming Optimization

From beamforming optimization, to make the objective function convex, a slack variable $\alpha$ is introduced to (P6) and (P6) can be transformed to the following equivalent form:

$$\max_{\mathbf{w}_1, \ldots, \mathbf{w}_K, \alpha} \alpha,$$ \hspace{1em} (7a)

s.t. \hspace{1em} \frac{\sum_{k=1}^{K} R_k}{\frac{1}{\eta} \sum_{k=1}^{K} \|w_k\|^2 + P_c} \geq \alpha, \quad (7b)$$

$$\frac{1}{\eta} \sum_{k=1}^{K} \|w_k\|^2 + P_c \geq \rho. \quad (7c)$$

Although the objective function of (P6) has been transformed to an affine function, the constraint (7b) is not convex. In order to solve it effectively, one slack variable $\rho$ is introduced to make the total power expression of (7b) convex. Thus, (7b) can be further transformed to the following form

$$\sum_{k=1}^{K} R_k \geq \alpha \rho, \quad (8)$$

and the constraint of total power expression can be written as followed:

$$\frac{1}{\eta} \sum_{k=1}^{K} \|w_k\|^2 + P_c \leq \rho. \quad (9)$$

Based on the constraints transformation, constraint (8) is still not convex. Then, a new variable vector $\gamma = [\gamma_1, \ldots, \gamma_K]^T$ is used to relax (8), which can be rewritten as

$$\sum_{k=1}^{K} \log_2(\gamma_k) \geq \alpha \rho, \quad (10a)$$

$$1 + \text{SINR}_k \geq \gamma_k. \quad (10b)$$

Subsequently, use another variable vector $\delta = [\delta_1, \ldots, \delta_K]^T$ to make constraint (10a) convex, which can be rewritten as followed:

$$\sum_{k=1}^{K} \delta_k \geq \alpha \rho, \quad (11a)$$

$$\gamma_k = 2^{\delta_k}. \quad (11b)$$

Now, the relationship between these slack variables introduced based on (8), (10a), (11a) and (11b) can be summarized as followed:

$$\sum_{k=1}^{K} \log_2(1 + \text{SINR}_k) \geq \sum_{k=1}^{K} \log_2(\gamma_k) \geq \sum_{k=1}^{K} \delta_k \geq \alpha \rho. \quad (12)$$

Considering the fractional form of SINR, one can introduce a series of variables with the form of $\Omega_{k,i}$, where $k \leq \ i, i = 1, \ldots, K$. Therefore, (10b) is equivalent as followed:

$$|h_{i,H}^H w_k|^2 \geq (\gamma_k - 1)\Omega_{k,i}, \quad (13a)$$

$$\sum_{k=1}^{K} |h_{i,H}^H w_k|^2 + \sigma^2 \geq \Omega_{k,i}. \quad (13b)$$

However, (13a) and (13b) are not applicable for the situation that $i$ and $k$ are equal to $K$ simultaneously. When both of $i$ and $k$ are equal to $K$, (13a) and (13b) can be written as followed:

$$|h_{K,H}^H w_K|^2 \geq (\gamma_K - 1)\Omega_{K,K}. \quad (14a)$$

$$\sigma^2 \leq \Omega_{K,K}. \quad (14b)$$

In the following, those steps in [9] are used to convert (13a) to a convex form. Firstly, an arbitrary phase rotation of the beamforming vector is introduced to make the imaginary part of $h_{i,H}^H w_k$ equal to zero for the two-user case in this model. However, this method cannot be straightforwardly applied to the multi-user case considered.
in this paper because only one given arbitrary phase rotation for \( w_k \) cannot guarantee that all \( \exists \{ h^H_k w_k \} = 0 \). Therefore, at this stage, one can apply additional variables in the form of \( w_{k,i}^R \) and \( w_{k,i}^m \), which

\[
\begin{align}
w_{k,i}^R &= \Re \{ h^H_k w_k \}, \\
w_{k,i}^m &= \Im \{ h^H_k w_k \},
\end{align}
\]

(15a) and (15b) are convex constraints. Although (11a) and (14a) are still non-convex constraints, instead of introducing new slack variables, SCA is applied to deal with these non-convex constraints. The main idea of SCA is to use the First-order Taylor approximation to convert the non-convex functions to affine [13]. In this paper, the constraints (11a), (13a) can be approximated to affine functions by applying SCA, which can be shown as follows:

\[
\sum_{k=1}^{K} \delta_k \geq \alpha (t)^2 \left( \alpha - \alpha (t) \right) + \alpha (t)^2 (\rho - \rho (t)),
\]

