Self Energy Recycling Techniques for MIMO Wireless Communication Systems

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Abstract—**In this paper, we study self energy recycling techniques for point-to-point multiple-input multiple-output systems where a full-duplex transmitter with multiple antennas communicates with a multi-antenna receiver. Due to the full-duplex nature, the transmitter receives a signal transmitted by itself through a loop-back channel. Then, the energy of the signal is harvested and stored in an energy storage. Assuming time-slotted systems, we propose a new communication protocol in which the harvested energy at the transmitter is recycled for future data transmissions to the receiver. Under this setup, we present a transmit covariance matrix optimization method in order to maximize the sum rate performance for two different cases. First, for a perfect channel state information (CSI) case, the globally optimal algorithm for the sum rate maximization problem is proposed. Next, for an imperfect CSI case, we provide a robust covariance matrix optimization approach where the worst-case sum rate performance can be maximized. Numerical results demonstrate that the proposed methods offer a significant performance gain over conventional schemes.**

I. Introduction

Recently, energy harvesting (EH) techniques based on radio frequency (RF) signals have received great attentions which can replace traditional energy sources owing to its convenience and cost-effectiveness. When applied to conventional wireless communication systems, such a wireless power transfer method becomes a promising solution to supply energy to wireless networks [1] [2]. Normally, EH schemes can be classified into two different research branches, namely simultaneous wireless information and power transfer (SWIPT) [3]–[6] and wireless powered communication network (WPCN) [7]–[10]. In the SWIPT system, a receiver can decode the signal and harvest the energy at the same time during the downlink transmission. In contrast, the WPCN adopts the downlink wireless energy transfer and the uplink wireless information transmission process.

Meanwhile, a new concept called self energy recycling (ER) has been recently studied in [11]–[15]. In the self ER systems, communication nodes operate in a full-duplex (FD) mode so that the nodes can harvest energy of the RF signals transmitted by themselves. Then, this harvested energy can be recycled for conveying data to other nodes. In [11], a two-phase self ER multi-antenna relay scheme was provided where the optimal power allocation and beamforming at the ER relay were designed. Also, [12] employed a self ER method for a multi-antenna relay in order to improve secrecy performance in the presence of a passive eavesdropper. The authors in [13] considered a scenario where a multi-antenna transmitter is powered by both an external energy source and the self ER. The self ER concept was applied to the WPCN system in [14], where the time duration for multiple receivers were optimized to maximize the sum rate performance. In addition, the weighted sum power minimization problem was solved in [15] for bidirectional FD multi-antenna systems. Note that these works [11]–[15] assumed that the recycled energy is available before the transmission, and thus it would result in a non-causal energy issue at the self ER transmitters.

In this paper, we propose self ER methods for point-to-point multiple-input multiple-output (MIMO) systems where a multi-antenna transmitter operating in a FD mode transmits the information signals to a multi-antenna receiver. Since the FD mode is adopted, the transmitter receives its own signal intended to the receiver through a loop-back channel. Then, the energy of these loop-back signals is collected and stored in an energy storage for future data transmission.

To tackle the non-causal energy issue in prior works on the self ER systems, we assume the time-slotted transmission protocol so that the transmitter can only utilize the energy recycled during the past time slots. In this system, the sum rate performance is maximized by optimizing the transmit covariance matrix at each time slot. We consider the sum rate maximization problem in two cases according to the level of the channel state information (CSI) knowledge. First, when perfect CSI is available, the optimal covariance matrix can be obtained by using the Lagrange duality method. Subsequently, we consider the imperfect CSI case, where the transmitter only knows the estimated channel matrices with certain estimation error bounds. In this case, we maximize the worst-case sum rate performance by employing the S-procedure approach [16]. Numerical results confirm that the proposed schemes provide substantially enhanced sum rate performance over conventional methods, which do not adopt the self ER technique.

This paper is organized as follows: In Section II, we explain a system model and formulate the sum rate maximization problem. The optimal covariance matrix for the perfect CSI case is proposed in Section III, and a robust solution is provided for the imperfect CSI case in Section IV. Then, we evaluate the performance of the proposed solutions through numerical simulations in Section V. Finally, we terminate this paper with summary and conclusion in Section VI.

Throughout this paper, we employ upper-case boldface

This work was supported by the National Research Foundation of Korea (NRF) funded by the Korea Government (MSIP) under Grant 2014R1A2A1A10049769.

