Non-orthogonal unicast and multicast transmission with IRS-assisted Rate-Splitting Multiple Access in multiuser MISO systems

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Abstract. In MISO systems, novel communication technologies such as NOMA and multicast transmission have attracted widespread attention to meet the diverse needs of users. However, traditional NOMA and multicast transmission schemes have certain limitations in dynamic interference management and resource allocation. To resolve this issue, this paper proposes a RSMA scheme assisted by phase quantized Intelligent Reflecting Surface (IRS) for downlink MISO systems with nonorthogonal transmission of unicast and multicast signals. In this scheme, through reconfiguring unicast and multicast signals and combining them into a super-common stream and partial unicast messages, RSMA achieves dynamic interference management of multi-user while effectively separating unicast and multicast streams. To maximize the weighted sum rate(WSR), we put forward an alternating optimization(AO) algorithm that utilizes Weighted Minimum Mean Square Error (WMMSE) estimation and convex set intersection representation, which jointly optimizes the equivalent beamforming matrix,rate allocation and phase shift matrix. Simulation results illustrate that the proposed single-layer RSMA exhibits performance closer to that of DPC encoding compared to traditional NOMA and MULP schemes. Furthermore, we extensively investigate the relationship between the WSR of RSMA and system parameters, providing important guidance for practical engineering applications.

Keywords: RSMA, phase-quantized IRS,non-orthogonal transmission of unicast and multicast signals, Weighted sum rate, Phase shift matrix.

1. Introduction

The advancements in 5G have supported various technologies. However, the advancement of novel multiple access technologies for 6G systems is driven by the limited availability of wireless resources and the diverse nature of radio applications in 5G and future networks.

Rate-splitting multiple access (RSMA) is one of the novel multiple access technologies, which users' messages are divided into public and individual parts. The public portion is decoded first by all users and eliminated following successive interference cancellation (SIC), while the individual portion is decoded solely by the intended recipient and perceived as interference by other users. Therefore, RSMA technology can be utilized to handle interference by partially decoding it and partially ignoring it as background noise.[1]. RSMA can achieve better spectrum efficiency and maintain the fairness of users, which can also better cope with inter-user interference and multipath fading [2]. The performance of RSMA under different scenarios has been researched in recent years. The MISO BC scenario has been extensively studied [3]-[5]. Apart from the typical MISO BC scenario, MIMO has also been widely reported [6]-[8]. In addition, RSMA for different kinds of signals has been researched in [3]-[4] and [9]-[11]. Furthermore, RSMA exhibits certain advantages in millimeter-wave systems [12]-[13], multicell cooperative multi-point joint transmission [14], wireless powered communication [15], and cloud radio access networks [16].

In addition, the IRS is regarded as one of the key technological innovations for wireless communications in the future. It is adopted to reconstruct the wireless transmission environment by comprising a multitude of reflecting elements, significantly enhancing the efficiency of wireless communication networks[17]. IRS has been widespread applied in capacity/data rate analysis [18][19], power/spectrum optimization [20][21], deep learning-assisted communication design [22],and physical layer security enhancement [23]-[24].

In order to combine the advantages of IRS and RSMA, an increasing amount of research has researched IRS-aided RSMA under different scenarios [25]-[28]. These studies demonstrate that combining RSMA with IRS can effectively enhance transmission rates and improve communication performance. In practical engineering applications, due to cost and technical limitations, it is challenging to achieve continuous phase variations in IRS. In addition, in complex network environments, the coexistence of unicast and multicast signals is becoming increasingly common to meet various types of communication needs. However, existing research mostly only considers the case where IRS has continuous phase variations or only considers the transmission of unicast signals.

In this paper, we propose the IRS-assisted RSMA in non-orthogonal transmission of unicast and multicast signals with the coexistence of direct links and IRS-aided links. In this study, the unicast messages are divided into common and individual segments. The common segment is combined with the multicast message and encoded into a super common stream, which is decoded by all users. IRS is employed in downlink split multiple access for MISO systems. Furthermore, we compare RSMA with three MIMO transmission schemes: dirty paper coding (DPC), NOMA, and MULP.

Inspired by reference [11], we establish an equivalent optimization scheme on the basis of the WMMSE algorithm. The objective of maximizing the WSR is transformed into minimizing mean square error and solved by AO algorithm. The conclusion drawn in this paper demonstrates that RSMA's performance closely approaches the optimal DPC region compared to MULP and NOMA, which presents relative advantages. In addition, phase quantization, coexistence of direct links and IRS-aided links, and joint transmission of unicast and multicast messages are more practical for engineering applications.

