Joint Pilot and Payload Power Control for Uplink MIMO-NOMA with MRC-SIC Receivers

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Abstract—This letter proposes a joint pilot and payload power allocation (JPA) scheme to mitigate the error propagation problem for uplink multiple-input multiple-output non-orthogonal multiple access (MIMO-NOMA) systems. A base station equipped with a maximum ratio combining and successive interference cancellation (MRC-SIC) receiver is adopted for multiuser detection. The average signal-to-interference-plus-noise ratio (ASINR) of each user during the MRC-SIC decoding is analyzed by taking into account the error propagation due to the channel estimation error. Furthermore, the JPA design is formulated as a non-convex optimization problem to maximize the minimum weighted ASINR and is solved optimally with geometric programming. Simulation results confirm the developed performance analysis and show that our proposed scheme can effectively alleviate the error propagation of MRC-SIC and enhance the detection performance, especially for users with moderate energy budgets.

I. INTRODUCTION

Non-orthogonal multiple access (NOMA) has recently been recognized as a promising multiple access solution to fulfill the stringent quality of service (QoS) requirements of the fifth-generation (5G) wireless networks, such as high spectral efficiency and massive connectivity [1]. The principle of NOMA is to exploit the power domain for multiuser multiplexing and to adopt the successive interference cancellation (SIC) decoding at receivers to mitigate the multiuser interference [1]. In recent years, downlink NOMA has been extensively studied in the literature and it has been shown that downlink NOMA can achieve a considerable performance gain over conventional orthogonal multiple access (OMA) schemes in terms of spectral efficiency and energy efficiency.

In fact, NOMA inherently exists in uplink communications, since the electromagnetic waves are naturally superimposed at a receiving base station (BS) and the implementation of SIC is more affordable for BSs than user terminals. For instance, a simple back-off power control scheme was proposed for uplink NOMA [2], while an optimal resource allocation algorithm to maximize the system sum rate was developed in [3]. The authors in [4] proposed a general power control framework to guarantee the QoS in downlink and uplink NOMA. Most recently, multiple-input multiple-output NOMA (MIMO-NOMA) systems are of more interests [5], [6]. In particular, maximum ratio combining with successive interference cancellation (MRC-SIC) receiver is adopted for multiuser detection. In the meantime, the reduced payload power allocation and ideal SIC decoding are considered in most of existing works, e.g. [3], [7]. For both single-antenna and multiple-antenna systems, it is well-known that error propagation of SIC decoding limits the promised performance gain brought by NOMA. In practice, the sources of error propagation are two-fold: one is the channel estimation error (CEE) and the other is the erroneous in data detection. This letter focuses on tackling the former issue via exploiting the non-trivial trade-off between the pilot and payload power allocation for uplink MIMO-NOMA systems for a given total energy budget. Specifically, a higher pilot power yields a better channel estimation but leads to a less payload power for data detection. In the meantime, the reduced payload power would introduce a lower inter-user interference (IUI) for other users. Therefore, jointly designing the pilot and payload power allocation is critical for mitigating the error propagation.

In this letter, to alleviate the error propagation in SIC, we propose a joint pilot and payload power allocation (JPA) scheme for uplink MIMO-NOMA with a MRC-SIC receiver based on a practical minimum mean square error (MMSE) channel estimator. We analyze the average signal-to-interference-plus-noise ratio (SINR) of each user during the MRC-SIC decoding. Furthermore, under a total energy budget constraint for each user, the JPA design is formulated as a non-convex optimization problem to maximize the minimum weighted average SINR (ASINR). The globally optimal solution of the JPA design problem is obtained by geometric programming. Simulation results demonstrate that the proposed JPA scheme is beneficial to mitigate the error propagation, which enhances the data detection performance, especially in the moderate energy budget regime.

II. SYSTEM MODEL

A. System Model

We consider an uplink MIMO-NOMA communication system in a single-cell with a BS equipped with $M$ antennas serving $K$ single-antenna users. All the $K$ users are allocated on the same frequency band. Every user transmits multiple frames over multiple coherence time intervals (CTI) to the BS, where we assume that the duration of each frame is comparable to that of a CTI. In particular, each frame consists of $T$ pilot symbols and $D$ data symbols consecutive in time, as shown in Figure 1. We assume that $T$ and $D$ are fixed as it is commonly implemented in practical systems for simplifying.
time synchronization. Instead of considering symbol-level SIC as in most of existing works in NOMA \[5, 7\], we adopt the codeword-level SIC to exploit coding gain. Note that, a codeword is usually much longer than the duration of a CTI and is spread over \( N \) frames, which is an important scenario for time-varying channels with a short coherence time.