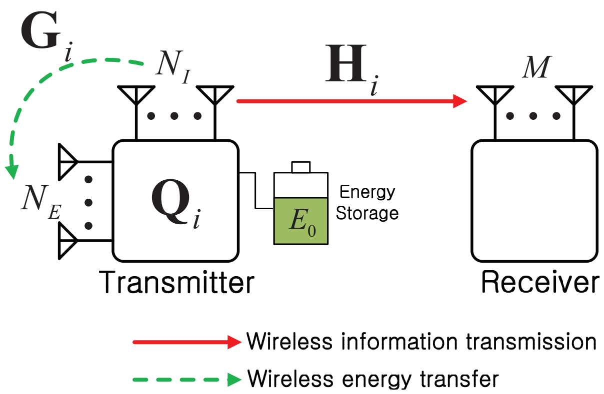

Fig. 1. Block diagram for a self-energy recycling system

letters for matrices, lower-case boldface letters for vectors, and normal letters for scalar quantities. A set of complex matrices of size m-by-n is defined as $\mathbb{C}^{m\times n}$. For matrices $\mathbf{A}$ and $\mathbf{B}$, $\mathbf{A}\otimes\mathbf{B}$ denotes the kronecker product. In addition, transpose, conjugate transpose and determinant of a matrix are denoted by $(\cdot)^T$ and $(\cdot)^H$, and $|\cdot|$, respectively. Trace, rank, and the vectorization operation of a matrix are represented by tr$(\cdot)$, rank$(\cdot)$, and vec$(\cdot)$, respectively. Also, $\mathbf{I}_m$ equals an identity matrix of size m-by-m, and diag$(a_1, a_2, \cdots, a_m)$ stands for a diagonal matrix of size m-by-m with diagonal elements $a_1, \cdots, a_m$. For a complex vector, $\|\cdot\|$ and $\|\cdot\|_F$ indicate the Euclidean norm and the Frobenius norm, respectively. In addition, for a scalar x, $[x]^+$ denotes $\max(0, x)$, and Re$\{x\}$ represents the real value of x.

II. System Model

In this section, we describe a system model for a point-to-point MIMO system with self ER. As shown in Fig. 1, there are one transmitter and one receiver each equipped with multiple antennas. In specific, the transmitter operates in a FD mode, and has $N_I \geq 1$ transmit and $N_E \geq 1$ receive antennas, respectively, while the receiver is equipped with $M \geq 1$ receive antennas. Also, it is assumed that the transmitter has no external power supply except for an energy storage with non-zero initial energy E_0.

In this paper, we consider a time-slotted system with total K time slots. At each time slot, the transmitter sends an information signal to the receiver. Concurrently, the transmitter receives this transmitted signal through a loop-back channel, which is utilized for harvesting energy. Then, this energy is stored in the energy storage of the transmitter and can be recycled for the data transmission in the future.

Denoting $\mathbf{H}_i \in \mathbb{C}^{M\times N_I}$ as the channel matrix at the i-th time slot between the transmitter and the receiver, the received signal $\mathbf{y}_i \in \mathbb{C}^{M\times 1}$ at the receiver can be written by

$$\mathbf{y}_i = \mathbf{H}_i\mathbf{x}_i + \mathbf{n}_i,$$

where $\mathbf{x}_i \in \mathbb{C}^{N_I\times 1} \sim \mathcal{CN}(\mathbf{0}, \mathbf{Q}_i)$ denotes the transmitted signal at the i-th time slot with $\mathbf{Q}_i \in \mathbb{C}^{N_I\times N_I}$ being the transmit covariance matrix, and $\mathbf{n}_i \in \mathbb{C}^{M\times 1} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ indicates the complex Gaussian noise at the receiver. Then, the achievable rate R_i at the i-th time slot is expressed as

$$R_i = \log_2 |\mathbf{I}_M + \mathbf{H}_i\mathbf{Q}_i\mathbf{H}_i^H|.$$

In the mean time, at the i-th time slot, the transmitter also receives the signal $\mathbf{r}_i$ through the loop-back channel $\mathbf{G}_i \in \mathbb{C}^{N_E\times N_I}$, which can be written by

$$\mathbf{r}_i = \mathbf{G}_i\mathbf{x}_i + \mathbf{z}_i,$$

where $\mathbf{z}_i \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{N_E})$ stands for the Gaussian noise at the transmitter. Then, the harvested energy E_i at the i-th time slot can be obtained as [3]

$$E_i = \zeta\mathbb{E}[\|\mathbf{r}_i\|^2] = \zeta\text{tr}(\mathbf{G}_i\mathbf{Q}_i\mathbf{G}_i^H),$$

where $0 < \zeta \leq 1$ is a constant associated with an energy loss during the energy harvest. For convenience, we assume $\zeta = 1$ throughout this paper. Note that the harvested energy E_i at the i-th time slot would be utilized for the data transmission at future time slots $j = i+1, \cdots, K$.

