Energy Efficiency Optimization of Intelligent Reflective Surface-assisted Terahertz-RSMA System

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Abstract—This paper examines the energy efficiency optimization problem of Intelligent Reflective Surface (IRS)-assisted multi-user Rate-Splitting Multiple Access (RSMA) under terahertz propagation. Comparing Salp Swarm Algorithm (SSA) and Successive Convex Approximation (SCA), it is found that SCA requires multiple iterations to solve non-convex resource allocation problems. At the same time, SSA can consume less time to improve energy efficiency.

Index Terms—Intelligent Reflective Surface, Terahertz Communication, Energy Efficiency, Rate-Splitting Multiple Access, Salp Swarm Algorithm, Successive Convex Approximation

I. INTRODUCTION

The rate requirements of communication networks are continuously increasing with the advent of the sixth generation (6G). Terahertz bandwidth can meet the rate requirements of 6G communication networks. However, terahertz signals can be affected by obstacles resulting in high reflective attenuation, severely impairing signal coverage and causing degraded communication performance. In this paper, an Intelligent Reflective Surface (IRS) is used to create a controlled propagation environment. By deploying IRS, blocking problems in the Light-of-Sight (LoS) link can be well avoided [1]. The application of IRS as a phase-shifting structure to antenna array signals can help to sharpen the beam by changing the electromagnetic properties of the electromagnetic wave to adjust the beam direction. Therefore, improving the system’s energy efficiency at a reasonable cost is essential.

To meet the demand for high energy efficiency and Quality of Service (QoS) heterogeneity in wireless networks, Rate-Splitting Multiple Access (RSMA) is developed in [2]. RSMA is considered as an indispensable technology to support large-scale connections of 6G wireless communication networks. To overcome the two extreme interference management strategies of Space-Division Multiple Access (SDMA) and Non-Orthogonal Multiple Access (NOMA), RSMA is a multiple access scheme for multi-antenna multi-user communication based on Rate-Splitting (RS) and linear precoding. RSMA splits the messages of users into public and private parts and encodes the public part into one or more public streams while encoding the private part into a separate private stream [3]. In [4], it demonstrates that RSMA outperforms SDMA and NOMA over a wide range of network loads. The main advantage of RSMA is that it flexibly manages interference, allowing it to be partially decoded and partially treated as noise.

RSMA can be used in fast user movement scenarios to optimize the user rate with shorter codes, hence eliminating difficulties with reduced latency and enhanced mobile broadband [5]. It is proposed in [6] to optimize the RS pre-coder using the weighted Minimum Mean Square Error (WMMSE) and Sample Average Approximation (SAA) by constraining Weight Sum-Rate (WSR), and the results show that RSMA outperforms NOMA in the MIMO case. In [7], it is mentioned that the combination of IRS and RSMA can optimize the performance, and a method combining Successive Convex Approximation (SCA) and Alternating Optimization (AO) is proposed to optimize the performance. After optimization, RSMA can allocate resources effectively and fairly increase user speed. In [8], a comparison of RSMA with SDMA and NOMA for Energy Efficiency (EE) maximization is presented. However, the SCA approach is relatively iteratively complex, computationally intensive and generally effective. Therefore, in this paper, the Salp Swarm Algorithm (SSA) is used for optimization.

The main contributions of this paper as follows:
Firstly, a new IRS-assisted terahertz RSMA framework is proposed.
Secondly, this paper uses SSA to optimise EE problems under power and quality of service constraints.
Finally, simulation results show that SSA not only outperforms SCA in EE optimisation, but also its time...
where the frequency band [10], which is shown as follows:

\[ f = \frac{P_{\text{sat}}(T,P)}{1000} \]

is the mixing ratio of water vapor in unit volume, where \( \rho \) and \( v \) are relative humidity and atmospheric pressure, respectively, where \( \rho = 0.5 \) and \( p = 101325 \). \( p_w(T,p) \) is the partial pressure of saturated water vapor at temperature \( T \), expressed as follows:

\[ p_w(T,p) = g_1(g_2 + g_3 \eta_0) e^{4.57(T - 273)}, \]

where \( g_1 = 6.1121, g_2 = 1.0007, g_3 = 3.46 \times 10^{-6}, g_4 = 17.502, g_5 = 273.15 \text{K}, g_6 = 32.18^\circ \text{K}, T = 296, \eta_0 \) is the pressure, which is 1013.15 hPa [10].