In frame \( n \), the received signal at the BS during pilot transmission and data transmission are given by

\[
Y^p_n = H_n \mathbf{A} T + Z^p_n \quad \text{and} \quad Y^d_n = H_n \mathbf{B} D_n + Z^d_n, \tag{1}
\]

respectively. \( T \in \mathbb{C}^{K \times T} \) denotes the pilot matrix and \( D_n = \{d_{n,1}, \ldots, d_{n,K}\} \in \mathbb{C}^{K \times D} \) denotes the data matrix in frame \( n \). The diagonal matrices \( \mathbf{A} \) and \( \mathbf{B} \) are defined by \( \mathbf{A} = \text{diag} \{\sqrt{\alpha_1}, \ldots, \sqrt{\alpha_K}\} \) and \( \mathbf{B} = \text{diag} \{\sqrt{\beta_1}, \ldots, \sqrt{\beta_K}\} \), respectively, where \( \alpha_k \) and \( \beta_k \) denote the pilot and payload power of user \( k \), respectively.\[1\]

We assume that normalized orthogonal pilots are assigned to all the users exclusively, i.e., \( TT^H = I_K \) with \( T \geq K \). The matrices \( Z^p_n \in \mathbb{C}^{M \times T} \) and \( Z^d_n \in \mathbb{C}^{M \times D} \) denote the additive zero mean Gaussian noise with covariance matrix \( \sigma^2 \mathbf{I}_M \) during training phase and data transmission phase in frame \( n \), respectively. The matrix \( \mathbf{H}_n = \{h_{n,1}, \ldots, h_{n,K}\} \in \mathbb{C}^{M \times K} \) contains the channels of all the users in frame \( n \), where column \( k \) denotes the channel vector of user \( k \). Rayleigh fading assumption is adopted in this letter, i.e., \( h_{n,k} \sim \mathcal{CN}(0, \sqrt{\nu} \mathbf{I}_M) \), where \( \mathcal{CN}(0, \nu \mathbf{I}_M) \) denotes a circularly symmetric complex Gaussian distribution with zero mean and covariance matrix \( \nu \mathbf{I}_M \). Scalar \( \nu \) denotes the large scale fading of user \( k \) capturing the effects of path loss and shadowing. Since all the users are usually sufficiently separated apart compared to the wavelength, their channels are assumed to be independent with each other. Therefore, their channel correlation matrix is given by a diagonal matrix \( \mathbf{R}_H = M \text{diag} \{\nu_1^2, \ldots, \nu_K^2\} \). Without loss of generality, we assume that users are indexed in the descending order of large scale fading, i.e., \( \nu_1^2 \geq \nu_2^2 \geq \ldots \geq \nu_K^2 \). In this letter, we define strong or weak user based on the large scale fading since it facilitates the characterization of the channel ordering statistically across the codeword, i.e., user 1 is the strongest user, while user \( K \) is the weakest user. As a result, the SIC decoding order is assumed to be the descending order of large scale fading, i.e., users \( 1, 2, \ldots, K \) are decoded sequentially.

### III. Performance Analysis on ASINR

In the \( k \)-th step of the MRC-SIC decoding, after cancelling the signals of the previous \( k-1 \) users, the post-processing signal of user \( k \) in frame \( n \) is given by

\[
y^p_{n,k} = \hat{h}^H_{n,k} \hat{h}_{n,k} \sqrt{\beta_k} y^k_{n,k} + \hat{h}^H_{n,k} \sum_{l=1}^{k} \varepsilon_{n,l} \sqrt{\beta_l} d^l_{n,l} + \hat{h}^H_{n,k} Z^d_n d^k_{n,d}, \tag{2}
\]