Now, we explain the transmit energy constraint issue in the ER system. At the i-th time slot, the transmitter extracts the transmit energy tr$(\mathbf{Q}_i)$ from the energy storage in order to transfer the data signal $\mathbf{x}_i$. After the transmission, the transmitter stores the harvested energy E_i at the i-th time slot in the energy storage. As a result, the available energy B_i in the energy storage at the i-th time slot can be expressed as

$$B_i = E_0 + \sum_{j=1}^{i-1}\text{tr}(\mathbf{G}_j\mathbf{Q}_j\mathbf{G}_j^H) - \sum_{j=1}^{i-1}\text{tr}(\mathbf{Q}_j), \quad \forall i, \quad (1)$$

where the second term in (1) indicates the harvested energy during the past time slots and the third term represents the energy utilized for the data transmission in the past. Thus, the transmit energy constraint at the i-th time slot is given by tr$(\mathbf{Q}_i) \leq B_i$.

In this paper, we aim to maximize the sum rate performance by optimizing the transmit covariance matrices $\mathbf{Q}_i$ for $i = 1, \cdots, K$. The sum rate maximization problem is formulated as

$$\max_{\{\mathbf{Q}_i\succeq 0\}} \frac{1}{K}\sum_{i=1}^{K}\log_2|\mathbf{I}_M + \mathbf{H}_i\mathbf{Q}_i\mathbf{H}_i^H| \quad (2)$$
$$s.t. \ \ \text{tr}(\mathbf{Q}_i) \leq E_0 + \sum_{j=1}^{i-1}\text{tr}(\mathbf{G}_j\mathbf{Q}_j\mathbf{G}_j^H) - \sum_{j=1}^{i-1}\text{tr}(\mathbf{Q}_j), \quad \forall i.$$

In the following sections, we provide methods for solving problem (2) in two different cases. First, when perfect CSI is available, the optimal transmit covariance matrices will be presented in Section III. Next, we discuss a robust solution to (2) for the imperfect CSI case in Section IV.

III. Perfect CSI Case

In this section, we propose the optimal algorithm for problem (2) in the perfect CSI case. Note that problem in (2) is convex and satisfies the Slater's condition, and thus strong duality holds for this problem [17]. Therefore, it can be solved by using the Lagrange duality method. The Lagrangian can be formulated as

$$L(\{\mathbf{Q}_i\},\{\mu_i\}) = \frac{1}{K}\sum_{i=1}^{K}\log_2|\mathbf{I}_M+\mathbf{H}_i\mathbf{Q}_i\mathbf{H}_i^H| - \sum_{i=1}^{K}\mu_i\left(\text{tr}(\mathbf{Q}_i)-E_0-\sum_{j=1}^{i-1}\text{tr}\left((\mathbf{G}_j^H\mathbf{G}_j-\mathbf{I}_{N_I})\mathbf{Q}_j\right)\right) \quad (3)$$

where μ_i for $i=1,\cdots,K$ is the dual variable associated with the constraint in (2).

Then, the dual function is defined as $g(\{\mu_i\}) = \max_{\{\mathbf{Q}_i\succeq 0\}} L(\{\mathbf{Q}_i\},\{\mu_i\})$, and the corresponding dual problem can be written as $\min_{\{\mu_i\geq 0\}} g(\{\mu_i\})$. Thus, to optimally solve (2), we first compute the dual function $g(\{\mu_i\})$ and then find the optimal dual variable $\{\mu_i^\star\}$ which minimizes the dual function. It is worthwhile to note that the Lagrangian (3) can be rewritten by $L(\{\mathbf{Q}_i\},\{\mu_i\}) = \sum_{k=1}^{K} L_k(\mathbf{Q}_k,\{\mu_i\})$, where

$$L_k(\mathbf{Q}_k,\{\mu_i\}) = \frac{1}{K}\log_2|\mathbf{I}_M+\mathbf{H}_k\mathbf{Q}_k\mathbf{H}_k^H| - \text{tr}(\mathbf{A}_k\mathbf{Q}_k), \quad \forall k,$$

with $\mathbf{A}_k \triangleq \sum_{i=k}^{K}\mu_i\mathbf{I}_{N_I} - \sum_{i=k+1}^{K}\mu_i\mathbf{G}_k^H\mathbf{G}_k$.

Since $L_k(\mathbf{Q}_k,\{\mu_i\})$ is a function of $\mathbf{Q}_k$ and is independent of other $\mathbf{Q}_j$ for $k\neq j$, the dual function can be identified by addressing the following K independent optimization problems:

$$\max_{\mathbf{Q}_k\succeq 0} \frac{1}{K}\log_2|\mathbf{I}_M+\mathbf{H}_k\mathbf{Q}_k\mathbf{H}_k^H| - \text{tr}(\mathbf{A}_k\mathbf{Q}_k), \quad \forall k. \quad (4)$$

Note that $\mathbf{A}_k$ in (4) must be a positive definite matrix, since otherwise the dual function becomes infinity. For this reason, the dual variables μ_i for $i=1,\cdots,K$ must satisfy $\sum_{i=k}^{K}\mu_i > \sum_{i=k+1}^{K}\mu_i g_k$, where $g_k \triangleq \lambda_{\max}(\mathbf{G}_k^H\mathbf{G}_k)$ with $\lambda_{\max}(\mathbf{X})$ being the maximum eigenvalue of a matrix $\mathbf{X}$.