The equivalent channel transfer function is given by:

\[ H(f,r) = H^{\text{LOS}}(f,r) e^{-j2\pi f^{\tau_{\text{LOS}}}}, \]

where \( \tau_{\text{LOS}} = r/c \) is the propagation delay of the LOS path.

### B. Rate-Splitting Multiple Access

RSMA’s message \( W_k, \forall k \in \{1,2\} \) is split into a common part \( W_{c,k} \) and a private part \( W_{p,k} \). The common parts of the two users, \( W_{c,1}, W_{c,2} \) are jointly encoded into a common stream \( s_c \) using a codebook shared by the two users. The common stream \( s_c \) works for both users. The private part is encoded as \( s_1 \) and \( s_2 \) of user-1 and user-2, respectively. Stream vector \( s = [s_c, s_1, s_2]^T \) linearly precoded using beamformer \( P = [P_c, P_1, P_2] \). The base station sends a superimposed signal stream containing public message streams and \( K \) private message streams for \( K \) users.

\[ x = \sum_{k=1}^{K} P_k s_k, \forall k \in \{1,2\}. \]

The total transmit power of the base station is affected by the power constraint \( P_t \), that is, \( \mathbb{E}[\|x\|^2] \leq P_t \).

### C. System Model

As shown in Figure 2, an IRS-assisted multi-user MISO with RSMA downlink system is considered in this paper. BS is equipped with \( N_t \) transmit antennas, serving two single-antenna users. The direct path is the
The phase difference of the RF signal of frequency $f$ entering the $n$-th reflective element relative to the first element, where $| \mathbf{r} |$ represents the Euclidean norm of vector $\mathbf{r}$; $\mathbf{r}_l = [X - x_l, Y - y_l, H - z_l]^T$ denote the distance of BS-IRS; $c$ is the speed of light.

- The coordinates of BS are represented by $w_k = [x_k, y_k, z_k]^T$. The transmit steering vector of the BS-IRS link is defined as

$$\mathbf{e}_l(f, l) = [1, e^{-j\phi_l(f, l)}, ..., e^{-j\phi_{N_{IRS}}(f, l)}]. \quad (11)$$

The phase difference of the RF signal of frequency $f$ received from the $n$-th reflective element at UE $k$ relative to the first reflective element is $\phi_{N_{IRS}}(f, l) = \frac{2\pi f x_k l}{c |\mathbf{r}_l(1)|}$, where $\mathbf{r}_k = [x_k - X, y_k - Y, z_k - H]^T$ denotes the distance of the IRS-user $k$ links. The link from IRS to UE $k$ defines the receive steering vector as

$$\mathbf{e}_k(f, l) = [1, e^{-j\phi_1(f, l)}, ..., e^{-j\phi_{N_{IRS}}(f, l)}]. \quad (12)$$

According to [13], the channel attenuation of the BS-IRS-user $k$ link is:

$$h_k(f, l) = \frac{\sqrt{G_t \sqrt{G_r c}}}{8\sqrt{\pi^2 f}} e^{-\frac{j}{2} K_{n}(f) \tau_{l}(1) \rho_{\tau_{LOS}}}, \quad (13)$$

where $G_t$ is the transmission antenna gain and $G_r$ is receiving antenna gain; $| \mathbf{r}(1) | = | \mathbf{r}_t(1) | + | \mathbf{r}_k(1) |$; $\tau_{LOS} = | \mathbf{r}(1) | / c$ is the propagation delay of the LOS path.

Therefore, the effective combined end-to-end channel from the BS to users with the existence of the IRS can be expressed as:

$$\mathbf{h}_k^H = h_k(f, l)\mathbf{e}_k(f, l)H \Phi \mathbf{e}_l(f, l). \quad (14)$$

The configuration of the IRS is determined by the diagonal phase-shift matrix $\Phi = diag(\beta_1 e^{-j\theta_1}, ..., \beta_{N_{IRS}} e^{-j\theta_{N_{IRS}}})$, where $\beta$ is amplitude modulation and $\theta$ is the phase shift of the $n$-th reflecting element of the IRS.