(16)

\[
\begin{align}
\left( (w_{k,i}^R)^2 \right)^2 + \left( (w_{k,i}^m)^2 \right)^2 &+ 2 (w_{k,i}^R)^2 (w_{k,i}^R - (w_{k,i}^R)^2) \\
&\quad + 2 (w_{k,i}^m)^2 \sum_{k=1}^{K} (w_{k,i}^R - (w_{k,i}^R)^2) \\
&\quad \geq (\gamma_k (t) - 1)(\Theta_{k,i}) + (\Theta_{k,i}) (\gamma_k - (\gamma_k (t))) \\
&\quad + (\gamma_k (t) - 1)(\Theta_{k,i} - (\Theta_{k,i}) (\gamma_k),
\end{align}
\]

(17)

where \( t \) denotes the \( t \)th iteration. (6b) is a non-convex constraint and it can be rewritten as follows:

\[
\sum_{k=1}^{K} |h_k^H w_k|^2 \geq 2 R_{k,\text{min}} - 1,
\]

(18)

where \( R_{k,\text{min}} \) is a constant. After that, this constraint can be reformulated with SCA as

\[
\begin{align}
&\left( (w_{k,i}^R)^2 \right)^2 + \left( (w_{k,i}^m)^2 \right)^2 + 2 (w_{k,i}^R)^2 (w_{k,i}^R - (w_{k,i}^R)^2) \\
&\quad + 2 (w_{k,i}^m)^2 \sum_{k=1}^{K} (w_{k,i}^R - (w_{k,i}^R)^2) \\
&\quad \geq (2 R_{k,\text{min}} - 1) \left( \sum_{k=1}^{K} |h_k^H w_k|^2 + \sigma ^2 \right),
\end{align}
\]

(19)

where \( k + 1 \leq l \leq K \). Constraint (19) is convex because it satisfies the quadratic form of second-order-cone (SOC). In summary, the convex problem can be formulated as

\[
\begin{align}
\max &\quad \omega_1, ..., \omega_K, \alpha, \gamma, \delta, \Omega, \alpha, \mu, \omega_{k,i}^R, \omega_{k,i}^m \\
\text{s.t.} &\quad (6c), (9), (11b), (15a), (15b), (16), (17), (19),
\end{align}
\]

(20a)

where \( t \) is the \( t \)th iteration of the First-order Taylor expansion. (P20) is a convex optimization problem.

### B. Phase Shift Optimization

In this section, we focus on the phase shift optimization for RIS-NOMA. In the above section, the beamforming optimization has been solved with the fixed phase shifts. Given the optimized beamforming vectors \( w_k \), the denominator of the objective function (6a) is a constant and the energy-efficiency problem can be transformed to a sum-rate optimization problem as followed:

\[
\begin{align}
\max &\quad \sum_{k=1}^{K} R_k, \quad (21a) \\
\text{s.t.} &\quad R_k \geq R_{k,\text{min}}, k = 1, ..., K, \\
&\quad \theta_n \in [0, 2\pi], n = 1, ..., N.
\end{align}
\]

In [14], the phase shift optimization is dealt with semi-definite relaxation (SDR). In this work, (P21) is optimized via SCA. Similar to (P6), (21a) is still a non-convex problem because \( R_k \) is not convex with respect to \( \Theta \). Define a variable vector \( v = [v_1, ..., v_N]^H = [\phi \theta \gamma \delta \mu \omega_k]^H \) and vectors \( a_{k,i} = \text{diag}(h^H_k \omega_k)Gw_k \) which \( k \leq i \leq K \) and \( w_k^i \) denotes the optimized beamforming vector, which is fixed. Thus, the SINR of the \( k \)th user decoded at the \( i \)th iteration \((k \leq i)\) can be expressed as

\[
\text{SINR}_{k,i} = \frac{|v^H a_{k,i} + h_{k,i}^H w_k^i|^2}{\sum_{l=k+1}^{K} |v^H a_{l,i} + h_{l,i}^H w_k^i|^2 + \sigma^2}.
\]

(22)

For the case of \( k = i = K \), the SINR expression can be written as

\[
\text{SINR}_K = \frac{|v^H a_{K,K} + h_{K,K}^H w_k^i|^2}{\sigma^2}.
\]