Then, one can prove that the optimal solution to problem (4) can be obtained as [3]

$$\mathbf{Q}_k^\star = \mathbf{A}_k^{-1/2}\tilde{\mathbf{V}}_k\mathbf{\Sigma_k}\tilde{\mathbf{V}}_k^H\mathbf{A}_k^{-1/2}, \quad \forall k, \quad (5)$$

where $\tilde{\mathbf{V}}_k$ stands for the right singular vector matrix of $\mathbf{H}_k\mathbf{A}_k^{1/2}$, and the diagonal matrix $\mathbf{\Sigma}_k$ is defined as $\mathbf{\Sigma}_k = \text{diag}(\tilde{p}_{k,1},\cdots,\tilde{p}_{k,T})$ with $\tilde{p}_{k,l} = [1/\log 2 - 1/\tilde{h}_{k,l}]^+$. Here, $\tilde{h}_{k,l}$ for $l=1,\cdots,T$ represents the singular value of $\mathbf{H}_k\mathbf{A}_k^{1/2}$ where T equals $T=\min(M,N_I)$.

After computing the dual function from (5), it remains to solve the dual problem $\min_{\{\mu_i\}} g(\{\mu_i\})$ under the constraints $\mu_i \geq 0$ and $\sum_{i=k}^{K}\mu_i > \sum_{i=k+1}^{K}\mu_i g_k$ for $i=1,\cdots,K$. To this end, we employ the subgradient method, e.g., the ellipsoid method [17]. The subgradient of the dual function $g(\{\mu_i\})$ with respect to μ_i can be calculated as $E_0 - \text{tr}(\mathbf{Q}_i^\star) + \sum_{j=1}^{i-1}\text{tr}(\mathbf{G}_j\mathbf{Q}_j^\star\mathbf{G}_j^H) - \sum_{j=1}^{i-1}\text{tr}(\mathbf{Q}_j^\star)$. Then, we summarize an algorithm which optimally solves problem (2) as below.

Algorithm 1 : Proposed optimal algorithm for problem (2) in the perfect CSI case

Initialize $\mu_i \geq 0$ for $i=1,\cdots,K$.
Repeat
    Compute $\mathbf{Q}_k^\star = \mathbf{A}_k^{-1/2}\tilde{\mathbf{V}}_k\mathbf{\Sigma_k}\tilde{\mathbf{V}}_k^H\mathbf{A}_k^{-1/2}$ with given $\{\mu_i\}$.
    Compute the subgradient of the dual function $g(\{\mu_i\})$.
    Update $\{\mu_i\}$ using the ellipsoid method.
Until $\{\mu_i\}$ converge to the prescribed accuracy

IV. Imperfect CSI Case

In the previous section, we assume that the transmitter and the receiver have perfect CSI for all time slots. In contrast, in this section, we propose a robust covariance matrix solution that maximizes the worst-case sum rate performance under the channel uncertainty model [18] [19]. We first present the following lemma which is useful for deriving the robust solution.

Lemma 1: Let us define Π_i as the representation of the energy stored in the energy storage, i.e., a difference between the harvested energy $\text{tr}(\mathbf{G}_i\mathbf{Q}_i\mathbf{G}_i^H)$ and the recycled energy $\text{tr}(\mathbf{Q}_i)$. The problem (2) can be equivalently formulated as

$$\max_{\{\mathbf{Q}_i\succeq 0\},\{\Pi_i\}} \frac{1}{K}\sum_{i=1}^{K}\log_2|\mathbf{I}_M+\mathbf{H}_i\mathbf{Q}_i\mathbf{H}_i| \quad (6)$$

$$\begin{aligned} s.t.\ & \text{tr}(\mathbf{Q}_i) \leq \sum_{j=0}^{i-1}\Pi_j, \quad \forall i,\\ & \text{tr}\big((\mathbf{G}_i^H\mathbf{G}_i-\mathbf{I}_{N_I})\mathbf{Q}_i\big) \geq \Pi_i, \quad \forall i,\\ & \Pi_i \leq [g_i-1]^+\cdot\sum_{j=0}^{i-1}\Pi_j, \quad \forall i, \end{aligned}$$

where $\Pi_0 \triangleq E_0$ is a constant.

