Antenna Selection for Energy Efficiency in MIMO Wireless Energy Transfer Systems

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Abstract: In this paper, we consider point-to-point multiple-input multiple-output (MIMO) wireless energy transfer system in which one energy receiver harvests energy from radio frequency (RF) signal transmitted from one energy transmitter. We deal with an antenna selection problem to maximize a harvested power to total power consumption ratio (HPCR). It is shown that the singular value of the reconstructed channel by selection determines the HPCR. Against high computation complexity of the exhaustive search for optimal selection, we propose a greedy selection algorithm ...based on the norm of column associated with each antenna. Simulation results show that the proposed algorithm achieves near optimal performance.

Keywords—**WET, Energy efficiency, Antenna selection**

1. Introduction

In recent years, there has been a lot of interest to wireless energy transfer (WET) technology due to increased number of electric devices and limited battery issues [1]. The WET technology is classified into three types named as inductive coupling, resonant coupling and radio frequency (RF) radiation based on their basic principles [2]. Although the inductive coupling and the resonant coupling have been well studied and standardized due to those high charging efficiency and easy implementation, RF radiation charging type has been attracting popularity nowadays by virtue of long-range wireless charging [3]. Especially, applications to low power consuming systems such as wireless sensor networks (WSNs) are introduced in academia and industry by the nature of low charging efficiency [4]-[6]. Furthermore, adoption to multiple-input multiple-output (MIMO) systems in which multiple antennas are utilized to focus the energy on certain direction has been considered for enhancement of WET [7].

On the other hand, energy efficiency is also one of the main issues in modern wireless communications [8]. MIMO systems have been studied intensively for the demand on high data rate and improved performance is guaranteed by the use of multiple antennas [9]. However, it is generally not optimal to use the large number of antennas in the energy efficiency sense because using more antennas requires more energy consumption of circuit elements such as RF-chains [10]. Enhancing the energy efficiency in MIMO data transmission systems has been studied in various scenario [8], but it cannot be applied to MIMO WET systems in the same manner because the characteristics of data transmission and energy transfer are different. Hence, new approaches to improve energy efficiency in MIMO WET are needed to be investigated.

In this paper, we consider two aforementioned topics, MIMO WET and energy efficiency, simultaneously and present a transmit antenna selection problem. The objective is selecting antenna subset to maximize harvested power to total power consumption ratio (HPCR). To deal with high complexity of searching the optimal selection by an exhaustive search, we propose a greedy selection algorithm in which the transmitter priorly selects the antenna having the largest Frobenius norm of associated column in the channel matrix.

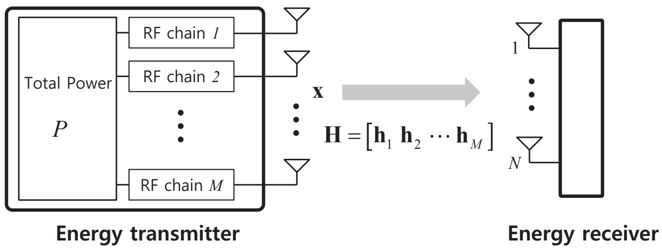

Figure 1. Point-to-Point MIMO energy transfer system

The rest of this paper is organized as follows. In Section 2, we introduce the system model for point-to-point MIMO WET and state the problem. In section 3, we propose the algorithm to find suboptimal selection. In section 4, we evaluate the performance of the proposed algorithm compared with the optimal selection. Throughout the paper, matrices and vectors are represented by bold letters and the notations $(\mathbf{A})^H$, $\operatorname{tr}(\mathbf{A})$ and $\{\mathbf{A}\}_{i,j}$ denotes the conjugate transpose, the trace and the element in i-th row and j-th column of $\mathbf{A}$ respectively. $||\mathbf{A}||$ denotes the Frobenius norm of $\mathbf{A}$ and $|\mathcal{A}|$ denote the size of set $\mathcal{A}$. $\mathcal{CN}(\mathbf{0}, \mathbf{I})$ denotes a circularly symmetric complex Gaussian (CSCG) random vector with mean $\mathbf{0}$ and covariance matrix $\mathbf{I}$ and $\mathbb{C}^{x \times y}$ denotes a space of $x \times y$ matrices with complex entries.

