Complex Rotation-based Linear Precoding for Physical Layer Multicasting and SWIPT

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Abstract—With the goal of improving spectral efficiency, complex rotation-based precoding and power allocation schemes are developed for two multiple-input multiple-output (MIMO) communication systems, namely, simultaneous wireless information and power transfer (SWIPT) and physical layer multicasting. While the state-of-the-art solutions for these problems use very different approaches, the proposed approach treats them similarly using a general tool and works efficiently for any number of antennas at each node. Through modeling the precoder using complex rotation matrices, objective functions (transmission rates) of the above systems can be formulated and solved in a similar structure. Hence, this approach simplifies signaling design for MIMO systems and can reduce the hardware complexity by having one set of parameters to optimize. Extensive numerical results show that the proposed approach outperforms state-of-the-art solutions for both problems. It increases transmission rates for multicasting and achieves higher rate-energy regions in the SWIPT case. In both cases, the improvement is significant (20%-30%) in practically important settings where the users have one or two antennas. Furthermore, the new precoders are less time-consuming than the existing solutions.

I. INTRODUCTION

Efficient spectrum usage and management are of vital importance in modern communication systems. To meet the communication requirements of multiple users, efficient spectrum management and spectrum sharing are required to capture and schedule the best available spectrum [1]. By exploiting multipath propagation, multiple-input multiple-output (MIMO) communication has significantly improved the spectrum efficiency and has become an essential element of today’s wireless communication standards. It is known that the design of the precoder at the transmitter largely affects the performance of MIMO systems. From an information-theoretic perspective, linear precoding is optimal to achieve high spectral efficiency [2]; it also keeps the complexity low [3].

Besides spectral efficiency and high-speed transmission, in modern wireless systems, there is a desire to improve multiple other objectives, such as energy-efficient, multicasting, and security. Such needs have motivated linear precoding for various objectives such as wireless information transfer (WIT), energy harvesting (EH) [4], simultaneous wireless information and power transmission (SWIPT) [4, 5], physical layer multicasting [6, 7], and so forth. While some of the above problems have analytical precoding design—for example, singular value decomposition (SVD) for WIT [8] and EH [4]—some others such as SWIPT and multicasting transmission only have numerical optimization based solutions. Moreover, these solutions differ from a problem to another since their optimization problems have different structures.

Actually, all of those problems can be solved using one general approach, named rotation-based precoding. This approach simplifies positive semidefinite (PSD) constraint to a set of linear constraints and enables us to solve the related problems using general optimization tools like fmincon in MATLAB. The rotation-based precoding was first proposed in [9] for the MIMO wiretap channels with two antennas. Later, in [10], this method was extended to the cases for an arbitrary number of antennas at each node. This method applies Givens rotation to build the precoding matrix to maximize secure transmission rates. In [11], this method was applied to energy harvesting maximization with a secrecy rate constraint. In all of these cases, there is merit in applying this method to design precoder matrices. Rotation-based precoding can provide an analytical solution for the cases in which the number of transmit antennas is two [9, 11]. For other cases, this method is shown to provide more robust solutions than existing solutions [10], [12]. Overall, the rotation-based method is a general tool for precoding design and has great potential for extension to other related problems [10]. The above solutions are, however, based on real rotation matrices which work only for real-valued channels.

In this paper, we develop complex rotation-based precoders for two applications: SWIPT and physical layer multicasting. In SWIPT, one user receives information at a high rate, and the other user simultaneously harvests energy from the common transmitter. Linear precoding and power allocation solution can be iteratively optimized in [4] using time-switching and power-splitting (TS-PS). Multicasting is used when a transmitter broadcasts public messages, such as advertisements and forecasts. This is a min-max fair problem to enlarge the transmission rate for all users. In the MIMO case, a cyclic alternating ascent (CAA) precoder is proposed in [7]. In the multiple-input single-output (MISO) case, semidefinite relaxation (SDR) techniques yield a closed-form solution [6]. These methods yield approximate solutions and their performance is affected by the number of antennas.