Proof: The proof is similar to Theorem 1 in [5] and thus omitted here for brevity. ■

Based on this lemma, we now identify the robust covariance matrix in the following. First, we assume that the estimated channel and the estimated error bound at all time slots are available at the transmitter. In addition, the true channel lies in an ellipsoid centered at each estimated channel. Then, for the i-th time slot, the true channels $\mathbf{H}_i$ and $\mathbf{G}_i$ can be respectively expressed as

$$\mathbf{H}_i = \tilde{\mathbf{H}}_i + \mathbf{\Phi}_{H,i} \quad \text{and} \quad \mathbf{G}_i = \tilde{\mathbf{G}}_i + \mathbf{\Phi}_{G,i},$$

where $\tilde{\mathbf{H}}_i$ and $\tilde{\mathbf{G}}_i$ are the estimated channels for the link between the transmitter and the receiver and for the loop-back link, respectively, and $\mathbf{\Phi}_{H,i}$ and $\mathbf{\Phi}_{G,i}$ denote errors associated with the channels $\mathbf{H}_i$ and $\mathbf{G}_i$, respectively. In the ellipsoid model, the error bound sets $\Omega_{H,i}$ and $\Omega_{G,i}$ can be represented as [17]

$$\Omega_{H,i} = \{\mathbf{\Phi}_{H,i} : \|\mathbf{\Phi}_{H,i}\|_F^2 \leq \varepsilon_{H,i}^2\},$$
$$\Omega_{G,i} = \{\mathbf{\Phi}_{G,i} : \|\mathbf{\Phi}_{G,i}\|_F^2 \leq \varepsilon_{G,i}^2\},$$

where $\varepsilon_{H,i}$ and $\varepsilon_{G,i}$ indicate the error bounds for $\mathbf{H}_i$ and $\mathbf{G}_i$, respectively.

Then, we can reformulate the optimization problem (6) for the worst case as

$$\max_{\{\mathbf{Q}_i \succeq 0\}} \min_{\|\mathbf{\Phi}_{H,i}\|_F \leq \varepsilon_{H,i}} \sum_{i=1}^{K} \log_2 |\mathbf{I}_M + \mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i^H| \tag{7}$$

$$\begin{aligned} s.t.\ \ & \mathrm{tr}(\mathbf{Q}_i) \leq \sum_{j=0}^{i-1} \Pi_j, \quad \forall i, \\ & \min_{\|\mathbf{\Phi}_{G,i}\|_F \leq \varepsilon_{G,i}} \mathrm{tr}\left(\left(\mathbf{G}_i^H \mathbf{G}_i - \mathbf{I}_{N_I}\right) \mathbf{Q}_i\right) \geq \Pi_i, \quad \forall i, \\ & \Pi_i \leq \min_{\|\mathbf{\Phi}_{G,i}\|_F \leq \varepsilon_{G,i}} [g_i - 1]^+ \cdot \sum_{j=1}^{i-1} \Pi_j, \quad \forall i. \end{aligned}$$

To solve (7) efficiently, we apply a lower bound on the determinant as [20]

$$|\mathbf{I}_M + \mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i^H| \geq 1 + \mathrm{tr}(\mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i^H), \tag{8}$$

where the equality holds when $\mathrm{rank}(\mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i^H) \leq 1$. Note that the bound in (8) becomes tight in the low E_0 regime.

By using the epigraph formulation [17], the robust optimization problem (7) can be established as

$$\max_{\{\mathbf{Q}_i \succeq 0\}, \{t_i \geq 0\}, \{\Pi_i\}} \sum_{i=1}^{K} \log_2(1 + t_i) \tag{9}$$

$$s.t.\ \ \mathrm{tr}(\mathbf{Q}_i) \leq \sum_{j=0}^{i-1} \Pi_j, \quad \forall i,$$

$$\min_{\|\mathbf{\Phi}_{G,i}\|_F \leq \varepsilon_{G,i}} \mathrm{tr}\left(\mathbf{G}_i^H \mathbf{G}_i - \mathbf{I}_{N_I}) \mathbf{Q}_i\right) \geq \Pi_i, \quad \forall i, \tag{10}$$

$$\min_{\|\mathbf{\Phi}_{H,i}\|_F \leq \varepsilon_{H,i}} \mathrm{tr}\left(\mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i^H\right) \geq t_i, \quad \forall i, \tag{11}$$

$$\Pi_i \leq \min_{\|\mathbf{\Phi}_{G,i}\|_F \leq \varepsilon_{G,i}} [g_i - 1]^+ \cdot \sum_{j=0}^{i-1} \Pi_j, \quad \forall i, \tag{12}$$

where t_i is introduced for the epigraph formulation $\mathrm{tr}(\mathbf{H}_i \mathbf{Q}_i \mathbf{H}_i) \geq t_i$.

Still, it is not easy to solve (9) due to the minimum operation with respect to the error matrices $\mathbf{\Phi}_{G,i}$ and $\mathbf{\Phi}_{H,i}$ in the constraints. To this end, we employ the S-procedure technique [16], which is summarized in the following lemma.

