International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 20 (2017) pp. 10073-10076

Joint Beam Forming and Resource Allocation for WPCN with Distributed Massive MIMO System

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Abstract

In this paper, we propose a joint beamforming and resource allocation scheme to maximize the minimum capacity for wireless powered communication network (WPCN) with multi-user distributed massive multi-input multi-output (DM-MIMO) system. The minimum capacity is maximized by a proposed algorithm based on the non-negative matrix theory. The simulation results show that the proposed scheme can achieve a significant max-min capacity improvement for both CMMIMO and DM-MIMO. Also, the achievable max-min capacity of the DM-MIMO is considerably higher compared to that of the centralized massive multi-input multi-output (CM-MIMO) system.

INTRODUCTION

Wireless powered communication network (WPCN) has recently drawn significant attention in energy constrained wireless networks [1-2]. In WPCN, terminals harvest energy from radiated signals by transmitters and then transmit information signals by using the harvested energy. However, the transmission efficiency of the wireless power transmission decreases rapidly depending on the transmission distance. Fortunately, the distributed massive multi-input multi-output (DM-MIMO) system is a promising solution since it can solve the double near-far problem [3]. In DM-MIMO, radio remote heads (RRHs) are geographically distributed to mitigate the path loss. In addition, DMMIMO system can achieve high frequency efficiency [4-5] and energy efficiency [6]. Nevertheless, most of the existing WPCN studies have been performed in centralized massive MIMO (CM-MIMO) systems.

In this paper, we focus to study an optimal transmit and receive beamformer, power allocation and time allocation for WPCN with a multi-user DM-MIMO system. The object is to maximize the minimum user throughput subject to total transmit power constraints and time constraints. The problem is nonconvex due to the non-linear constraints and the coupled optimization variables. We propose a joint beamforming and resource allocation algorithm to solve the optimization problem based on the non-negative matrix theory [7]. Simulation results are provided to compare the max-min capacity and to show the convergence performance of the proposed algorithm with both CM-MIMO and DM-MIMO systems.

SYSTEM MODEL

We consider a WPCN consisting of N RRHs and K users. The RRHs and each user are equipped with M antennas and a single antenna, respectively. The RRHs are connected to a baseband process unit (BPU) via optical fibers. We assume a flat-fading channel where the channel is constant for a given transmission block. A frame-based transmission is considered and without loss of generality, the frame duration is normalized to be 1. It is assumed that the channel matrix is known perfectly at the BPU. In the downlink (DL) wireless energy transfer (WET) phase, the RRH radiates radio frequency (RF) signals via beamforming for a time $\tau(0<\tau<1)$. In the uplink (UL) wireless information transfer (WIT) phase, all of the users simultaneously transmit data to the RRHs using their harvested energy for the remaining time$(1-\tau)$.

The channel vector from all the RRHs to user k are denoted by

$$\mathbf{g}_k=\mathbf{\Lambda}_k^{1/2}\mathbf{h}_k \qquad (1)$$

where $\mathbf{\Lambda}_k=\mathrm{diag}\left(\left[\xi_{1,k}\ .\ .\ .\ \xi_{N,k}\right]\right)\otimes\mathbf{I}_M$ and $\mathbf{h}_k=\left[\mathbf{h}_{1,k}^T\dots\mathbf{h}_{N,k}^T\right]^T$. Here $(.)^T$ and $\xi_{n,k}$ denote the transpose and the path loss of the channel between the RRH n and user k, respectively. $\otimes$ denotes the Kronecker product and $\mathbf{h}_{n,k}$ represents an $M\times 1$ independent Rayleigh fading coefficients between the RRH n and user k, i.e., $\mathbf{h}_{n,k}\sim\mathcal{CN}(0,1)$. In the DL WET phase, channel reciprocity is assumed. The received signal at the user k can be written as:

$$x_k=\sqrt{p_k}\mathbf{g}_k^H\mathbf{w}+n_k \qquad (2)$$

where p_k is the DL transmission power to user k, $\mathbf{w}=\sum_{k=1}^{k}\mathbf{u}_k$, and n_k is the user noise with independent and identically distributed (i.i.d.) elements distributed as