2. System Model

This paper explores an IRS-assisted multi-user MISO system. We examine a MISO system that comprises a BS with M antennas, a reflective IRS, and K single-antenna users, where K = 1,...,K and M ≥ K. The IRS is equipped with N reflective elements. The BS transmits K synchronous data streams from its M antennas. As Fig.1 shows, a portion of the signals initially reaches the reflective IRS and then reaches the receiver through reflection from the IRS, while another portion is directly transmitted from the BS to users via the direct link.

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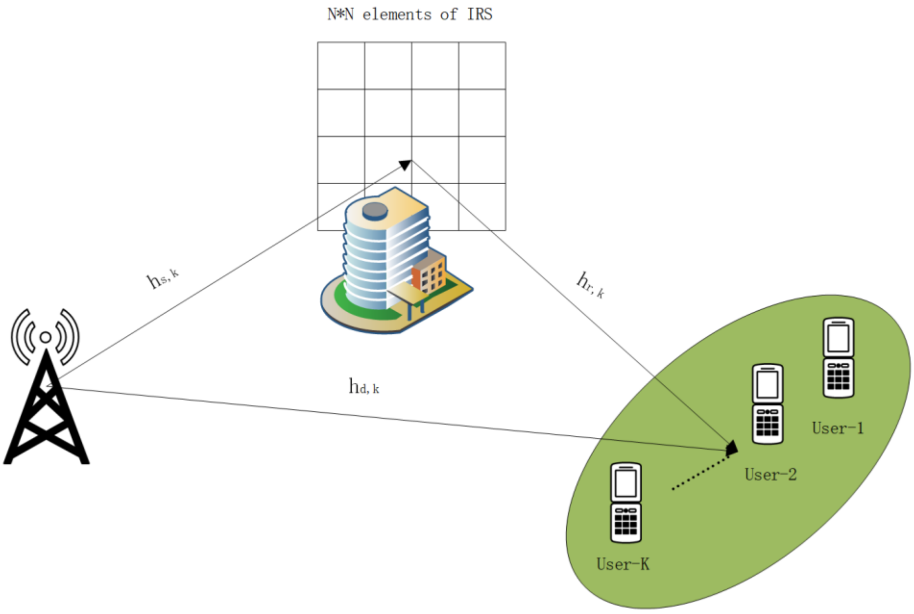

Figure 1. An MISO system with IRS-aided link and direct link.

The message directed to user k is segregated into unicast and multicast constituents. Specifically, the unicast message W_k, for all k in K, is partitioned into a common component $W_{k,c}$ and a individual component $W_{k,p}$. $W_{k,c}$ is encoded alongside the multicast message W_c into a super common stream s_c, necessitating decoding by all users. It's worth noting that s_c encompasses not just the entirety of the multicast message, but also segments of unicast messages directed towards distinct users. The individual segments $W_{1,p}$, ..., $W_{k,p}$ of unicast streams are autonomously encoded into individual streams s_1, ..., s_K. Furthermore, we assume that the channel matrix $\mathbf{h}_{s,k} \in \mathrm{C}^{(N\times M)}$ (between the BS and the IRS), the channel vectors $\mathbf{h}_{r,k} \in \mathrm{C}^{(1\times N)}$(between the IRS and users), and the channel vectors $\mathbf{h}_{d,k} \in \mathrm{C}^{(M\times 1)}$ (between the BS and users) are fully understood and can be inferred from pilot signal transmissions and feedback channels.

During each time slot, the BS transmits a multicast message W_c for all k users and transmits K unicast messages W_1, ..., W_k, each intended for a specific user. The common components of the multicast message Wc and unicast messages are encoded into the data stream s_c independently, whereas the individual components of the unicast messages are encoded into data streams s_c, s_1, ..., s_K, independently. These encoded streams are subsequently subjected to precoding utilizing the matrix $\mathbf{P} = (\mathbf{P}_c, \mathbf{P}_1, \cdots, \mathbf{P}_K)$, where $\mathbf{p}_c \in \mathrm{C}^{(M\times 1)}$ and $\mathbf{p}_k \in \mathrm{C}^{(M\times 1)}$ denote the precoding matrices for the super common stream $\mathbf{s}_c$ and the individual segments $\mathbf{s}_k$ of unicast messages, respectively, $k \in$ K. Given the assumption $E\{\mathbf{ss}^H\} = \mathbf{I}$, where $\mathbf{H}$ represents the conjugate transpose, the power of the BS is restricted to $\mathrm{tr}\{\mathbf{PP}^H\} \leqslant P_t$. The signal acquired by user k is given by

$$\begin{aligned} y_k &= \mathbf{h}_{d,k}^H \mathbf{PS} + \mathbf{h}_{r,k}^H \mathbf{\Phi} \mathbf{h}_{s,k}^H \mathbf{PS} + n_k \\ &= (\mathbf{h}_{d,k}^H + \mathbf{h}_{r,k}^H \mathbf{\Phi} \mathbf{h}_{s,k}^H)\mathbf{PS} + n_k \end{aligned} \tag{1}$$

where yk denotes the signal acquired by user k. G represents the beamforming matrix utilized at the base staion. The phase shift matrix Φ of the IRS, denoted as $diag(\phi_1, \phi_2, \cdots, \phi_N) \in \mathbb{C}^{(N\times N)}$, where Φn = ejφn, and φn denotes the phase shift induced by all elements of IRS. The additive white Gaussian noise, which has a variance of σ2 and a mean of zero, is denoted by nk.