This paper considers that the phase shift of each element of the IRS can only take a finite number of discrete values obtained through the uniform quantization interval $[0, 2\pi)$. Therefore, the following equation gives the set of discrete phase shift values of each element:

$$\mathcal{F} = \{0, \frac{2\pi}{2^b}, ..., \frac{2\pi}{2^b}(2^b - 1)\}, \quad (15)$$

where constant $b$ denotes the number of bits used to indicate the maximum number of phase shift levels.

Therefore, the received signal of user-$k$ is

$$y_k = \mathbf{h}_k^H (\mathbf{P}_c s_e + \sum_{k=1}^{K} \mathbf{P}_k s_k) + n_k, \forall k \in \{1, 2, ..., K\}, \quad (16)$$

where $n_k \sim \mathcal{CN}(0, \sigma^2_k)$ is additive white Gaussian noise (AWGN) with zero mean and variance $\sigma^2_k$ at user $k$.

III. OPTIMIZATION PROBLEM FORMULATION

A. Problem Formulation

This paper adopts the linear power model specified in [10]. The common stream $s_e$ is first decoded at both users by treating the interference from the private streams $s_1$ and $s_2$ as noise. Since $s_e$ contains part of the intended message and part of the message that interferes with the user, it is able to decode the partial interference and treat
the interfered part as noise. The SINR for decoding the common stream \(s_c\) at user-\(k\), \(\forall k \in \{1, 2\}\) is

\[
\gamma_{ck}(P) = \frac{|h_k^H P_c|^2}{|h_k^H P_1|^2 + |h_k^H P_2|^2 + \sigma_k^2}.
\]  

(17)

According to the traditional ordered RS decoding system [14], [1], the achievable rate (bits/sec/Hz) for the common stream based on SSA. In SSA, salps are divided into leaders and followers. The leader moves towards the optimal solution of the objective function and guides the movement of the followers, who are only affected by the previous salps. The leader performs global exploration in an iteration, and the followers perform local exploration.

1) Initialization: Let the search space be a Euclidean space of \(D \times N\), where \(D\) is the space dimension, and \(N\) is the number of populations. The position of salps in space is represented by \(X_n = [X_{n1}, X_{n2}, ..., X_{nD}]^T\), and the position of the optimal result is represented by \(F_n = [F_{n1}, F_{n2}, ..., F_{nD}]^T\) with \(n = 1, 2, 3, ..., N\). The upper bound of the search space is \(ub = [ub_1, ub_2, ..., ub_D]\), and the lower bound is \(lb = [lb_1, lb_2, ..., lb_D]\).

\[
X_{D \times N} = rand(D, N)(ub(D, N) - lb(D, N)) + lb(D, N).
\]  

(23)

The leader in the population is represented by \(X^1_d\), and the follower is represented by \(X^i_d\) with \(i = 2, 3, 4, ..., N\) and \(d = 1, 2, 3, ...D\).

2) Leader Position Update: During the movement and the search for the optimal result of the salp chain, the leader’s position update is expressed as:

\[
X^1_d = \begin{cases} 
F_d + c_1((ub - lb)c_2 + lb), & c_3 \geq 0 \\
F_d - c_1((ub - lb)c_2 + lb), & c_3 < 0 \end{cases},
\]  

(24)

where \(X^1_d\) and \(F_d\) are the position of the first salp (leader) and the optimal result in the \(d\)-th dimension, respectively; \(ub\) and \(lb\) are the corresponding upper and lower bounds, respectively. \(c_1\) is the convergence factor in the optimization algorithm, which balances global exploration and local development. The expression of \(c_1\) is:

\[
c_1 = 2e^{-\frac{l}{L}} \leq c_3 < 1,
\]  

(25)

where \(l\) is the current iteration number, and \(L\) is the maximum iteration number. The control parameters \(c_2\) and \(c_3\) are random numbers, which are used to enhance the randomness of \(X^1_d\) and improve the global search and individual diversity of the chain group.