The rotation-based precoders we develop for the above-mentioned two problems improve the performance, work for an arbitrary number of antennas at each node, reduce the computational complexity, and can be applied to complex- and
real-valued channels. The main contributions of this paper are summarized as follows:

- For SWIPT, our precoder is more robust than state-of-the-art solutions and increases the data transmission rates particularly when harvesting users have one or two antennas (which is of great importance in practice). In particular, the rate improvement can reach as high as 20% when compared with the TS-PS [4].
- For multicasting, our precoder enlarges the data transmission rates while lowering the computational complexity compared to the state-of-the-art methods. For example, compared to the SDR, the rate improvement can be up to nearly 30% for practical antenna settings while reducing the computational complexity more than an order of magnitude.

The remainder of this paper is organized as follows. Channel models and objective functions are discussed in Section III. The precoder design is discussed in Section IV. Numerical results are illustrated in Section V. Finally, we conclude the paper in Section VI.

II. CHANNEL MODELS AND PRELIMINARIES

A. Channel Models

Consider a two-user MIMO wireless communication system with one transmitter (Tx) and two receivers as shown in Fig. 1. The Tx is equipped with \( m \) antennas and sends information to two receivers. At the Tx, a linear precoder is applied, in which the input covariance matrices corresponding to Rx1 and Rx2, and \( \mathbf{w} \in \mathbb{C}^{n \times 1} \) and \( \mathbf{H} \in \mathbb{C}^{n \times m} \) denote the independent and unit power symbol vector, that is, \( \mathbb{E}\{\mathbf{s}^{H}\mathbf{s}\} = \mathbf{I}_m \), \( \mathbf{A} \triangleq \text{diag}(\lambda_1, \ldots, \lambda_m) \) represents the power allocation factors and \( \mathbf{V} \in \mathbb{C}^{m \times m} \) is the precoding matrix, \( \mathbf{A} \) and \( \mathbf{V} \) together define precoding and power allocation, where the transmitted signal is

\[
\mathbf{x} = \mathbf{V}\mathbf{A}\mathbf{s}.
\]  

Then, the covariance matrix of \( \mathbf{x} \) becomes \( \mathbf{Q} \triangleq \mathbb{E}\{\mathbf{x}\mathbf{x}^{H}\} = \mathbf{V}\mathbf{A}\mathbf{V}^{H} \). At the receiver side, receiver 1 (Rx1) and receiver 2 (Rx2) are equipped with \( n_1 \) and \( n_2 \) antennas. They access and decode the information for their users respectively. Assuming transmission is over flat fading channels, the received signals can be formed as

\[
\begin{align*}
\mathbf{y}_1 &= \mathbf{H}_1\mathbf{x} + \mathbf{w}_1, \\
\mathbf{y}_2 &= \mathbf{H}_2\mathbf{x} + \mathbf{w}_2,
\end{align*}
\]

in which \( \mathbf{H}_1 \in \mathbb{C}^{n_1 \times m} \) and \( \mathbf{H}_2 \in \mathbb{C}^{n_2 \times m} \) are the channel matrices corresponding to Rx1 and Rx2, and \( \mathbf{w}_1 \in \mathbb{C}^{n_1 \times 1} \) and \( \mathbf{w}_2 \in \mathbb{C}^{n_2 \times 1} \) are independent and identically distributed (i.i.d.) Gaussian noises with zero means and unit variances.

B. Objective Functions and State-of-the-Art Solutions

Many wireless communication systems aim to build a green and secure ecosystem with a variety of services, including SWIPT and multicasting. Signaling should be designed in a way that the two users in Fig. 1 efficiently access the spectrum resource. Essentially, these problems require input covariance matrix design, or equivalently precoding and power allocation matrices, that can maximize the corresponding objective functions. The goal is to find analytical solutions or effective numerical approaches for each problem. In the following, the objective functions of these communications services are explained.