Lemma 2: ([16]) For $k = 1$ and 2, $f_k(x)$ is defined as

$$f_k(\mathbf{x}) = \mathbf{x}^H \mathbf{A}_k \mathbf{x} + 2\mathrm{Re}\{\mathbf{b}_k^H \mathbf{x}\} + c_k,$$

where $\mathbf{A}_k \in \mathbb{C}^{m \times n}$ represents a Hermitian matrix, $\mathbf{b}_k \in \mathbb{C}^{n \times 1}$ indicates a column vector, and c_k is a real scalar. Suppose that there is an some $\mathbf{x}$ that satisfies the inequality $f_k(\mathbf{x}) \geq 0$. Then, the implication $f_1(\mathbf{x}) \geq 0 \Rightarrow f_2(\mathbf{x}) \geq 0$ holds if and only if there exists a nonnegative number μ such that

$$\begin{bmatrix} \mathbf{A}_2 & \mathbf{b}_2 \\ \mathbf{b}_2^H & c_2 \end{bmatrix} - \mu \begin{bmatrix} \mathbf{A}_1 & \mathbf{b}_1 \\ \mathbf{b}_1^H & c_1 \end{bmatrix} \succeq 0. \qquad \blacksquare$$

By applying this lemma, the constraint in (10) can be derived as

$$\begin{aligned} & \mathbf{e}_{G,i}^H \tilde{\mathbf{Q}}_i \mathbf{e}_{G,i} + 2\mathrm{Re}\{\mathbf{g}_i^H \tilde{\mathbf{Q}}_i \mathbf{e}_{G,i}\} + \mathbf{g}_i^H \tilde{\mathbf{Q}}_i \mathbf{g}_i \\ & \qquad - \mathrm{vec}(\mathbf{I}_M)^T \mathrm{vec}(\mathbf{Q}_i) \geq \Pi_i, \\ & \mathbf{e}_{G,i}^H \mathbf{e}_{G,i} \leq \varepsilon_{G,i}^2, \end{aligned} \tag{13}$$

where $\mathbf{e}_{G,i} \triangleq \mathrm{vec}(\mathbf{\Phi}_{G,i})$, $\tilde{\mathbf{Q}}_i \triangleq \mathbf{Q}_i^T \otimes \mathbf{I}$, $\mathbf{g}_i \triangleq \mathrm{vec}(\tilde{\mathbf{G}}_i)$, and $\mathrm{Re}\{a\}$ accounts for the real value of a. Here, (13) comes from the identities on matrices $\mathbf{A}, \mathbf{B}$, and $\mathbf{X}$ as $\mathrm{vec}(\mathbf{AXB}) = (\mathbf{B}^T \otimes \mathbf{A})\mathrm{vec}(\mathbf{X})$, $\mathrm{tr}(\mathbf{A}^T \mathbf{B}) = \mathrm{vec}(\mathbf{A})^T \mathrm{vec}(\mathbf{B})$, and $(\mathbf{A} \otimes \mathbf{B})^T = \mathbf{A}^T \otimes \mathbf{B}^T$.

Similarly, the constraint (11) can be rewritten by

$$\begin{aligned} & \mathbf{e}_{H,i}^H \tilde{\mathbf{Q}}_i \mathbf{e}_{H,i} + 2\mathrm{Re}\{\mathbf{h}_i^H \tilde{\mathbf{Q}}_i \mathbf{e}_{H,i}\} + \mathbf{h}_i^H \tilde{\mathbf{Q}}_i \mathbf{h}_i \geq t_i, \\ & \mathbf{e}_{H,i}^H \mathbf{e}_{H,i} \leq \varepsilon_{H,i}^2, \end{aligned}$$

where $\mathbf{e}_{H,i} \triangleq \mathrm{vec}(\mathbf{\Phi}_{H,i})$ and $\mathbf{h}_i \triangleq \mathrm{vec}(\tilde{\mathbf{H}}_i)$. Also, we can compute the constraint (12) as

$$\begin{aligned} & \min_{\|\mathbf{\Phi}_{G,i}\|_F \leq \varepsilon_{G,i}} \lambda_{\max}\left((\tilde{\mathbf{G}}_i + \mathbf{\Phi}_{G,i})^H (\tilde{\mathbf{G}}_i + \mathbf{\Phi}_{G,i})\right) \\ & \qquad = \tilde{g}_i - \varepsilon_{G,i}, \end{aligned} \tag{14}$$

where $\tilde{g}_i \triangleq \lambda_{\max}(\tilde{\mathbf{G}}_i^H \tilde{\mathbf{G}}_i)$ and (14) can be obtained by setting $\mathbf{\Phi}_{G,i} = -\varepsilon_{G,i} \mathbf{u}_{i,1} \mathbf{v}_{i,1}^H$ with $\mathbf{u}_{i,1}$ and $\mathbf{v}_{i,1}$ equal to the left and the right singular vector of $\mathbf{G}_i$ corresponding to the maximum singular value, respectively.