$\mathcal{CN}(0,\sigma_d^2)$. Here $(.)^H$ and $\mathbf{u}_k$ denote the conjugate transpose and the DL energy beamforming vector for user k, respectively. It is assumed that the noise power is too small for energy to be harvested from it. Therefore, the harvested energy at the user k is given by:

$$E_k = \varepsilon\tau\mathbb{E}[|x_k|^2] = \varepsilon\tau p_k \mathbb{E}\left[\left|\mathbf{g}_k^H\mathbf{w}\right|^2\right] \qquad (3)$$

where $\mathbb{E}[.]$ denotes the statistical expectation and $0 < \varepsilon \leq 1$ is the energy conversion efficiency.

In the UL WIT phase, the received signal vector at the BPU can be written as:

$$\mathbf{r} = \mathbf{Gs} + \boldsymbol{z} \qquad (4)$$

where $\mathbf{G} = \left[\mathbf{g}_1. \;\; . \;\; . \;\; \mathbf{g}_k\right]$, $\mathbf{s}$ is the UL information carrying signal of the users, and $\mathbf{z}$ is the receiver noise vector with zero mean and variance σ_u^2. We assume that the BPU decodes the received signals from user k via a receive beamforming vector denoted $\mathbf{v}_k$, $k = 1, \ldots, K$. Thus, the achievable UL capacity for user k can be written as:

$$C_k = (1-\tau)\log_2(1+\gamma_k) \qquad (5)$$

where γ_k is the signal to interference plus noise ratio (SINR) given by

$$\gamma_k = \frac{q_k\left|\mathbf{v}_k^H\mathbf{g}_k\right|^2}{\sum_{i=1,i\neq k}^{K} q_i|\mathbf{v}_k^H\mathbf{g}_i|+|\mathbf{v}_k^H\mathbf{v}_k|\sigma_u^2}. \qquad (6)$$

Here, q_k denotes the average UL transmit power for user k.

PROBLEM FORMULATION

In this section, we maximize the minimum UL capacity of all users by optimizing over $\tau, p, \mathbf{w}, \mathbf{v}$, i.e.

$$\max_{\tau,p,\mathbf{w},\mathbf{V}} \; \min_k \; C_k \qquad (7)$$

$$\text{s.t } 0 < \boldsymbol{\tau} < 1 \qquad (8)$$

$$(1-\tau)q_k = E_k, \; \forall k \qquad (9)$$

$$\textstyle\sum_k p_k < p_{\max} \qquad (10)$$

$$\|\mathbf{w}\| = 1 \qquad (11)$$

where $\mathbf{p} = [p_1 \; \ldots \; p_k]$, $\mathbf{V} = [\mathbf{v}_1 \ldots \mathbf{v}_k]$, and (10), (11) are due to the total power constraint. The problem is non-convex due to the coupling between optimization variables.

Joint beamforming and resource allocation

In order to make the problem tractable, we separate the optimization variable $\mathbf{w}$ from the others. Note that the DL energy beamformer only affects the amount of harvested energy. The harvested energy at user k in (3) can be rewritten as

$$E_k = \varepsilon\tau p_k \mathbb{E}\left[\mathbf{w}^H\mathbf{g}_k\mathbf{g}_k^H\mathbf{w}\right]. \qquad (12)$$

Let $\mathbf{u}_k^*$ represents the optimal beamforming vector for maximizing the harvested energy of the user k which is the dominant eigenvector of $\mathbf{g}_k\mathbf{g}_k^H$. Thus, the proposed optimal beamforming vector is a linear combination of $\mathbf{u}_k^*/\|\mathbf{u}_k^*\|$, i.e., $\mathbf{w}^* = \sum_{k=1}^{K}\frac{1}{K}\frac{\mathbf{u}_k^*}{\|\mathbf{u}_k^*\|}$.