where \( y^k_{n,k} \in \mathbb{C}^{T \times 1} \), \( \hat{h}_{n,k} \in \mathbb{C}^{M \times 1} \) denotes the MMSE channel estimates of user \( k \) in frame \( n \), and \( \varepsilon_{n,l} = h_{n,k} - h_{n,l} \) denotes the corresponding CEE. In \( 3 \), we assume that the error propagation is only caused by the CEE but not affected by the erroneous in data detection. It is a reasonable assumption if we can guarantee the ASINR of each user larger than a threshold to maintain the required bit-error-rate (BER) performance through the power control in the following. To this end, we first define the instantaneous SINR of user \( k \) in frame \( n \) as:

\[
\text{SINR}_{n,k} = \frac{s_{n,k}}{G_{n,k} + Q_{n,k} + \sigma^2} \quad \forall n, k, \tag{3}
\]

with \( s_{n,k} = \hat{h}^H_{n,k} \hat{h}_{n,k} \beta_k \), \( G_{n,k} = \sum_{l=k+1}^{K} \hat{h}^H_{n,k} h_{n,l} \beta_l \), and \( Q_{n,k} = \sum_{l=1}^{k} \hat{h}^H_{n,k} (h_{n,l} - h_{n,k}) (h_{n,k} - h_{n,l}) \beta_l \), while the ASINR of user \( k \) is defined by:

\[
\text{ASINR}_k = E \left\{ \frac{s_{n,k}}{G_{n,k} + Q_{n,k} + \sigma^2} \right\} \quad \forall k, \tag{4}
\]

where \( E \{ \} \) denotes the expectation operation. In fact, for codeword-level SIC, it is the ASINR rather than the instantaneous SINR that determines the detection performance \[9\].

Yet, for mathematical tractability, in the sequel, we adopt the lower bound of \( \text{ASINR}_k \) proposed in \( 9 \) as

\[
\text{ASINR}_k = \frac{E \{s_{n,k}\}}{E \{G_{n,k}\} + E \{Q_{n,k}\} + \sigma^2} \leq \text{ASINR}_k, \quad \forall k, \tag{5}
\]

Variable \( s_{n,k} \) denotes the desired signal power of user \( k \) in frame \( n \), \( G_{n,k} \) denotes the IUI power in the \( k \)-th step of MRC-SIC, and \( Q_{n,k} \) denotes the residual interference power caused by CEE. Clearly, \( s_{n,k}, G_{n,k}, \) and \( Q_{n,k} \) are functions of pilot and payload power allocation. Now, we express the closed-form of \( 5 \) through the following theorem.

**Theorem 1:** For two independent random vectors \( x, y \in \mathbb{C}^{M \times 1} \) with distribution of \( x \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_M) \), we define a scalar random variable \( \phi = y^H x / |y| \). Then, \( \phi \) is independent with \( y \) and it is distributed as a complex Gaussian distribution with zero mean and variance of \( \sigma^2 \), i.e., \( \phi \sim \mathcal{CN}(0, \sigma^2) \).

**proof 1:** It is clear that the random variable \( \phi \) for a given \( y \) is complex Gaussian distributed, where its conditional mean and variance are given by

\[
E \{ \phi | y \} = y^H E \{ x \} / |y| = 0 \quad \text{and} \quad \text{Var} \{ \phi | y \} = y^H E \{ xx^H \} y / |y|^2 = \sigma^2, \tag{6}
\]

respectively. Since the conditional mean and variance of \( \phi \) are uncorrelated with \( y \), hence \( \phi \) is independent of \( y \) with zero mean and variance of \( \sigma^2 \). This completes the proof.

Now, following the MMSE channel estimation \[10\] and invoking Theorem 1, we can easily obtain \( E \{s_{n,k}\} = A^H \Phi^{-1} A \) and \( E \{G_{n,k}\} = \sum_{l=k+1}^{K} \beta_l \), where \( \Phi = \mathbf{H}_n^H \mathbf{H}_n + \sigma^2 \mathbf{M} \), \( \mathbf{A} = \mathbf{H}_n^H \mathbf{A} \), and \( \mathbf{R}_H \) denotes the \( k \)-th column of \( \mathbf{R}_H \). Then, based on the orthogonal principle of the MMSE channel estimation \[10\] and Theorem 1, we have \( E \{Q_{n,k}\} = \sum_{l=1}^{k} \beta_l \). Therein, variable \( \sigma^2 \) is the variance of the CEE of user \( k \), which is obtained based on equation \( 27 \) in \[10\] as \( \sigma^2 = \nu^2 - \frac{1}{M} \mathbf{A}^H \mathbf{A} \). Further, Substituting \( E \{s_{n,k}\}, E \{G_{n,k}\}, \) and \( E \{Q_{n,k}\} \) into \( 5 \) and using the matrix inverse lemma on \( \Phi^{-1} \), we have