1) SWIPT: When Rx1 requires WIT and Rx2 orders EH at the same time, the SWIPT problem arises which needs a balanced precoder that can ensure the wireless transmission from Tx to Rx1 and energy harvesting from Tx to Rx2 simultaneously and efficiently. As defined in [4], SWIPT characterizes the optimal trade-off between the maximum energy and information transfer by the rate-energy boundary, which is given by

\[
\begin{align}
(P1) & \quad \mathcal{C}_1 \triangleq \max_{\mathbf{Q}} \log_2 |\mathbf{I}_{n_1} + \mathbf{H}_1\mathbf{Q}\mathbf{H}_1^{H}|, \\
& \quad \text{s.t.} \quad \eta \cdot \text{tr}(\mathbf{H}_2\mathbf{Q}\mathbf{H}_2^{H}) \geq \bar{\mathcal{E}}, \\
& \quad \mathbf{Q} \succeq 0, \mathbf{Q} = \mathbf{Q}^{H}, \text{tr}(\mathbf{Q}) \leq P,
\end{align}
\]

in which \( \eta \) is the converting rate of the harvested energy (we assume \( \eta = 1 \) throughout the paper), \( \bar{\mathcal{E}} \) is a threshold representing the required EH level at Rx2, and \( P \) is the transmit power. The value of \( \bar{\mathcal{E}} \) is between the minimum (\( \mathcal{E}_{\text{min}} \)) and maximum (\( \mathcal{E}_{\text{max}} \)) harvested energy level, that is

\[
\bar{\mathcal{E}} \triangleq \mathcal{E}_{\text{min}} + q(\mathcal{E}_{\text{max}} - \mathcal{E}_{\text{min}}),
\]

where \( q \) is a factor between 0% and 100%. Since we are looking for the maximum rate-energy boundary, \( \mathcal{E}_{\text{min}} \) is defined as the energy received by Rx2 when Rx1 reaches its optimal data rate. This can be obtained by solving

\[
\begin{align}
(P1-1) & \quad \max_{\mathbf{Q} : \text{tr}(\mathbf{Q}) \leq P} \log_2 |\mathbf{I}_{n_1} + \mathbf{H}_1\mathbf{Q}\mathbf{H}_1^{H}|, \\
& \quad \text{which is the well-known WIT problem with an analytical solution [3] } \mathbf{Q}^*_1 \text{ by using singular value decomposition (SVD) and water filling (WF). Then, we have } \mathcal{E}_{\text{min}} = \eta \cdot \text{tr}(\mathbf{H}_2\mathbf{Q}^*_1\mathbf{H}_2^{H}).
\end{align}
\]

On the contrary, \( \mathcal{E}_{\text{max}} \) can be obtained when Rx2 reaches the maximum EH level, i.e.,

\[
\begin{align}
(P1-2) & \quad \mathcal{E}_{\text{max}} \triangleq \max_{\mathbf{Q} : \text{tr}(\mathbf{Q}) \leq P} \eta \cdot \text{tr}(\mathbf{H}_2\mathbf{Q}\mathbf{H}_2^{H}),
\end{align}
\]

which is a typical EH problem and the solution is given in [4] in an analytical form. So, when \( q = 0% \), \( (P1) \) degenerates...
to (P1-1); When \( q = 100\% \), (P1) is equivalent to (P1-2); Otherwise, \( q \) controls the balance between the WIT for Rx1 and EH for Rx2. Since both (P1-1) and (P1-2) are related to the channels, \( \bar{E} \) is a dynamic threshold that varies from \( H_1 \) and \( H_2 \) and is controlled by \( q \). Although numerical solutions are studied in [4], [5] for SWIPT, these solutions are specifically designed and they are difficult to be generalized for other precoding problems as a unified solution.