At the user side, considering the signals from all individual streams as interfering factors, each user decodes the supercommon stream. The SINR of the super-common stream at user k is given as

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$$\gamma_{c,k} = \frac{|(\mathbf{h}_{d,k}^H+\mathbf{h}_{r,k}^H\mathbf{\Phi}\mathbf{h}_{s,k}^H)\mathbf{p}_c|^2}{\sum_{i=1}^K |(\mathbf{h}_{d,k}^H+\mathbf{h}_{r,k}^H\mathbf{\Phi}h_{s,k}^H)\mathbf{p}_i|^2+\sigma^2} \tag{2}$$

Once $\mathbf{s}_c$ is decoded successfully and extracted from original received signal, user k proceeds to decode its individual stream $\mathbf{s}_k$, treating other users' streams as interference. The SINR of the individual stream at user k is given as

$$\gamma_{k,c} = \frac{|(\mathbf{h}_{d,k}^H+\mathbf{h}_{r,k}^H\mathbf{\Phi}\mathbf{h}_{s,k}^H)\mathbf{p}_k|^2}{\sum_{i=1,i\neq k}^K |(\mathbf{h}_{d,k}^H+\mathbf{h}_{r,k}^H\mathbf{\Phi}\mathbf{h}_{s,k}^H)\mathbf{p}_i|^2+\sigma^2} \tag{3}$$

Based on Shannon's formula, the corresponding achievable rate for both the super-common stream and the individual stream is given by

$$\mathbf{R}_{k,c} = \log_2(1+\gamma_{k,c}) \text{ and } \quad \mathbf{R}_k = \log_2(1+\gamma_k) \tag{4}$$

To guarantee successful decoding of $\mathbf{s}_c$ by all of the users, its achievable rate must not surpass

$$R_c = \min_k\{R_{1,c}, \cdots, R_{k,c}\}. \tag{5}$$

where $\mathbf{R}_c$ is allocated to accommodate the transmission rates of both the multicast message $\mathbf{W}_c$ and the shared components of unicast messages across all users, denoted as $\mathbf{W}_{1,c}, \cdots, \mathbf{W}_{k,c}$. Define $\mathbf{C}_0$ as the portion of $\mathbf{R}_c$ dedicated to transmitting the multicast message $\mathbf{W}_c$, and $\mathbf{C}_{k,c}$ denote the portion allocated to transmit the individual message $\mathbf{W}_k$ for user k. Hence, the attainable super common rate is given by

$$\mathbf{R}_c = \mathbf{C}_0 + \sum_{K\in\mathcal{K}} \mathbf{C}_{k,c} \tag{6}$$

The purpose of this paper is to optimize the WSR of the unicast messages, while adhering to limitations on the multicast message rate and the BS power. The overall attainable rate of the unicast message for user k is represented as $\mathbf{R}_{k,tol} = \mathbf{C}_{k,c} + \mathbf{R}_k$. Using a predefined weight vector u, the WSR attained by the individual messages in the K user transmission system with RSMA for non-orthogonal unicast and multicast streams is given as

$$\mathbf{R}_{WSR} = \max_{\mathbf{P},\mathbf{c},\mathbf{\Phi}}\{\sum_{k=1}^{K} u_k R_{k,tol}\}$$

$$s.t \begin{cases} \mathbf{C}_0 + \sum_{K\in\mathcal{K}} C_{k,c} \leq R_{k,c} \\ \mathbf{C}_0 \geqslant R_0^{th} \\ \mathbf{C}_{k,c} \geqslant 0, \forall k \in \mathcal{K} \\ \mathrm{tr}\{\mathbf{P}\mathbf{P}^H\} \leq P_t \\ |\phi_n| = 1, n = 1, \cdots, N \end{cases} \tag{7}$$

where $\mathbf{c} = [c_0, c_{1,c}, \cdots, c_{k,c}]$ is the common rate vector and $\mathbf{R}^{th}_0$ is the multicast message rate limitation.

3. Optimization Framework

The non-convex nature of the WSR optimization problem derived from the equations presents significant challenges for mathematical solutions. Hence, we reframe it into a convex optimization problem.

Inspired by the WMMSE algorithm proposed in reference [11] for maximizing the weighted sum-rate without considering multicast messages, we tackle the WSR optimization problem for single-layer RS based on the WMMSE algorithm.