\[
\text{ASINR}_k = \frac{M \left( \sigma^2 - \frac{\nu^2}{\sigma^2 + \nu^2} \right) \beta_k}{\sum_{l=k+1}^{K} \beta_l^2 + \sum_{l=1}^{K} \frac{\nu^2 \sigma^2}{\sigma^2 + \nu^2} \beta_l + \sigma^2}. \tag{7}
\]
We note that ASINR increases with \( \{\alpha_1, \ldots, \alpha_k, \beta_k\} \), but decreases with \( \{\beta_1, \ldots, \beta_{k-1}, \beta_{k+1}, \ldots, \beta_K\} \). In other words, there exists a non-trivial trade-off between the allocation of pilot power and payload power. Indeed, a higher pilot power \( \alpha_k \) and payload power \( \beta_k \) of user \( k \) result in a higher ASINR, while a higher payload power of other users \( \beta_1, \ldots, \beta_{k-1}, \beta_{k+1}, \ldots, \beta_K \) will introduce more IUI for user \( k \). In contrast, high pilot powers \( \alpha_1, \ldots, \alpha_{k-1} \) are beneficial to increase ASINR, since they can reduce the residual interference by improving the quality of channel estimation.

**IV. Joint Pilot and Payload Power Allocation**

The JPA design can be formulated to maximize the minimum weighted ASINR as follows:

\[
\text{maximize} \quad \min_{\{c_1, \ldots, c_K\}} \{c_k \text{ASINR}_k\}
\]

s.t. \( C1: \alpha_k T + \beta_k D \leq E_{\text{max}}, \forall k \),
\( C2: \alpha_k \geq 0, \beta_k \geq 0, \forall k \), \( C3: \text{ASINR}_k \geq \gamma, \forall k \). \( (8) \)

The constants \( c_k = [c_1, \ldots, c_K] \) are predefined weights for all the \( K \) users. Constraint \( C1 \) limits the pilot power \( \alpha_k \) and the payload power \( \beta_k \) with the maximum energy budget \( E_{\text{max}} \) for each user. Constraint \( C2 \) ensures the non-negativity of \( \alpha_k \) and \( \beta_k \). Constraint \( C3 \) requires the ASINR of user \( k \) to be larger than a given threshold \( \gamma \) to guarantee the data detection performance during SIC decoding. Note that since the message of each user is decoded only once at the BS for uplink NOMA, a SIC decoding constraint is not required as imposed for downlink NOMA.

This max-min problem formulation aims to mitigate the error propagation of the MRC-SIC decoding, which is dominated by the user with the minimum ASINR. Furthermore, since the error propagation caused by the users at the forefront of the MRC-SIC decoding process, e.g. user 1, affects the data detection of remaining undecoded users, and thus affects the system performance more significantly than other users. Therefore, we have \( c_1 \leq c_2, \ldots, c_K \) to assign different priorities to users in maximizing their ASINRs. The formulated problem in (9) is a non-convex problem, where \( \alpha_k \) and \( \beta_k \) are coupled with each other severely in ASINR. Defining new optimization variables \( t_k = \frac{\sigma^2 c^2_k}{\sigma^2 + \alpha_k^2}, \forall k \), the problem in (9) is equivalent to the following optimization problem (10):

\[
\text{maximize} \quad \sum_{k=1}^{K} \lambda_k \sum_{l=1}^{K} \beta_l - \lambda \gamma t_k \beta_k - \lambda \gamma t_k(\beta_k^{-1} - 1) - \lambda \gamma t_k^2 \beta_k^{-1} + M t_k \beta_k^{-1}, \forall k
\]