2) Multicasting: The Tx broadcasts a public message, such as advertisements and weather forecasts, to all users. In this case, the performance of the multicasting rate is subject to the minimum rate of the receivers. Therefore, this problem is to maximize the rate of the receiver with the minimum WIT rate in the context of common information [6]. The capacity region of the Gaussian MIMO multicasting is formulated as

\[
(P2) \quad C_2 \triangleq \max_{Q} \min_{k=1,2} \log_{2} |I_{n_k} + H_k Q H_k^H| \quad \text{s.t.} \quad Q \succeq 0, \quad Q = Q^H, \quad \text{tr}(Q) \leq P.
\]  

In the MISO case, semidefinite relaxation (SDR) techniques yield a closed-form solution. In the MIMO case, linear precoding methods are popular for their lower complexity. A cyclic alternating ascent (CAA) is proposed in [7], and [13] mentions that the problem can be solved by semidefinite programming (SDP) solver directly. Moreover, a real-valued rotation-based precoding method together with random search was proposed in [12] for integrated services with common and confidential messages. However, the existing methods are limited by the computational complexity and are only available in some cases of antennas.

In summary, previous works resort to different solutions to solve for (P1)-(P2). We propose a unified solution for (P1)-(P2), and the proposed approach is robust to the changes in the number of antennas at the Tx, Rx1, and Rx2.

### III. THE ROTATION MODELING AS A GENERAL PRECODING TOOL

The aforementioned precoding problems are a series of optimization problems on the covariance matrix \( Q \). The PSD and symmetry requirements of \( Q \) increase the difficulty of reaching the optimal solution. Our proposed complex rotation modeling (CRM) circumvents these constraints by converting them to a set of linear constraints, as explained in the following.

#### A. Complex Rotation Modeling (CRM)

The covariance matrix \( Q \) can be formed using the eigenvalue decomposition as

\[
Q = \begin{bmatrix} V \Lambda V^H \end{bmatrix}, \quad \Lambda \in \mathbb{C}^{m \times m}
\]

is a diagonal matrix, whose diagonal elements \( [\lambda_1, \ldots, \lambda_m] \) are non-negative due to the PSD constraint. Moreover, the average power constraints in (P1)-(P2) are equivalent to \( \lambda_1 \leq P \). To this end, the PSD and power constraints can be represented as a set of linear constraints

\[
\{ \lambda_i | \lambda_i \geq 0, \sum_{i=1}^{m} \lambda_i \leq P \}.
\]  

Besides, \( V \in \mathbb{C}^{m \times m} \) is a unitary matrix due to the symmetric property. Then it can be modeled by complex Given’s matrix [14] or named rotation matrix as

\[
V = \prod_{i=1}^{m-1} \prod_{j=i+1}^{m} V_{i,j},
\]

where \( V_{i,j} \) is equal to an identity matrix \( I \in \mathbb{C}^{m \times m} \) except for the following four elements

\[
\begin{bmatrix} v_{i,i} & v_{i,j} \\ v_{j,i} & v_{j,j} \end{bmatrix} = \begin{bmatrix} \cos \theta_{i,j} & -e^{-j\phi_{i,j}} \sin \theta_{i,j} \\ e^{j\phi_{i,j}} \sin \theta_{i,j} & \cos \theta_{i,j} \end{bmatrix},
\]

where \( v_{a,b}, a, b \in \{i,j\} \), represents the entry \((a,b)\) of matrix \( V_{i,j} \). Totally, it requires \( n_a = m(m-1)/2 \) rotation angles to represent \( V \) in (9). There is no constraint on rotation angles, i.e., \( \theta_{i,j}, \phi_{i,j} \in \mathbb{R} \). Therefore, the optimization on \( Q \) can be equivalently transferred to optimize the parameters using CRM with a linear constraint as (8).