Without sacrificing generality, we focus on user k, while the process of the WMMSE algorithm for other users follows a comparable pattern. The received signal by the user k is denoted as $\mathbf{Y}_k = (h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H)$PS+$\mathbf{n}_k$. The User-k employs

SIC to sequentially decode $\mathbf{s}_{k,c}$ and $\mathbf{s}_k$. Initially, the super-common stream $\mathbf{s}_{k,c}$ is decoded, estimated as $\hat{\mathbf{s}}_{k,c} = g_{k,c}y_k$, where $\mathbf{g}_{k,c}$ represents the equalizer for the super-common stream. Subsequently, $\mathbf{s}_{k,c}$ is decoded and subtracted from $\mathbf{y}_k$ to calculate the estimate of the private stream $\mathbf{s}_k$, denoted as $\hat{\mathbf{s}}_k = g_k\big(y_k - \big(h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H\big)p_c\hat{s}_{k,c}\big)$, where $\mathbf{g}_k$ is the equalizer for the private stream.

Due to the constraints of engineering requirements, the phase can be uniformly quantized and the set of quantized phase is given by $\{0, \frac{2\pi}{2Q}, \dots, \frac{(2^Q-1)2\pi}{2Q}\}$. Hence, denote $\mathbf{b}_q^n \in \{0,1\}$. Thus, φ_n can be represented by Q bits, the phase of each RIS element can be encoded by

$$\varphi_n = \frac{\pi}{2^{Q-1}} * (b_{Q-1}^n * 2^{Q-1}, \dots, b_0^n * 2^0) \tag{8}$$

3.1. Weight Allocation and Equalizer Optimization

The problem (7), involving the simultaneous optimization of ($\mathbf{P}$,$\mathbf{c}$,$\mathbf{\Phi}$), presents a non-convex challenge. Inspired by the WMMSE algorithm, with other variables fixed, the $\mathbf{g}^{MMSE}$ represents the MMSE optimal equalizer. With other variables fixed, the $\mathbf{u}^{MMSE}$ represents the MMSE optimal weight. Hence, we optimize the $\mathbf{u}$ and $\mathbf{g}$ firstly.

The MSE for the common and individual streams are given as $\varepsilon_{k,c} \triangleq E\{|s_{k,c} - \hat{\mathbf{s}}_{k,c}|^2\}$ and $\varepsilon_k \triangleq E\{|s_k - \hat{\mathbf{s}}_k|^2\}$, respectively. The mean square errors for the super-common and individual parts of user k is calculated as

$$\varepsilon_{k,c} = |g_{k,c}|^2 T_{k,c} - 2\mathcal{R}\{g_{k,c}H_k p_c\} + 1,$$
$$\varepsilon_k = |g_k|^2 T_k - 2\mathcal{R}\{g_k H_k p_k\} + 1 \tag{9}$$

Where, $\mathbf{H}_k = h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H$ is thee quivalent channel matrix $\mathbf{T}_{k,c} \triangleq |(h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H)p_c|^2 + \sum_{i=1}^k |(h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H)p_i|^2 + \sigma 2$ and $\mathbf{T}_k \triangleq |\sum_{i=1}^k |(h_{d,k}^H + h_{r,k}^H \Phi h_{s,k}^H)p_i|^2 + \sigma^2$. The optimal MMSE equalizers are then calculated by solving $\frac{\partial \xi_{k,c}}{\partial g_{k,c}} = 0, \frac{\partial \xi_k}{\partial g_k} = 0$, which are given by

$$\mathbf{g}_{k,c}^{MMSE} = p_c^H H_k T_{k,c}^{-1}$$
$$\mathbf{g}_k^{MMSE} = p_k^H H_k T_k^{-1} \tag{10}$$

Substituting (9) into (8), we derive the MMSEs for both the super-common and individual streams

$$\varepsilon_{k,c}^{MMSE} \triangleq \min_{\mathbf{g_{k,c}}\boldsymbol{\varepsilon_{k,c}}} = T_{k,c}^{-1} T_k \varepsilon_k^{MMSE} \triangleq \min_{\mathbf{g_k}\boldsymbol{\varepsilon_k}} = T_k^{-1}(T_k - |H_k p_k|^2) \tag{11}$$

The augmented weighted mean square error (WMSEs) are as follows

$$\xi_{k,c} \triangleq u_{k,c}\varepsilon_{k,c} - \log_2(u_{k,c}) \xi_k \triangleq u_k \varepsilon_k - \log_2(u_k) \tag{12}$$

here, $u_{k,c}$ and u_k denote the weights corresponding to the MSEs of user k.And then, substituting MMSEs into (11), we obtain

$$\xi_{k,c}^{MMSE} = u_{k,c}\varepsilon_{k,c}^{MMSE} - \log_2(u_{k,c}) \, \xi_k^{MMSE} = u_k \varepsilon_k^{MMSE} - \log_2(u_k) \tag{13}$$