2. System model

As shown in Figure 1, this paper consider a point-to-point MIMO energy transfer system consisting of one energy transmitter and one energy receiver. It is assumed that the transmitter is equipped with M antennas, and the receiver is equipped with N antennas. The channel between the transmitter and the receiver is assumed frequency flat and can be modeled by $N \times M$ complex baseband channel matrix, which is written as

$$\mathbf{H} = [\mathbf{h}_1\ \mathbf{h}_2\ \cdots\ \mathbf{h}_M], \tag{1}$$

where $\mathbf{h}_m$, $m = 1, ..., M$ denotes $N \times 1$ channel vector between m-th transmit antenna and N receive antennas. It is

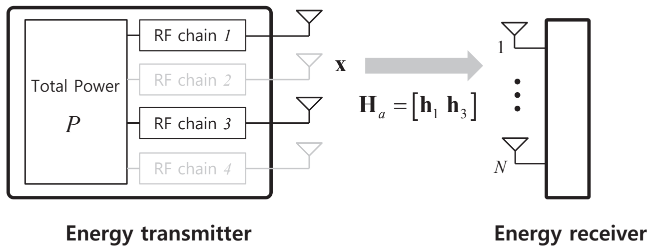

Figure 2. $M = 4$, $N = 2$ and $\mathcal{S} = \{1, 3\}$ case

assumed that $\mathbf{H}$ is full rank matrix and the transmitter has knowledge of the channel state information $\mathbf{H}$ perfectly. The received signal $\mathbf{y} \in \mathbb{C}^{N\times 1}$ can be written as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{2}$$

where $\mathbf{x} \in \mathbb{C}^{M\times 1}$ is the transmit signal vector in which the energy can be conveyed. We use $\mathbf{Q} = E\left[\mathbf{x}\mathbf{x}^H\right]$ to denote the covariance matrix of the transmit signal and assume consistent transmit power P, i.e., $\text{tr}\left(\mathbf{Q}\right) = P$. $\mathbf{n} \in \mathbb{C}^{N\times 1}$ denotes the receiver noise vector and it is assumed that $\mathbf{n} \sim \mathcal{CN}\left(\mathbf{0}, \mathbf{I}\right)$.

2.1 HPCR

Total harvested power P_h which is harvested energy normalized by the baseband symbol period at the energy receiver is given by [7]

$$\begin{aligned} P_h &= \zeta E\left[\|\mathbf{y}\|^2\right] \\ &= \zeta \text{tr}\left(\mathbf{H}\mathbf{Q}\mathbf{H}^H\right), \end{aligned} \tag{3}$$

where ζ denotes efficiency constant for converting harvested energy to effective electrical energy to be stored. We assume $\zeta = 1$ in the paper for simplicity. Note that we assume that additive noise is negligible compared to harvested energy at the energy receiver [7].

We define HPCR of the energy transfer system as

$$\text{HPCR} = \frac{P_h}{P_{tot}}, \tag{4}$$

where P_h and P_{tot} denote harvested power at the energy receiver and total power consumption at the energy transmitter, respectively. P_{tot} reflects practical model consistng of three different types of power consumption factor as [10]

$$P_{tot} = \eta P_T + K P_R + P_C. \tag{5}$$

Here, P_T is total transmit signal power at the energy transmitter related to power consumption of power amplifier (PA) and η is a coefficient of PA inefficiency and it is assumed that $\eta = 1$ in this paper for simplicity. P_T is equal to previously mentioned transmit signal power $\text{tr}\left(\mathbf{Q}\right)$, i.e., $P_T = P$. P_R is power consumption of RF chain of each antenna and K is the number of active transmit antennas among total M transmit antennas. P_C is the power consumption of other circuits of the energy transmitter.

2.2 Problem statement

Our objective is to select K transmit antennas among total M transmit antennas and to determine the covariance matrix $\mathbf{Q}$ to maximize the HPCR in (4). We donote $\mathcal{S} \subset \{1, \ldots, M\}$ as a set of selected transmit antenna indices and $\mathbf{H}_a \in \mathbb{C}^{N\times K}$ is a channel coefficient matrix reconstructed by $\mathcal{S}$. For given channel coefficient matrix $\mathbf{H}$, our problem can be formulated as

$$\begin{aligned} \max_{\mathcal{S},\mathbf{Q}} \ & \frac{\text{tr}\left(\mathbf{H}_a\mathbf{Q}\mathbf{H}_a^H\right)}{\eta P + K P_R + P_C} \\ \text{s.t. } & \mathcal{S} \subset \{1, 2, \ldots, M\} \\ & |\mathcal{S}| = K \\ & \text{tr}\left(\mathbf{Q}\right) = P. \end{aligned} \tag{6}$$

Total transmit power P is allocated among K selected antennas according to transmit covariance matrix $\mathbf{Q}$. For example, in the case of $M = 4$, $N = 2$ and $S = \{1, 3\}$, the activated antennas are the first and the third antenna as shown in Figure 2. Note that reconstructed channel $\mathbf{H}_a$ between selected transmit antennas and receive antennas can be represented as $\mathbf{H}_a = [\mathbf{h}_1\ \mathbf{h}_3]$.