Next, by fixing $\tau_k = \bar{\tau}$, problem (7) is reduced to the following SINR balancing problem, i.e.,

$$\max_{\mathbf{p},\mathbf{V}} \; \min_k \; \gamma_k \qquad (13)$$

$$\text{s.t } (1-\bar{\tau})q_k = E_k, \; \forall k \qquad (14)$$

$$\textstyle\sum_k p_k < P_{\max}. \qquad (15)$$

First, we obtain the optimal $\mathbf{P}^*$ and $\mathbf{V}^*$ by solving problem (13). Then, we find the optimal τ_k^* by performing a line-search algorithm over $0 < \tau < 1$. We present an algorithm to obtain the optimal $\mathbf{P}^*$ and $\mathbf{V}^*$ based on the non-negative matrix theory.

Define $\mathbf{D} = \text{diag}\left\{1/\left\|\mathbf{v}_1^H\;\mathbf{g}_1\right\|^2, \ldots, 1/\left\|\mathbf{v}_1^H\;\mathbf{g}_K\right\|^2\right\}$ $\boldsymbol{\sigma} = [\sigma_u^2, . \, . \, .\sigma_u^2\,]^T$, and the non-negative matrix $\boldsymbol{\Psi}$ as

$$[\boldsymbol{\Psi}]_{ik} = \begin{cases} \left\|\mathbf{v}_k^H\;\mathbf{g}_i\right\|^2, & k \neq i, \\ 0, & k = i. \end{cases} \qquad (16)$$

where $[\boldsymbol{\Psi}]_{ik}$ denotes the entry on the *i-th* row and *k-th* column of $\boldsymbol{\Psi}$. Given any $\mathbf{V}$, the optimal balanced SINR of (13) is given by [8]

$$\gamma = \frac{1}{\lambda_{\max}(\boldsymbol{\Lambda}(\mathbf{V},P_{\max}))} \qquad (17)$$

where $\boldsymbol{\Lambda}$ is defined as:

$$\boldsymbol{\Lambda} = \begin{bmatrix} \mathbf{D\Psi} & \mathbf{D}\boldsymbol{\sigma} \\ \frac{1}{P_{\max}}1^T\mathbf{D}\boldsymbol{\Psi}^T & \frac{1}{P_{\max}}1^T\mathbf{D}\boldsymbol{\sigma} \end{bmatrix}. \qquad (18)$$

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The optimal uplink power vector $\mathbf{q}^* = [q_1^*, \ldots, q_K^*]^T$ is obtained as $\hat{\mathbf{q}} = \begin{pmatrix}\mathbf{q}^*\\1\end{pmatrix}$ where $\hat{\mathbf{q}}$ is the dominant eigenvector of $\mathbf{\Lambda}$. Next, the optimal receive beamformer $\mathbf{V}^*$ for a given $\mathbf{q}^*$ is obtained by solving the following problem

$$\mathbf{v}_k^* = \arg\max \frac{\|\mathbf{v}_k^H \mathbf{g}_k\|^2}{\mathbf{v}_k^H \mathbf{Q}_k \mathbf{v}_k}, s.t. \|\mathbf{v}_k\| = 1, \ \forall k \qquad (19)$$

where $\mathbf{Q}_k = \sum_{i=1,i\neq k}^{K} q_i^* \mathbf{g}_i \mathbf{g}_i^H + \mathbf{I}, \ \forall k.$ It is noticeable that $\mathbf{v}_k^*$ is the dominant generalized eigenvectors of the matrix pairs $(\mathbf{g}_k \mathbf{g}_k^H, \mathbf{Q}_k), \forall k$ since $\mathbf{Q}_k$ is non-singular and symmetric. The proposed algorithm iteratively finds $\mathbf{q}^*$ and $\mathbf{V}^*$ until convergence which is summarized in Algorithm 1. Finally, we can obtain the optimal WET time τ by the bisection method over $0 < \tau < 1$.