Then solve the equations $\frac{\partial \xi_{k,c}}{\partial u_{k,c}} = 0, \frac{\partial \xi_k}{\partial u_k} = 0$, we obtain the optimal MMSE weights as

$$u_{c,k}^* = u_{k,c}^{MMSE} \triangleq (\varepsilon_{c,k}^{MMSE})^{-1} u_k^* = u_k^{MMSE} \triangleq (\varepsilon_k^{MMSE})^{-1} \tag{14}$$

3.2. Common Rate and Precoderding matrix Optimization

When ($\mathbf{u}$,$\mathbf{g}$) are fixed, the optimization problem (7) transforms into a convex QCQP, amenable to solution via interior-point methods. Therefore, we optimize the $\mathbf{P}$ and $\mathbf{x}$ secondly.

Substituting (13) into (12), we finally derive the rate WMMSE relationship as

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$$\begin{aligned}\xi_{k,c}^{MMSE} &\triangleq \min_{u_{k,c},g_{c,k}} \xi_{k,c} = 1 - R_{k,c}\\ \xi_{k}^{MMSE} &\triangleq \min_{u_k,g_k} \xi_{k} = 1 - R_{k}\end{aligned} \tag{15}$$

Therefore, we can build the relationships between rate and WMMSE for other users by the same approach. According to the relationship between rate and WMMSE in (14), the optimization problem described in (7) is equivalently reformulated as the WMMSE problem given by

$$\mathbf{R}_{WSR} = \max_{\mathbf{P},\mathbf{x},\mathbf{\Phi},\mathbf{u},\mathbf{g}} \{\sum_{k=1}^{K} u_k \xi_{k,tol}\}$$
$$s.t\begin{cases}\mathbf{X}_0 + \sum_{K\in\mathcal{K}} X_{k,c} + 1 \geq \xi_{k,c}, \forall k \in \mathcal{K}\\ X_0 \leqslant -R_0^{th}\\ \mathbf{X}_{k,c} \leqslant 0, \forall k \in \mathcal{K}\\ tr\{\mathbf{P}\mathbf{P}^H\} \leq P_t\\ |\phi_n| = 1, n = 1,\cdots,N\end{cases} \tag{16}$$

where $\xi_{tol,k} = X_{k,c} + \xi_k, \xi_c = \max\{\xi_{k,c}\}, X_{k,c} \triangleq -C_{k,c}$ and $\mathbf{x} = (X_0, X_{1,c},\ldots,X_{k,c})$ is the conversion of the common rate $\mathbf{c}.\mathbf{u} = (u_{1,c},\ldots,u_{K,c},u_1,\ldots,u_k)$ and the weights and equalizers vector is $\mathbf{g} = (g_{1,c},\ldots,g_{K,c},g_1,\ldots,g_k)$

3.3. *IRS Phase Shift Optimization*

With fixed $(\mathbf{u},\mathbf{g},\mathbf{P},\mathbf{x})$, we can optimize $\{\mathbf{b},\mathbf{\Phi}\}$ in the end.However, the $\mathbf{b}_q^n \in \{0,1\}$ is non-convex set, we should convert it into a convex one.

It is equivalent to $\mathbf{b}_q^n(\mathbf{b}_q^n - 1) = 0$,Denoting $\mathbf{b} = \left(b_0^1,\ldots,b_{Q-1}^1,\ldots,b_0^n,b_{Q-1}^n,\ldots,b_0^N,\ldots,b_{Q-1}^N\right)^T$ and 1 is a full 1-vector, the binary constraint can be represented by$\{\mathbf{b} : \mathbf{b}^{\mathbf{T}}\mathbf{b} - \mathbf{1}^{\mathbf{T}}\mathbf{b} = \mathbf{0}\}$,which is equivalent to the intersection of two conves sets, i,e,

$$\begin{aligned}&\{\boldsymbol{b}: \boldsymbol{b}^T\boldsymbol{b} - \mathbf{1}^T\boldsymbol{b} = \mathbf{0}\}\\ &\Leftrightarrow \{\boldsymbol{b}: \boldsymbol{b}^T\boldsymbol{b} - \mathbf{1}|^T\boldsymbol{b} \leq \mathbf{0}\} \cap \{\boldsymbol{b}: \mathbf{1}^T\boldsymbol{b} - \boldsymbol{b}^T\boldsymbol{a} \leq \mathbf{0}\}\\ &\Leftrightarrow \{\boldsymbol{b}: \mathbf{1}^T\boldsymbol{b} - \boldsymbol{b}^T\boldsymbol{b} \leq \mathbf{0}\} \cap \{\boldsymbol{b} \in [0,1]^{NQ}\}\end{aligned} \tag{17}$$