3. Proposed algorithm

3.1 Energy beamforming

For fixed antenna selection set $\mathcal{S}$, problem (6) is simplified to transmit covariance matrix optimization problem as

$$\begin{aligned} \max_{\mathbf{Q}} \ & \text{tr}\left(\mathbf{H}_a\mathbf{Q}\mathbf{H}_a^H\right) \\ \text{s.t. } & \text{tr}\left(\mathbf{Q}\right) = P. \end{aligned} \tag{7}$$

Let the reduced singular value decomposition (SVD) of $\mathbf{H}_a$ be

$$\mathbf{H}_a = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^H = [\mathbf{u}_1 \cdots \mathbf{u}_N]\,\boldsymbol{\Sigma}[\mathbf{v}_1 \cdots \mathbf{v}_K]^H, \tag{8}$$

in which $\mathbf{U} \in \mathbb{C}^{N\times N}$ and $\mathbf{V} \in \mathbb{C}^{K\times K}$ consist of orthonormal columns. The diagonal matrix $\boldsymbol{\Sigma} \in \mathbb{C}^{N\times K}$ comprises the singular values $\sigma_n = \{\boldsymbol{\Sigma}\}_{n,n}$, $n = 1, 2, ..., \min\left(N, K\right)$ in descending order, i.e., $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_{\min(N,K)}$. Then the optimal solution to (7) is given by $\mathbf{Q}^* = P\mathbf{v}_1\mathbf{v}_1^H$ where $\mathbf{v}_1$ is the first column of $\mathbf{V}$ [7].

If $\mathbf{Q} = \mathbf{Q}^*$, maximized harvested power at the receiver is given by ${P_h}^* = \sigma_1^2 P$. The optimal covariance matrix is achieved by the beamforming known as "energy beamforming", which aligns transmit signal with the strongest eigenmode of $\mathbf{H}_a^H\mathbf{H}_a$. Since the maximum harvested power only depend on the largest singular value of reconstructed channel $\mathbf{H}_a$, we can reformulate the problem (6) to

$$\begin{aligned} \max_{\mathcal{S}} \ & \frac{\sigma_1^2 P}{P + K P_R + P_C} \\ \text{s.t. } & \mathcal{S} \subset \{1, 2, \ldots, M\} \\ & K = |\mathcal{S}|. \end{aligned} \tag{9}$$

Table 1 Greedy Antenna Selection Algorithm

Input: $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_M]$
STEP 1. Sort the column indices into descending order for each norm
  $\mathbf{s} = [s_1, s_2, \ldots s_M \mid ||\mathbf{h}_{s_1}|| \geq ||\mathbf{h}_{s_2}|| \geq \ldots \geq ||\mathbf{h}_{s_M}||,$
   $s_i \in \{1, 2, \ldots, M\}]$
STEP 2. Compare HPCR for each K
  set $\mathcal{S}' = \emptyset$, HPCR $(\emptyset) = 0$
  for $K = 1$ to M **do**
   $\mathcal{S} \leftarrow \{s_1, \ldots, s_K\}$
   if HPCR $(\mathcal{S}) >$ HPCR $(\mathcal{S}')$
    $\mathcal{S}' \leftarrow \mathcal{S}$
   end
   $K \leftarrow K + 1$
  end for
Output: $\mathcal{S}_{opt} = \mathcal{S}'$

3.2 Greedy selection algorithm

The optimal antenna selection to (9) is found by calculating the largest singular value of reconstructed channel for all ${}_MC_K, K = 1, \ldots, M$ combinations and choosing the highest value. For fixed $N \times K$ matrix $\mathbf{H}_a$, it is known that time complexity to find singular values by the SVD is $O\left(NK^2\right)$ [11].

Intuited by the property of singular values

$$||\mathbf{H}_a||^2 = \sum_{n=1}^{\min(N,K)} \sigma_n^2, \tag{10}$$

we propose greedy selection algorithm based on the norm of each column comprising the channel matrix $\mathbf{H}$. In each step of searching best K transmit antennas, $K = 1, 2, \ldots, M$, we just select the K antennas which have K largest norm of the column associated with the antenna. The detail algorithm is described in Table 1 where HPCR $(\mathcal{S})$ denotes HPCR according to the selected antennas by $\mathcal{S}$. Note that column interchanging in the certain matrix does not change the singular values. In other words, K selected columns can make K factorial of reconstructed matrices but the singular values of the matrices are all the same.