Algorithm 1 SINR balancing algorithm

Step 1. initially set $i = 0, q = [0, \ldots, 0]^T$;

Step 2. **repeat**;

Step 3. compute $\mathbf{v}_k^i$ using (19)

Step 4. compute $\mathbf{q}^i$ by finding the dominant eigenvector of $\mathbf{\Lambda}$

Step 5. $i = i + 1$;

Step 6. **until** convergence of γ;

Step 7. **return** $\mathbf{v}_k^i$ and $\mathbf{q}^i$

SIMULATION RESULTS

In this section, we evaluate and present our results via simulations. We consider a hexagonal cell with radius 10m. It is assumed that N = 7 RRHs are distributed with radius $r_1 = 0, r_2 = \ldots = r_7 = (3-\sqrt{3})/2$ and angles $\theta_1 = 0$, $\theta_2 = \pi/6$,$\theta_4 = 5\pi/6$, $\theta_5 = 7\pi/6$, $\theta_6 = 9\pi/6$, $\theta_7 = 11\pi/6$. Each RRH is equipped with M = 50 antennas and the total number of antennas is MN = 350, which is assumed to be the same in CM-MIMO and DM-MIMO. There are K = 7 uniformly distributed users. We set $P_{max} = 1$Watt, $\varepsilon = 0.7$, and $\sigma_u^2 = \sigma_d^2 = -50dBm$. We use the path loss model $\xi_{n.k} = 10^{-3} d_{n,k}^{-3}$, where $d_{n,k}$ is the distance between the user k and the RRH n.

Figure 1 compares the max-min capacity of the proposed scheme with that of the equal power allocation and zero-forcing (ZF) receiver. It is observed that the proposed scheme can achieve a higher max-min capacity. It is also observed that the DM-MIMO achieves a considerably higher max-min capacity compared to the CM-MIMO. Figure 2 shows the convergence performance of the proposed scheme with both CM-MIMO and DM-MIMO. The proposed algorithm is rapidly converged to the optimal max-min capacity.

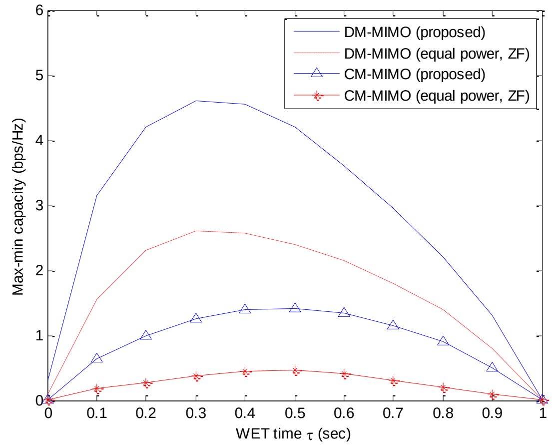

Figure 1. Comparison of max-min capacity versus WET time τ.

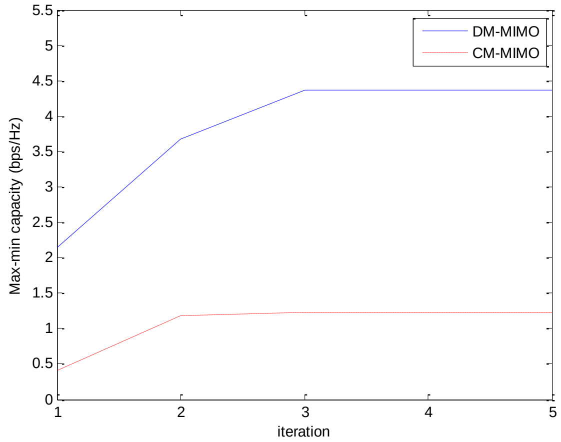

Figure 2. Max-min capacity achieved by Algorithm 1 versus iteration.

CONCLUSION

In this paper, we studied the max-min capacity optimization for WPCN. Based on the non-negative matrix theory, we proposed a max-min capacity optimization algorithm with a fast convergence rate. It is shown that the proposed scheme achieves a higher max-min capacity for both CM-MIMO and DM-MIMO. Further, the max-min capacity of the DM-MIMO is significantly higher compared to the CM-MIMO.

ACKNOWLEDGMENT

This research was supported by the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2016R1A2B4012752).

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