s.t. \( C1: \sigma^2 T k^{-1} + D \beta_k \leq \sigma^2 T / \nu_k^2 + E_{\text{max}}, \forall k \),
\( C2: 0 < t_k \leq \nu_k^2, \beta_k \geq 0, \forall k \),
\( C3: \sum_{l=1}^{K} \gamma t_l \beta_l^{-1} + \sum_{l=1}^{K} \gamma t_l (\beta_l^{-1} - 1) + \gamma t_l \beta_l^{-1} + M t_l \beta_l^{-1}, \forall k \),
\( C4: \sum_{l=1}^{K} \gamma t_l \beta_l^{-1} + \sum_{l=1}^{K} \gamma t_l (\beta_l^{-1} - 1) + \gamma t_l \beta_l^{-1} + M t_l \beta_l^{-1}, \forall k \),

where \( \lambda > 0 \) is an auxiliary optimization variable. We can easily observe that the objective function and the functions on the left side of constraints \( C1, C3, \) and \( C4 \) in (10) are all valid posynomial functions [13] Chapter 4). Therefore, the reformulated problem in (10) is a standard geometric programming (GP) problem [1], which can be solved efficiently by off-the-shelf numerical solvers such as CVX [14].

**V. Simulation Results**

We use simulations to verify the developed performance analysis and evaluate the performance of the proposed JPA scheme for both uncoded and coded systems. Two baseline schemes are introduced for comparison, where the equal power allocation (EPA) scheme sets the equal pilot and payload power, i.e., \( \alpha_k = \beta_k = \frac{E_{\text{max}}}{2D} \), but the payload power allocation (PPA) scheme only fixes the pilot power as \( \alpha_k = \frac{E_{\text{max}}}{2D} \) and optimizes over the payload power \( \beta_k \) subject to the same constraint set as in (9).

In the simulations, we set \( M = 2, T = K = 4, D = 96, \), \( c = [1, 1, 1, 1] \), \( \gamma = 5 \text{ dB}, E_{\text{max}} = 20 \text{ J}, \) and \( \sigma^2 = -100 \text{ dBm} \). It is assumed that there are \( T + D = 100 \text{ symbols in a CTI. All the K users are uniformly distributed in a single cell with a cell radius of 400 m. The weight c is selected deliberately to alleviate the impact of the error propagation from the previous users during the MRC-SIC decoding, where the optimal weight selection will be considered in future work. The 3GPP urban path loss model [15] is adopted and quadrature phase shift keying (QPSK) modulation is used for all the simulation cases. For the coded systems, we adopt the standard turbo code as stated in the 3GPP technical specification [16]. We assume that one codeword is spread over \( N = 10 \) coherence intervals, which results in a codeword length of 1920 bits.

**A. Individual ASINR**

Figure 2 depicts the individual ASINR for the considered three schemes for uncoded systems. We can observe that the simulation results match perfectly with the theoretical results in (7). Besides, it can be observed that the lowest ASINR achieved by the EPA scheme and our proposed JPA scheme both occur at 5 dB for user 4, which is much higher than the minimum ASINR provided by the EPA scheme occurring at 2.6 dB for user 3. This is owing to the adopted max-min principle and constraint C3 in the proposed problem formulation in (9). Nevertheless, it can be observed that our proposed scheme provides a 2 dB higher ASINR than that of the EPA scheme for users 1, 2, and 3. This is because our proposed scheme can utilize the energy more efficiently than that of the EPA scheme. Moreover, our simulation results demonstrate that the optimal power allocation \( \alpha_k \) and \( \beta_k \) can satisfy the energy budget constraint C1 in (9).

Furthermore, the Jain’s fairness index (JFI) of the weighted ASINR for the considered three schemes are given by \( J_{\text{EPA}} = 0.6174, J_{\text{PPA}} = 0.9436, \text{ and } J_{\text{JPA}} = 0.9983, \) respectively. The EPA scheme achieves the lowest JFI, while both the PPA and JPA schemes enjoy a high JFI since they are based on the max-min resource allocation in (9). In addition, our proposed

\[ \text{maximize} \quad \lambda_k \sum_{l=1}^{K} \beta_l - \lambda \gamma t_k \beta_k - \lambda \gamma t_k(\beta_k^{-1} - 1) - \lambda \gamma t_k^2 \beta_k^{-1} + M t_k \beta_k^{-1}, \forall k \]