Combining these results, the robust optimization problem (7) can be reformulated as

$$\max_{\substack{\{t_i\}, \{\gamma_i\}, \{\nu_i\}, \\ \{\mathbf{Q}_i \succeq 0\}, \{\Pi_i\}}} \sum_{i=1}^{K} \log_2(1 + t_i) \tag{15}$$

$$\begin{aligned} s.t.\ \ & \mathrm{tr}(\mathbf{Q}_i) \leq \sum_{j=0}^{i-1} \Pi_j, \quad \forall i, \\ & \begin{bmatrix} \gamma_i \mathbf{I} + \tilde{\mathbf{Q}}_i & \tilde{\mathbf{Q}}_i \mathbf{g}_i \\ \mathbf{g}_i^H \tilde{\mathbf{Q}}_i & -\gamma_i \varepsilon_{G,i}^2 - \Pi_i + \mathbf{g}_i^H \tilde{\mathbf{Q}}_i \mathbf{g}_i - q_i \end{bmatrix} \succeq 0, \quad \forall i, \\ & \begin{bmatrix} \nu_i \mathbf{I} + \tilde{\mathbf{Q}}_i & \tilde{\mathbf{Q}}_i \mathbf{h}_i \\ \mathbf{h}_i^H \tilde{\mathbf{Q}}_i & -\nu_i \varepsilon_{H,i}^2 - t_i + \mathbf{h}_i^H \tilde{\mathbf{Q}}_i \mathbf{h}_i \end{bmatrix} \succeq 0, \quad \forall i, \\ & \Pi_i \leq (\tilde{g}_i - \varepsilon_{G,i} - 1)^+ \cdot \sum_{j=0}^{i-1} \Pi_j, \quad \forall i, \\ & \gamma_i \geq 0, \quad \nu_i \geq 0, \quad t_i \geq 0, \quad \forall i, \end{aligned}$$

where $q_i \triangleq \mathrm{vec}(\mathbf{I})^T \mathrm{vec}(\mathbf{Q}_i)$. Note that the problem in (15) is convex, and it can be efficiently solved via existing convex solvers such as CVX.

V. Simulation Results

In this section, we provide numerical results for evaluating the average sum rate performance of the proposed schemes. For the simulations, we employ the Rayleigh fading model for $\mathbf{H}_i$ with the average pathloss 60 dB, and the Rician fading for the loop-back channel $\mathbf{G}_i$ with the K factor of $K = 5$ dB and the average pathloss 10 dB. Also, we set the noise variance as -60 dBm. We compare our proposed algorithms with the following baseline schemes.

- *Water-filling:* The covariance matrices are designed without considering the loop-back channels $\mathbf{G}_i$ for $i = 1, \cdots, K$, while the transmitter still harvests energy through the loop-back channel. In other words, for the i-th time slot, $\mathbf{Q}_i$ is determined as $\mathbf{Q}_i = \mathbf{V}_i \mathbf{D}_i \mathbf{V}_i^H$, where $\mathbf{V}_i$ stands for the right singular vector matrix of the channel $\mathbf{H}_i$ and the diagonal matrix $\mathbf{D}_i$ is obtained by

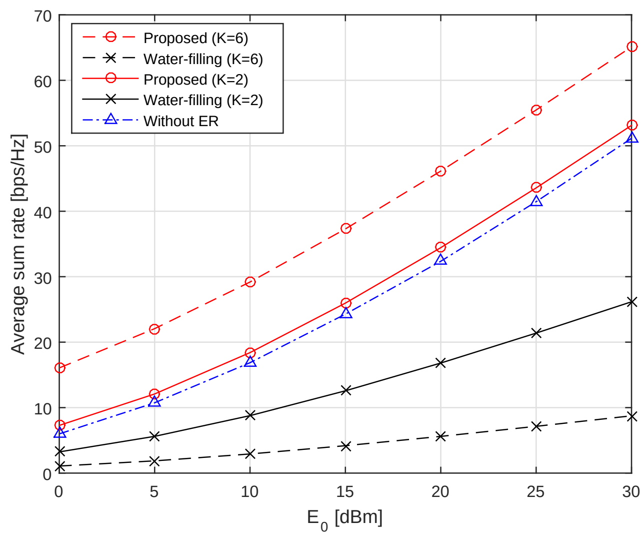

Fig. 2. Average sum rate performance as a function of E_0 for the perfect CSI case with $N_I = N_E = M = 6$