3) Follower Location Update: the position of the follower is expressed as:

\[
X^i_d = \frac{X^i_d - X^{i-1}_d}{2},
\]  

(26)

where \(X^i_d\) and \(X^{i-1}_d\) are the updated follower’s position and the pre-update follower’s position in the \(d\)-th dimension, respectively.

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Algorithm 1 Salp Swarm Algorithm intelligence-based optimization.

1: Initialize the position of salps $X_n (n = 1, 2, \ldots, N)$, considering upper bound and lower bound are $ub$ and $lb$ respectively.
2: while $\|P_c\|^2 + \sum_{k=1}^{K} \|P_k\|^2 \leq P_t$ do
3:   Calculate the initial fitness value of $N$ salps according to the upper and lower limits of each search space dimension.
4:   $F_n$ is the optimal search agent.
5:   Update $c_1$ according to equation (25).
6:   for each salp $x_i$ do
7:     if ($n == 1$) then
8:       Update the leader’s position according to equation (24).
9:     else
10:       Update the follower’s position according to equation (26).
11:     end if
12:   end for
13:   Limit each salp to the upper and lower bounds of the variable
14: end while
15: return $F_n$

IV. RESULTS AND ANALYSIS

This paper evaluates the performance of the SSA and SCA algorithms by calculating the maximum EE of two users. The EE of two users in RSMA is defined as

$$EE_1 = \frac{C_1 + R_1(P)}{tr(PP^H)} + P_0.$$  \hfill (27)$$

$$EE_2 = \frac{C_2 + R_2(P)}{tr(PP^H)} + P_0.$$  \hfill (28)$$

This experiment sets the frequency of the terahertz channel to $f = 0.2757 \text{THz}$. Molecular absorption coefficient is euqal to $2.8 \times 10^{-4}$. Assume that the BS has four transmit antennas $N_t = 4$. Noise variance is $\sigma_{nk} = 1$ and bandwidth is $W = 1\text{Hz}$. The transmit power is constrained to be $P_t = 40dBm$.

Figures 3 and 4 compare the eEE of RSMA, NOMA, and SDMA using the SCA and SSA methods at different phase shift angles of the IRS. It can be seen that SSA is much better than SCA in terms of overall EE optimization, an increase of 60%. From each subgraph, we can find that RSMA always outperforms NOMA and SDMA, especially when the phase shift angle needs to be orthogonal and aligned with the effective user receiver channel. As $\theta$ increases, the gap between RSMA and SDMA decreases because SDMA works well when the phase shift angle is sufficiently orthogonal to the user channel, where RSMA is significantly better than NOMA. So RSMA achieves more significant EE than SDMA and NOMA in the case of multiple phase shift angles and efficient user receiver channels.

Figure 5 compares the maximum EE of the system when the IRS phase shift $\theta = \frac{\pi}{9}$ and $\theta = \frac{4\pi}{9}$ using the SSA and SCA methods. Compared with SCA, SSA has a significant improvement in EE. The pictures clearly show that the EE of both algorithms increases significantly with the increase of the number of iterations under the limit of the total transmit power of the system.
addition, with fewer iterations, SSA can achieve the maximum EE of the system faster than SCA, regardless of whether the phase shift angle of the IRS is designed to be orthogonal or aligned with the effective user channel. The progressive time complexity of SSA is $O(t(d \times n + n))$, where $t$ is the number of iterations, $d$ is the number of variables, $n$ is the scale of the problem. However, the progressive time complexity of of SCA is $O(t^3 d^3)$. Obviously, the progressive time complexity of SCA is much higher than that of SSA. The experimental results show that the energy EE of SSA is significantly enhanced compared with SCA, while the time complexity is also reduced considerably. However, the global optimal result to the SSA optimization problem is unknown. In this case, it is assumed that the optimal solution obtained so far is the global optimal solution.

V. CONCLUSION

This paper introduces RSMA to the IRS-assisted terahertz system, focusing on solving the EE optimization problem. Simulation results show that RSMA is better than NOMA and SDMA regarding EE. SSA can prevent the results from falling into the local optimum, while SCA can easily approach singular points, resulting in inaccurate calculation results. SSA consumes less time and optimizes overall performance. At the same time, the IRS can intelligently improve wireless channel quality and promote wireless transmission.

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