For certain K, although this algorithm determines $\mathcal{S}_{opt}$ for $||\mathbf{H}_a||$ to be maximized, it does not guarantee that the largest singular value is maximized among all possible selections. However, by the property in (10), it is expected that our algorithm is effective to making reconstructed channel having large principal singular value. Also, the algorithm is effective in the complexity sense since the algorithm does not need additional computation of the SVD and searching for all possible combinations of antenna selections.

4. Simulation results

In this section, we present simulation results to verify our proposed scheme. The results are averaged over 10,000 channel realization and we assume that each element of channel matrix is independent and identically distributed (i.i.d) zero mean unit variance complex Gaussian random variable. In Figure 3, we consider point-to-point MIMO energy transfer system with $M = 10$ transmit antennas and $N = 2$ receive antennas and observe HPCR in each fixed the number of selected antennas for the exhaustive and the proposed methods. We set power consumption parameters to $P = 2W$, $P_C = 10W$ and $P_R = 0.5W$(star-marked line) or $2W$(circle-marked line). For the random selection method, we randomly select K columns among total M columns for each K. The simulation result shows that our proposed scheme achieves near optimal HPCR and considerable performance compared with the random selection method. Note that the number of selected antennas at the maximum HPCR point is larger in case of $P_R = 0.5W$. The reason is that since the burden of using more antennas is reduced, transmitter can exploit the merit of using multiple antennas for energy transmission and achieves better HPCR performance.

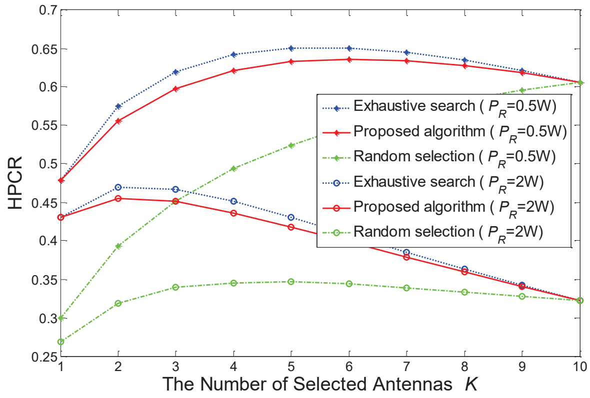

Figure 3. Comparison of HPCR with varying K

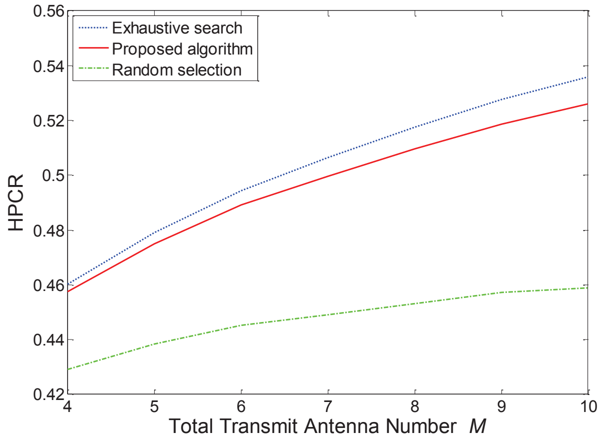

Figure 4. Comparison of HPCR with varying M

Figure 4 illustrates HPCR versus the number of total transmit antenna M with $N = 3$ receive antennas, $P = 2W, P_C = 10W$ and $P_R = 2W$. In random selection, we use the best subset for HPCR among randomly selected subset of each K. Here, we can also verify that our proposed scheme achieves near optimal performance especially in small total number of transmit antennas. In the case of large M, since there exists more columns having similar value of norm, maximizing sum of column norm does not guarantee maximizing the largest singular value. In addition, we can observe that HPCR performance is better in case that the total number of transmit antenna is large since more selection diversity is exploited in that case.

5. Conclusion

In this paper, we have considered the point-to-point MIMO WET system focusing on antenna selection to maximize HPCR. Intuited by the relation between the singular value of the channel matrix and maximum harvested energy, we have proposed the greedy selection algorithm in which the transmitter selects antennas in greedy manner based on the norm of associated column. Through the simulation results, we have shown that the proposed algorithm achieves the performance of near optimal in spite of the considerably reduced computation complexity. For future works, improved algorithm for determining the antenna subset more precisely to the optimal set is needed to be investigated.

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