s.t. \( C1: \sigma^2 T k^{-1} + D \beta_k \leq \sigma^2 T / \nu_k^2 + E_{\text{max}}, \forall k \),
\( C2: 0 < t_k \leq \nu_k^2, \beta_k \geq 0, \forall k \),
\( C3: \sum_{l=1}^{K} \gamma t_l \beta_l^{-1} + \sum_{l=1}^{K} \gamma t_l (\beta_l^{-1} - 1) + \gamma t_l \beta_l^{-1} + M t_l \beta_l^{-1}, \forall k \),
\( C4: \sum_{l=1}^{K} \gamma t_l \beta_l^{-1} + \sum_{l=1}^{K} \gamma t_l (\beta_l^{-1} - 1) + \gamma t_l \beta_l^{-1} + M t_l \beta_l^{-1}, \forall k \),

where \( \lambda > 0 \) is an auxiliary optimization variable. We can easily observe that the objective function and the functions on the left side of constraints \( C1, C3, \) and \( C4 \) in (10) are all valid posynomial functions [13] Chapter 4). Therefore, the reformulated problem in (10) is a standard geometric programming (GP) problem [1], which can be solved efficiently by off-the-shelf numerical solvers such as CVX [14].
iterative receiver [6] can be employed to lower the error floor. The early error floor is due to the joint effect of IUI, CEE, and ASINR, which will be considered in our future work.

10 appears at the BER region ranging from $10^{-2}$ to $10^{-3}$. In addition, it can be observed that an error floor for both schemes is observed at the BER region ranging from $10^{-2}$ to $10^{-3}$. This reveals the error propagation of the MRC-SIC decoding for the EPA scheme. The PPA scheme can improve the BER performance for users 1, 2, and 3 compared to the EPA scheme, while it fails to relieve user 4 from high BER. However, our proposed scheme always enjoys the lowest BER compared to the two baseline schemes for all the users, especially for coded systems. In fact, our proposed scheme can mitigate the error propagation more efficiently compared to the PPA scheme by optimally balancing the pilot and payload power. It is worth to note that, with constraint C3 in [6], our proposed PPA scheme can guarantee the BER of all the users to be smaller than $10^{-3}$ for the coded systems, which validates the assumption about the sources of the error propagation in [6].

C. BER versus Energy Budget

For coded systems, Figure 2 shows the BER performance of our proposed scheme over the PPA scheme versus the energy budget $E_{\text{max}}$. Note that we set $\text{BER} = 0.5$ if the optimization problem in [6] is infeasible to account the penalty of failure. We can observe that our proposed scheme offers a much lower BER than that of the PPA scheme for all four users. Interestingly, the BER performance gain is considerable in the moderate $E_{\text{max}}$ regime, while it is marginal in the high $E_{\text{max}}$ regime. In fact, in the high $E_{\text{max}}$ regime, the residual interference $Q_{n,k}$ vanishes owing to the high channel estimation accuracy. Therefore, our proposed scheme can only offer diminishing gains in alleviating the impact of error propagation for further reducing the BER. With the moderate $E_{\text{max}}$, our proposed scheme can substantially improve the channel estimation, which can mitigate the residual interference during MRC-SIC decoding, and thus reduce the BER effectively.

In addition, it can be observed that an error floor for both schemes appears at the BER region ranging from $10^{-2}$ to $10^{-5}$. This early error floor is due to the joint effect of IUI, CEE, and the error propagation of the MRC-SIC decoding. Note that an iterative receiver [6] can be employed to lower the error floor level, which will be considered in our future work.

VI. CONCLUSION

In this letter, a joint pilot and payload power control scheme was proposed for uplink MIMO-NOMA systems with MRC-SIC receivers to mitigate the error propagation problem. By taking into account the CEE, we analyzed the ASINR during the MRC-SIC decoding. The JPA design was formulated as a non-convex optimization problem for maximizing the minimum weighted ASINR and was solved by geometric programming. Simulation results verified our analysis and demonstrated that our proposed scheme is effective in mitigating the error propagation in SIC which enhances the BER performance, especially in the moderate energy budget regime.

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