(23)

Similar to process of beamforming optimization, define a slack variable \( q \) such that

\[
\sum_{k=1}^{K} R_k \geq q.
\]

(24)

Then, a new vector \( \lambda = [\lambda_1, ..., \lambda_K] \) is further introduced to rewrite (24)

\[
\sum_{k=1}^{K} \log_2 (\lambda_k) \geq q,
\]

(25a)

\[
1 + \text{SINR}_K \geq \lambda_k.
\]

(25b)

Then, another variable vector named \( \mu = [\mu_1, ..., \mu_K] \) is applied such that,

\[
\sum_{k=1}^{K} \mu_k \geq q,
\]

(26a)

\[
\lambda_k \geq 2^{\mu_k}.
\]

(26b)

By applying the similar method to deal with the SINR part, additional variables \( \varphi_{k,i} \) which have the same purpose with \( \Omega_{k,i} \) are applied as

\[
|v^H a_{k,i} + h_{k,i}^H w_k^i|^2 \geq (\lambda_k - 1) \varphi_{k,i}.
\]

(27a)

\[
\sum_{l=k+1}^{K} |v^H a_{l,i} + h_{l,i}^H w_k^i|^2 + \sigma^2 \leq \varphi_{k,i}.
\]

(27b)

For the situation of \( i = k = K \), the expressions should be written as

\[
|v^H a_{K,K} + h_{K,K}^H w_k^i|^2 \geq (\lambda_K - 1) \varphi_{K,K},
\]

(28a)

\[
\sigma^2 < \varphi_{K,K}.
\]

(28b)

Then, the First-order Taylor approximation is used to make (27a) convex. Introduce a series of variables \( v_{k,i}^R \) and \( v_{k,i}^m \), such that

\[
v_{k,i}^R = \Re \{ (v)^H a_{k,i} + h_{k,i}^H w_k^i \},
\]

(29a)

\[
v_{k,i}^m = \Im \{ (v)^H a_{k,i} + h_{k,i}^H w_k^i \}.
\]

(29b)
Then, extend (27a) via SCA,
\[
((v_{k,i}^{Re})^{(t)})^2 + ((v_{k,i}^{Im})^{(t)})^2 + 2(v_{k,i}^{Re})^{(t)}(v_{k,i}^{Re} - (v_{k,i}^{Re})^{(t)}) \\
+ 2(v_{k,i}^{Im})^{(t)}(v_{k,i}^{Im} - (v_{k,i}^{Im})^{(t)}) \\
\geq ((\lambda_{k})^{(t)} - 1)((\varphi_{k,i})^{(t)} + (\varphi_{k,i})^{(t)})\lambda_{k} - (\lambda_{k})^{(t)} \\
+ ((\lambda_{k})^{(t)} - 1)((\varphi_{k,i} - (\varphi_{k,i})^{(t)}).
\]
To deal with the QoS constraints, the same technique can still be applied to make it become a convex expression,
\[
((v_{k,i}^{Re})^{(t)})^2 + ((v_{k,i}^{Im})^{(t)})^2 + 2(v_{k,i}^{Re})^{(t)}(v_{k,i}^{Re} - (v_{k,i}^{Re})^{(t)}) \\
+ 2(v_{k,i}^{Im})^{(t)}(v_{k,i}^{Im} - (v_{k,i}^{Im})^{(t)}) \\
\geq (2^{R_{k,\text{min}} - 1} - 1)\left(\sum_{i=k+i}^{K} |(v_{k,i}^{H}a_{t,i} + h_{k,i}^{H}w_{t})^2 + \sigma^2\right).
\]
To (31) the transformation of (P21), the phase shift optimization can be expressed as
\[
\max_{\psi,\lambda,\mu,\varphi,\psi^{Re},\psi^{Im}} q, \quad (32a) \\
\text{s.t.} \quad (21c), (26b), (29a), (29b), (30), (31). \quad (32b)
\]
(P32) is a convex optimization problem.