Hence, the optimization problem (15) is reformulated as

$$\mathbf{R}_{WSR} = \max_{\mathbf{P},\mathbf{x},\mathbf{\Phi},\mathbf{u},\mathbf{g}} \{\sum_{k=1}^{K} u_k \xi_{k,tol}\}$$
$$s.t\begin{cases}\mathbf{X}_0 + \sum_{K\in\mathcal{K}_{k,c}} X_{k,c} + 1 \geq \xi_{k,c}, \forall k \in \mathcal{K}\\ X_0 \leqslant -R_0^{th}\\ \mathbf{X}_{k,c} \leqslant 0, \forall k \in \mathcal{K}\\ \mathbf{tr}\{\mathbf{P}\mathbf{P}^H\} \leq P_t\\ \mathbf{b}: \mathbf{1}^T\mathbf{b} - \mathbf{b}^T\mathbf{b} \leq \mathbf{0}\\ \mathbf{b} \in [0,1]^{NQ}\end{cases} \tag{18}$$

4. Alternating Optimization Algorithm of Irs-Rsma

Algorithm 1 outlines the procedures of AO, therefore, in the nth iteration, the weights and equalizers are computed through $(\mathbf{u},\mathbf{g})$=($\mathbf{u}MMSE(\mathbf{P}(n-1)$,$\mathbf{b}(n-1),\mathbf{x}(n-1)),\mathbf{g}MMSE(\mathbf{P}(n-1),\mathbf{b}(n-1),\mathbf{x}(n-1))$) based on the $\mathbf{P}(n-1),\mathbf{x}(n-1),\mathbf{b}(n-1)$ in the last iteration by using WMMSE algorithm. Then fix $(\mathbf{u},\mathbf{g},\mathbf{b})$, the

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previous optimization problem becomes a convex optimization problem , update the (**P**,**x**). Finally, with fixed (**P**,**x**,**u**,**g**), the CVX convex optimization toolbox is used to calculate **a** and update **Φ**. It should be noted that because of the constraint of the CVX convex optimization toolbox, the expressions $\mathbf{1}^T\mathbf{b}-\mathbf{b}^T\mathbf{b} \leqslant \mathbf{0}$ in (17) and $\phi_n = e^{j\varphi n}$ must be roughly represented as $\mathbf{1}^T\mathbf{b} - (2\mathbf{b}_{n-1}^T\mathbf{b} - \mathbf{b}_{n-1}^T\mathbf{b}_{n-1}) \leq 0, e^{j\varphi} \approx e^{j\varphi_{n-1}} + je^{j\varphi_{n-1}}(\varphi - \varphi_{n-1})$by using one-order Taylor expansion, where $\mathbf{a}_{n-1}$ and φ_{n-1} represent the encoded IRS phases in (n−1) iteration. (**u**,**g**) and (**x**,**P**,**b**,**Φ**) undergo iterative updates until achieving the desired coverage of the WSR. Here, β represents the error tolerance for coverage, and $\mathbf{WSR}^{[n]}$ is the WSR computed at the basis of the updated (**x**,**b**,**P**,**Φ**) and (**u**,**g**) in the n_{th} iteration.

Algorithm 1: AO Algorithm
1: Initialization: $n \leftarrow 0$, $\mathbf{P}^{[n]}$, $\mathbf{b}^{[n]}$, $\mathbf{x}^{[n]}$, $\mathbf{WSR}^{[n]}$
2: Repeat:
3: $n \leftarrow n + 1$
4: $\mathbf{u}[n] \leftarrow \mathbf{u}MMSE(\mathbf{P}[n-1],\mathbf{b}[n-1],\mathbf{x}[n-1])$
5: $\mathbf{g}[n] \leftarrow \mathbf{g}MMSE(\mathbf{P}[n-1],\mathbf{b}[n-1],\mathbf{x}[n-1])$
6: Update ($\mathbf{P}[n]$,$\mathbf{x}[n]$) using $\mathbf{u}[n]$ and $\mathbf{g}[n]$
7: Update ($\mathbf{b}[n]$, $\mathbf{\Phi}[n]$) using $\mathbf{P}[n]$, $\mathbf{u}[n]$, $\mathbf{x}[n]$, $\mathbf{g}[n]$
8: Calculate $\mathbf{WSR}^{[n]}$
9: **Until** $\lvert\mathbf{WSR}^{[n]} - \mathbf{WSR}^{[n-1]}\rvert \leq \beta$

5. Simulation Results

This section presents the characteristics of IRS-assisted RSMA through simulation. In the simulation, we analyze a MISO system comprising a multi-antenna BS, a reflective IRS, and several users. The BS is furnished with 4 antennas and communicates with 4 users, while the reflective IRS initially features 16 reflecting elements.