It is worth mentioning that the order of multiplication in (9) is not unique and different orders will lead to different rotation angles \( \theta_{i,j} \). In this paper, without loss of generality[7] we use the order definition in (9). Then, the rotation parameter vector can be defined as

\[
r \triangleq [\lambda, \theta, \phi]^H,
\]

where

\[
\lambda \triangleq [\lambda_1, \ldots, \lambda_m], \quad \theta \triangleq [\theta_1, \ldots, \theta_{m-1}, m], \quad \phi \triangleq [\phi_1, \ldots, \phi_{m-1}, m].
\]

1If the order in [9] is changed, \( V \) will be a different matrix. However, \( Q \) can be maintained the same if the order of diagonal elements of \( \Lambda \) is changed accordingly. A detailed analysis is given in [10].
To this end, $Q$ can be identified as a specific covariance matrix by the given parameter vector $r$, containing both $\lambda$ and $\theta$. The constraint becomes $Ar \leq b$, where

$$A \triangleq \begin{bmatrix} -I_m & 0_{m \times n_a} \\ I_{1 \times m} & 0_{1 \times n_a} \end{bmatrix}, \quad b \triangleq \begin{bmatrix} 0_{1 \times m} \\ P \end{bmatrix},$$

in which $0_{a \times b}$ (or $I_{a \times b}$) is a matrix with all zeros (or ones).

### B. CRM for Precoding

The fact that CRM converts the PSD constraint to a set of linear constraints in each problem, facilitates reshaping (P1)-(P2) to new optimization problems (see (P1a)-(P2a) in the following) and use general optimization tools to solve them. In this manner, we do not need to find the solution for each problem via a different approach.

1) **CRM for SWIPT**: Applying the CRM to (P1), the objective function of SWIPT becomes

$$\begin{equation} C_1 = \max_r \log_2 |1 + H_1QH_1^H|, \tag{14a} \end{equation}$$

subject to

$$\begin{equation} Ar \leq b, \tag{14b} \end{equation}$$

$$\eta \cdot \text{tr}(H_2QH_2^H) \geq \bar{\mathcal{E}}, \tag{14c}$$

where $Q$ is a function of $r$. This problem can be solved by a general optimization tool such as $\text{fmincon}$ in MATLAB. \[(14b)\] is a linear inequality constraint and \[(14c)\] can be treated as a non-linear constraint in $\text{fmincon}$. The initialization of $Q$ is given by the solution of (P1-2), so that \[(14b)\] and \[(14c)\] can be guaranteed. Then, we get the initial value of $r$ using Algorithm 1 in [10].

2) **CRM for Multicasting**: (P2) can be reformed as

$$\begin{equation} C_2 = \max_r \min \{R_1, R_2\}, \tag{15a} \end{equation}$$

subject to

$$\begin{equation} Ar \leq b, \tag{15b} \end{equation}$$

where $R_1$ and $R_2$ are WIT rates of Rx1 and Rx2, i.e.,

$$R_k \triangleq \log_2 |1 + H_kQH_k^H|, \quad k = 1, 2. \tag{16a}$$

Then the objective function can be considered as the minimum of two (P1-1) with different channels. Since (P1-1) is concave \[(18a)\], (P2a) is also concave. It can be solved by considering the following three sub-cases:

1) $R_1 \leq R_2$, when $R_1$ has reached its optimal.

This is the case that by obtaining $Q_1^*$ as the solution of (P1-1), the achievable rate of Rx1 is defined as $\hat{R}_1^*$. If $R_1^* \leq R_2(Q_1^*)$ is satisfied, $Q_1^*$ is the solution of (P2a).

2) $R_2 \leq R_1$, when $R_2$ has reached its optimal.

This is the case that by obtaining $Q_2^*$ as the solution of

$$R_2^* = \max_{\text{tr}(Q_2^*) \leq P} \log_2 |1 + H_2Q_2H_2^H|, \tag{17}$$

which also has an analytical solution as (P1-1). If $R_2^* \leq R_1(Q_1^*)$ is satisfied, $Q_2^*$ is the solution of (P2a).