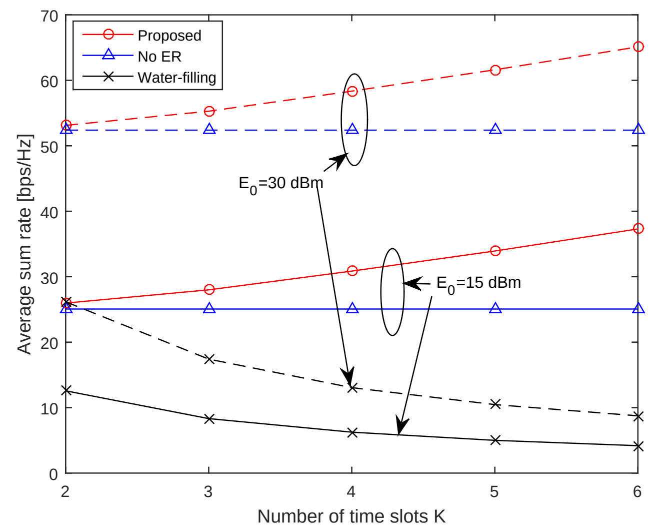

Fig. 3. Average sum rate performance as a function of K for the perfect CSI case with $N_I = N_E = M = 6$

the conventional water-filling algorithm under the energy constraint $\text{tr}(\mathbf{Q}_i) \leq B_i$, i.e, all the available energy is consumed at each time slot.

- *no ER:* The self ER technique is not employed at the transmitter, and thus the system reduces to the conventional point-to-point MIMO by setting $K = 1$.

Fig. 2 depicts the average sum rate performance as a function of the initial energy E_0 for the perfect CSI case with $N_I = N_E = M = 6$. We can first see that the proposed optimal algorithm outperforms the conventional schemes and performance gap increases as K grows. Also, it is emphasized that the performance of the water-filling scheme decreases as K gets larger, since the loop-back channels become more crucial for the sum rate performance. Compared with the systems which do not adopt the ER, it is confirmed that the average sum rate of the MIMO systems can be enhanced by employing the self ER technique at the transmitter. We can observe from the curve of the water-filling scheme, that the performance of the ER system becomes worse than that of the conventional no ER system if the covariance matrix is not properly optimized. This indicates that the covariance matrix optimization is important for the ER systems in order to achieve high spectral efficiency.

In Fig. 3, we illustrate the average sum rate performance as a function of the number of time slots K for the perfect CSI case with $N_I = N_E = M = 6$. It is interesting to remark that the performance of the proposed algorithm increases as K grows, while that of the conventional water-filling scheme decreases, since the loop-back channel $\mathbf{G}_i$ is not considered for the covariance matrix computation. Therefore, we can conclude that the loop-back channels should be taken into account for designing the ER systems.

Next, in Fig. 4, we evaluate the average sum rate performance of the proposed scheme in Section IV for the imperfect CSI case with $N_I = N_E = 6$, $M = 1$ and $K = 6$. Here, we employ the same error bounds for each time slot

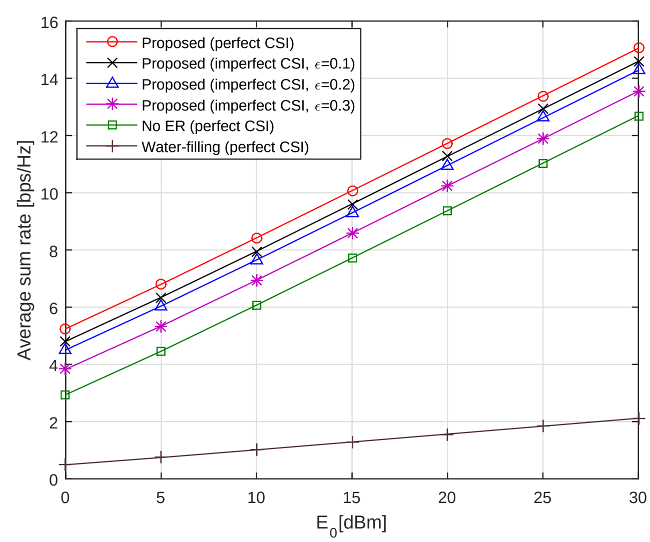

Fig. 4. Average sum rate performance as a function of E_0 for the imperfect CSI case with $N_I = N_E = 6$, $M = 1$ and $K = 6$

$(\varepsilon = \varepsilon_{H,i} = \varepsilon_{G,i}, \forall i)$. For comparison, the performance of the proposed optimal, no ER and the water-filling schemes for the perfect CSI case is also plotted. From the figure, it can be shown that the proposed robust design achieves good performance in the presence of estimation errors. Also, we can see that the proposed robust precoding method offers a significant performance gain over the conventional schemes. Thus, the proposed self ER MIMO systems provide substantially improved average sum rate performance.

VI. Conclusion

In this paper, we have examined the ER based point-to-point MIMO communication systems where the transmitter harvests energy from its own transmitted RF signals. In order to maximize the sum rate performance, we jointly optimize the transmit covariance matrices at all time slots in two different cases. First, in the perfect CSI case, the globally optimal algorithm has been provided for the sum rate maximization problem. Next, for the imperfect CSI case, we have presented the robust covariance matrix optimization method which maximizes the worst case sum rate performance. From numerical results, it has been confirmed that the proposed algorithms significantly outperform the conventional schemes.

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