To begin with, we compare the proposed quantized IRS-assisted 1-layer RSMA with other three ISR-assisted multiple access programs (i.e. DPC, NOMA, and MULP) using 100 Monte Carlo simulations. The BS has 4 transmit antennas and serves 4 users with only one antenna in all simulations. The SNR varies from 0 dB to 40 dB, and the rate limitation of multicast signal is set to 0.1 bit/s/Hz, thus $R_0^{th} =$ 0.1 bit/s/Hz. The channel realizations of $h_{s,k}$, $h_{r,k}$, $h_{d,k}$ are random, generalized by a complex standard normal distribution. In addition, the quantization of the IRS phase is taken into account, and randomly generated binary bits are adopted to initialize the phase. Moreover, we presume that the total weight assigned to users sums up to one, i.e. $\mathbf{u}_1+\mathbf{u}_2+\mathbf{u}_3+\mathbf{u}_4= 1$. The outcomes shown in Fig.1 correspond to the scenario where the weight vector **u** is set to [0.1, 0.2, 0.3, 0.4]. It is evident from the results that the proposed method of qualified IRS assisted RSMA outperforms NOMA and MULP, while achieving a weighted sum rate slightly lower than DPC. In the MISO (Gaussian) broadcast channel, with perfect CSIT, DPC encoding stands as the sole strategy capable of fully utilizing the channel capacity.

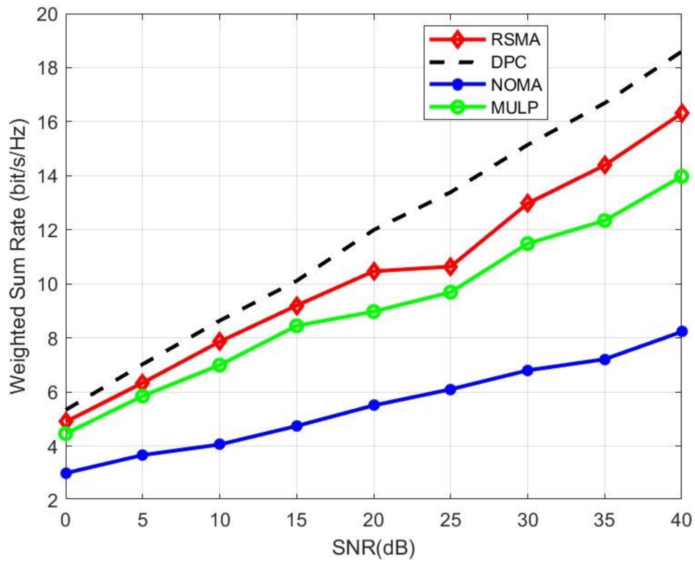

Figure 2. WSR under SNR comparision of different strategies.

Then, to visually demonstrate the improvement in channel communication quality with the use of IRS, we separately transmit the signal through the direct link and solely through the IRS-assisted link, while keeping other parameters constant.

Fig. 3 shows that the deployment of IRS can significantly enhance users' weighted sum rates, as the deployment of passive IRS can improve the quality of the weakest channel.

Next, we exam the influence of the number of antennas at the transmitter with a fixed SNR of 10 dB. The number of antennas varies from 4 to 20. The channel realizations via the IRS-assisted link and via the direct link are all randomly generated from the standard normal distribution. Other parameters remain consistent with the previous settings.

Figure 4 showns the WSR results across varying numbers of antennas at the BS. As illustrated in Figure 4, the WSR demonstrates improvement with an increasing number of antennas. This is because multiple transmit antennas can send data to