3) Otherwise, the solution of (P2a) can be obtained using $\text{fmincon}$ with linear inequality constraint as \[(15b)\]. The initialization of rotation parameters can be obtained from $Q_1^*$ or $Q_2^*$.

Since the first two sub-cases are a WIT problem with analytical solutions, the efficiency of the solution has been improved.

### C. CRM for More Than Two Users

The CRM-based solution can be applied to cases with multiple users. With more than two users, the rotation parameters may increase or remain the same depending on the specific problem. For example, for multicasting, there is always one covariance matrix to be optimized even if the number of users is more than two [7], in which CRM will be efficient in this case. On the other hand, if the number of covariance matrices increases by introducing more users in the network, CRM should be applied for each covariance matrix. The capacity region of SWIPT with multiple users is still an open problem. We take MIMO transmission with multiple users [15] and Gaussian MIMO multi-receiver wiretap channel [16] as examples, the covariance matrix $Q$ is constructed by $U$ independent covariance matrices, i.e., $Q = \sum_{i=1}^{U} Q_u$. Applying CRM to user $u$, we have $Q_u = V_u \Lambda_u V_u^H$. Thus, we will have independent rotation parameters for each user to optimize.

### IV. Simulation Results

In this section, we evaluate the performance of CRM in SWIPT and multicasting, respectively. In general, CRM can reach the SWIPT rate-energy region. For multicasting, CRM can achieve a higher transmission rate with better efficiency.

#### A. SWIPT

In Fig.2, the proposed CRM is compared with the TS-PS and random trials of $Q$. For CRM and TS-PS, eleven thresholds $\tilde{\mathcal{E}}$ equally dividing the interval $[\mathcal{E}_\text{min}, \mathcal{E}_\text{max}]$ are considered in the cases of $P = 10, 20$, and $30$ (W). In Fig.2(a), the channels are generated randomly as \[(18a)\]. The proposed CRM achieves the same performance as TS-PS. The random trials denoted as dots in Fig.2(a) are based on 10,000 realizations of $Q$. In the case of $H_1 = H_2 = [1, 0.5; 0.5, 1]$, and $P = 100$ (W), we found that the proposed method achieves the same rate-energy outer boundary and obtained the same figure with Fig. 7 in [4]. In Fig.2(b), the channels are also randomly given as [19]. Transmit through this channel, CRM can still reach the same rate-energy region, while TS-PS is not close to the upper rate-energy region.
The solution of SWIPT is a Pareto optimal among rate-energy pairs, however, TS-PS suffers from a non-convexity issue between the Lagrange multipliers and its objective function. The performance of TS-PS relies on the initial selection of the Lagrange multipliers and the algorithm may terminate at a local minimum. For TS-PS results presented in Fig. 2(b), we have chosen the best result (highest rate) after 20 trials of different initial Lagrange multipliers. This shortcoming cannot be ignored especially when \( m = 4 \) and \( n_2 \in \{1, 2\} \). All these cases are practically important as the users usually have one or two antennas. In general, CRM is more robust and reliable for various numbers of antennas in the users.

We compare the performance of CRM and TS-PS under \( m = 4, P = 20 \) (W), and two thresholds, \( q \in \{20\%, 60\%\} \), as representatives. The achievable rates are shown in Fig. 3. The two axes in the horizontal plane are \( n_1 \) and \( n_2 \); the vertical axis represents the rate achieved by Rx1. When \( n_2 \in \{1, 2\} \), which refers to the left edges in Fig. 3, clear gaps can be seen between CRM and TS-PS for both \( q = 20\% \) and \( q = 40\% \). When \( n_2 \) raises, the gap shrinks, and the surfaces in Fig. 3 almost overlap.