V. SIMULATION RESULT

In this section, we present the simulation results of the proposed algorithm to illustrate the performance of the optimization scheme in this paper. We consider that the distance between the BS and the RIS is 10 m [10]. The distance between the BS and every user is within the range between 16 m and 20 m and each user is also 16-20 m away from the RIS [10]. The channels from the BS to the RIS and from the RIS to the users are Rician fading channels. The Rician factor \( \kappa \) of the channel is set to 2. Besides, the channels from the BS to the users obey Rayleigh distribution. The path loss exponents from the BS to the RIS, the RIS to the users and the BS to the users are all set to 2.5. Without the loss of generality, the minimal SINR requirement for all users is \(-10 \text{ dB} \) and the additive white Gaussian noise (AWGN) \( \sigma^2 \) is \(-60 \text{ dB} \) [10].

Fig. 1 shows the relationship between energy efficiency and the number of the reflecting elements. Under this circumstance, \( P_c \) and \( P_{\text{max}} \) are set to \(-20 \text{ dB} \) and \(-10 \text{ dB} \), respectively. \( \eta \) is set to 0.8. For a comprehensive analysis, three different combinations of the numbers of the antennas and the users are selected to compare their energy efficiency values with those with random phase shifts and OMA cases. Initially, we use ‘4 antennas, 6 users’ as an example. From this graph, it can be seen that the energy efficiency values optimized by the proposed algorithm are from 416.63 bps/Hz/Joule to 816.57 bps/Hz/Joule as the number of elements increases. Meanwhile, the growth of energy efficiency values with random phase shifts is only from 223.4 bps/Hz/Joule to 313.05 bps/Hz/Joule and the energy efficiency for OMA case is within the range between 217.58 bps/Hz/Joule and 550.22 bps/Hz/Joule. It can be observed that the energy efficiency values optimized by the proposed algorithm are much higher than those with random phase shifts and OMA cases. Besides, it can be also found that the value of energy efficiency increases as the number of elements increases. At the beginning, energy efficiency increases very rapidly. However, the curve for each case is saturated gradually as the number of elements grows. This is because the effect of the phase shift optimization for EE becomes weaker as the number of the elements grows. When the number of elements reaches to a certain large value, the growth rate of the energy efficiency cannot be as high as those with less elements and the curve of the EE is likely to be more and more saturated. Therefore, a further increase of the elements cannot improve the energy efficiency as significantly as the cases with a relatively small quantity of the elements.

Fig. 2 shows the effect of the internal circuit consumption on energy efficiency value. The number of reflecting elements is set to 10 and \( P_{\text{max}} \) is set to \(-10 \text{ dB} \). The circuit power is set within the range from \(-20 \text{ dB} \) to \(-10 \text{ dB} \) and amplifier coefficient is 0.8, respectively. From the curves under both optimized and random phase shifts circumstances, it can be found that the energy efficiency value decreases as the internal circuit power increases. Besides, when \( P_c \) rises from \(-20 \text{ dB} \) to \(-10 \text{ dB} \), there is a sharp decrease in the energy efficiency value. The curve approaches to zero when \( P_c \) further rises. It is because the sum power consumption of beamforming is no more than \( P_{\text{max}} \). Energy efficiency could decline as \( P_c \) increase. As \( P_c \) approaches and is far more than \( P_{\text{max}} \), the rate of decline of energy efficiency is lower and lower because energy efficiency should not be less than zero in a network.

Fig. 3 shows the relationship between energy efficiency and the power amplifier coefficient. The number of elements is set to 10 and \( P_c \) is set to \(-20 \text{ dB} \). Meanwhile, two schemes with different transmitting power \( P_{\text{max}} \) are considered. From the curve, it can be observed that the energy efficiency can increase as the value of \( \eta \) increases. More importantly, when the numbers of antennas and users are fixed, the energy efficiency with a higher transmitting power budget is greater than that with a lower \( P_{\text{max}} \). It is because that the increase of \( P_{\text{max}} \) expands the domain of the beamforming vectors. Hence, the energy efficiency is more likely to be optimized to a higher value during the optimization process.
VI. CONCLUSION

In this paper, we designed an algorithm to maximize the system in a RIS-assisted NOMA system with the multi-user case. Firstly, we decoupled the primal problem into two suboptimal problems. By alternately optimizing the beamforming vectors and phase shifts, the optimal energy efficiency could be obtained through the proposed iterative algorithm. To deal with the non-convex constraints in these two subproblems, the problem relaxation method was firstly applied to simplify it by introducing slack variables. SCA was also applied as a mathematical tool to convert some non-convex constraints to convex. Note that this work can be extended to a MIMO RIS-assisted NOMA system. Machine learning is a promising method to be applied to address this new model.

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