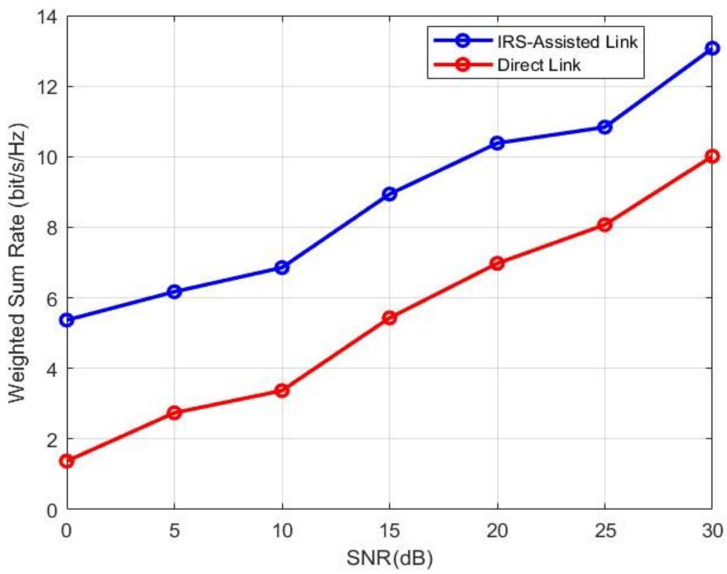

Figure 3. WSR versus two different links

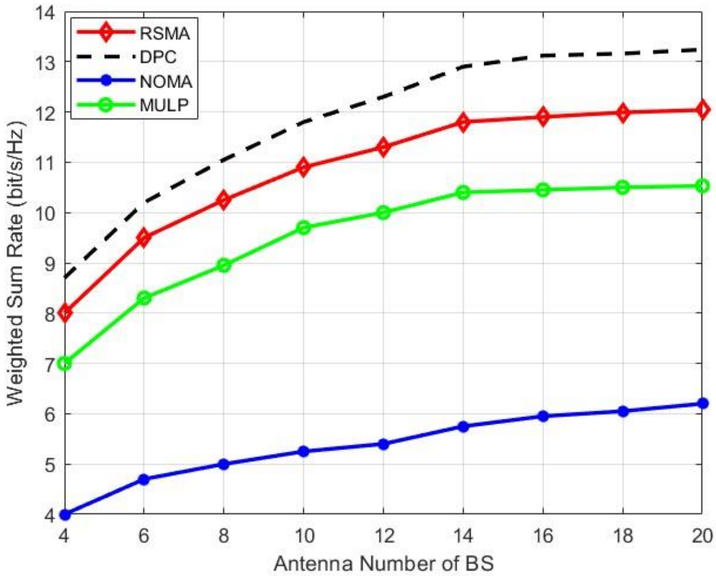

Figure 4. WSR under different number of antennas at the BS.

different receive antennas simultaneously, which improves the system's spectral efficiency and increase the data transmission rate of wireless communication. As the number of antennas continues to increase, the contribution to the weighted sum rate gradually tends to saturate, and the weighted sum rate remains closely unchanged.

Then, we fix the SNR and the number of antennas on the transmitter side, and change the number of IRS's reflective elements as N = [4, 9, 16, 25, 36, 49, 64]. The channel initialization and other parameters setting are consistant with the previous section.

Figure 5 shows the WSR across varying numbers of IRS reflective elements. As depicted in Figure 4, it's evident that the WSR escalates with the augmentation of IRS reflecting elements. This trend is credited to the expanded number of reflecting elements, facilitating additional signal paths and reflection opportunities, thereby enhancing the overall sum rate.

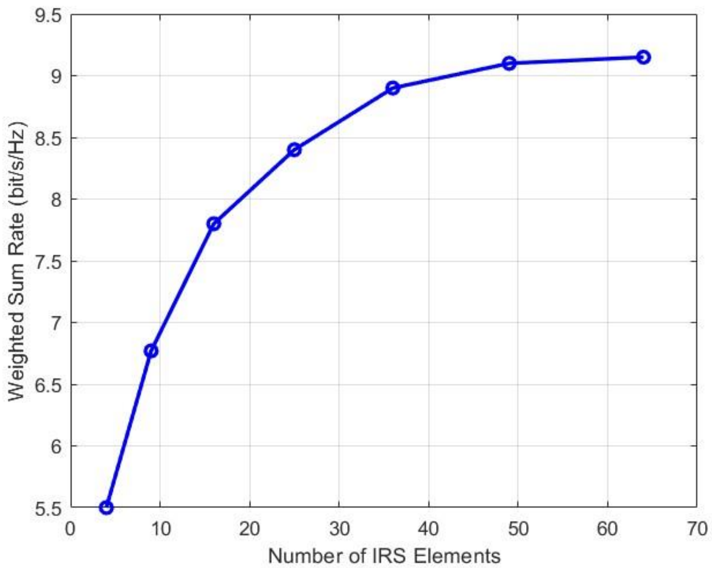

Figure 5. WSR under different number of IRS reflective elements.

6. Conclusion

In this paper, we propose a model for a phase-quantized IRS-aided multiple-input MISO downlink system employing rate-splitting multiple access for both unicast and multicast transmissions. To maximize the WSR, an alternating optimization algorithm based on WMMSE estimation and convex set intersection representation is proposed, jointly optimizing the equivalent beamforming matrix, phase shift matrix, and rate allocation. Simulation results demonstrate that compared to NOMA and MULP, the proposed single-layer-RSMA exhibits certain advantages, and a comprehensive simulation is conducted to explore the performance of the WSR of IRS assisted 1-layer RSMA with different scenario parameters. These findings provide significant guidance for practical engineering applications.

Authorship

Kuiliang Li: idea, Writing-Original draftm, Mathematical Modeling.
Rui Xue: Optimization and simulation.

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