To make the comparison clearer, we quantitatively show the result by using relative improvement, which is defined as

\[
\eta_r = \frac{R_c - R}{R} \times 100\% ,
\]

where \( R_c \) and \( R \) are the average rates achieved by CRM and the method compared with (for SWIPT, this method is TS-PS). A positive \( \eta_r \) means an increased rate that CRM can achieve. The values in the heat maps refer to the. We evaluate the relative improvement under various receiver antenna settings, more accurately \( n_1, n_2 \in \{1, \ldots, 6\} \) and average over 100 channel realizations. Each entry of the channel matrices follows the normal distribution. A positive number means the proposed CRM reaches that much higher rate and in general, CRM is reliable in these cases. As can be seen from the first two columns of Fig. 4(a)-4(b), the advantage of CRM is remarkable. These columns correspond to the cases in which the energy harvesting user has one or two antennas, which are the most common cases in practice.
B. Multicasting

To demonstrate the performance of CRM for multicasting, we compare it with CAA [7] and the standard SDP techniques solved by CVX [17]. We investigate a variety of combinations for \( n_1, n_2 \in \{1, \ldots, 6\} \) while \( m = 4 \) and \( P = 20 \) (W). The multicasting rates achieved by those three methods are shown in Fig. 5. The proposed method (CRM) can get the same rate as CAA. In comparison with SDP, clear gaps can be find when \( n_1 = 1, n_2 \in \{2, \ldots, 6\} \) or \( n_2 = 1, n_2 \in \{2, \ldots, 6\} \). Again we use relative improvement defined in (20) and the results are shown in the heat maps in Fig. 6. It can be seen from Fig. 6(a) that the proposed method gives a slight improvement to CAA. On the other hand, CRM outperforms SDP in most of the antenna settings when \( n_1 \neq n_2 \), as shown in Fig. 6(b). This improvement is especially remarkable when \( n_1 \) or \( n_2 \) is small. Such antenna settings are of great importance as real-world user equipment usually has one or two antennas.

Besides, the merit of CRM in reducing the computational complexity should not be ignored, which is analyzed in Fig. 7 by numerical simulations. This figure compares the time cost when \( n_1 = n_2 \) where SDP works well. It can be seen that the proposed method has the best efficiency, while CAA is computationally expensive due to the successive optimization. The improvement of CRM with respect to CAA is more than three orders of magnitude which is incredibly high. Moreover, the time consumption of CRM goes down when \( n_1 = n_2 \) becomes larger, whereas the time-cost of the other two methods slightly increases. Such an advantage is provided by CRM for multicasting due to the three sub-cases in Section III-B2. The probability of the first two sub-cases, which have an analytical solution, increases as \( n_1 = n_2 \) becomes larger. As a result, the average time consumption of the proposed method reduces with the number of antennas. Further, the results in Fig. 5 indicate that the highest rate will be obtained when \( n_1 = n_2 \), if \( n_1 + n_2 \) is a constant. This is a big advantage indicating that CRM has both high rates and high time efficiency in practice.

In summary, the proposed rotation-based precoder provides a robust and efficient solution for both problems studied in this paper, namely SWIPT and multicasting. The achievable rate is improved in both SWIPT and multicasting. The performance is no longer sensitive to the number of antennas at the receiver. Meanwhile, the time efficiency of multicasting is significantly reduced.

V. CONCLUSION

We have developed complex rotation-based precoding and power allocation for two different MIMO systems, namely, SWIPT and physical layer multicasting. This method is transforming positive semidefinite matrix constraints into a set of linear constraints which is much simpler. The corresponding problem then can be solved by general optimization methods rather than semidefinite programming solvers. For both problems, the proposed approach is feasible, reliable, and efficient and outperforms state-of-the-art solutions noticeably.

The complex rotation-based precoding approach developed in this paper can be applied to other emerging problems such as...
Fig. 6. Relative multicasting transmission rate improvement (%) obtained by CRM (the proposed method) compared to the existing solutions (CAA and SDP).

Fig. 7. The computational cost of achieving multicasting.

as SWIPT with multi-group model [18] and unmanned aerial vehicle and non-orthogonal multiple access scenario [19], and MIMO systems with finite alphabet [20], to name a few.

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