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MULTI-OBJECTIVE ENERGY EFFICIENT RESOURCE ALLOCATION FOR WPCN

S. Sharma[1], W. Yoon[2*]

[1,2]*Department of Electrical and Computer Eng.,*
Ajou University, South Korea

Abstract

In this paper, we propose an energy-efficient resource allocation scheme for a wireless powered communication network (WPCN). A multiple-objective optimization problem (MOOP) is formulated for the EE maximization for every user. We exploit fractional programming approach to convert the non-convex problem into a standard convex optimization problem. This allows us to derive an efficient iterative algorithm for Pareto optimal. Simulation results prove our theoretic findings and show that distributed massive multi input multi output (MIMO) performs better and higher as compared to that of centralized massive MIMO.

Keywords - Wireless powered communication network, Energy efficiency, Generalized fractional programming, Pareto optimal

I. INTRODUCTION

Various approaches have been devised for energy harvesting in modern electronics and mobile communication systems in last few decades. The natural and renewable sources of energy like solar or wind energy offer a non-vanishing source of energy for wireless networks [1]. More specifically, energy harvested from the radio-frequency (RF) waves opens up a new direction of simultaneous wireless power transmission (WPT) and communication where RF signals transfer both energy and information. In general, there exist two important paradigms of research. In the first scenario, simultaneous wireless information and power transfer (SWIPT) occurs in two stages, information decoding and the energy harvesting. In the other case, most of the research is focused to design wireless-powered communication network (WPCN) where wireless terminals communicate via the harvested energy from wireless power transmissions. The WPCN has been studied on a wide scale under various network configurations, such as random-access network, cellular/multicellular network, and multi-hop networks [2-5].

A half duplex massive multi input multi output (MIMO) system has been studied where base station is equipped with large number of antenna. Massive MIMO systems can perform better and gives higher spectral efficiency (SE) and energy efficiency (EE) [1, 6]. The distributed massive (DM) MIMO system is an auspicious solution to solve the double near-far problem [6]. Radio remote heads (RRHs) are geographically distributed in DM-MIMO to diminish the path loss. Additionally, it can achieve high frequency efficiency and energy efficiency [6]. However, most of the existing WPCN studies have been performed in centralized massive MIMO (CM-MIMO) systems.

In this paper, we study to improve and optimize energy efficiency. As different users have their different battery capacities, the energy of every single user should be separately measured. Maximizing the overall energy efficiency has been studied in [8] and it can be a general fractional programming. We formulate a multi-objective resource allocation problem, which in general has a Pareto optimal solution set. We first maximize the EE of each user and find their Pareto optimal EE by the weighted Tchebycheff method to convert the multi-objective optimization problem (MOOP) into a single objective optimization problem (SOOP). We develop an iterative algorithm to find the optimal solution. Simulation results are provided to compare the user capacity performance and confirm that this method succeeds in achieving better outcome with fast convergence speed.

The remainder of this paper is organized as follows. In Section II we describe the system model. In Section III, we describe the proposed algorithm. In Section IV, we evaluate the performance of the proposed method, and finally, in Section V, we conclude the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a WPCN with *N* RRHs equipped with *M* antennas and *K* users with a single antenna. The uplink (UL) information transmission time of user is (1- θ). The energy harvesting time for user is given by θ. Without loss of generality, the frame duration is normalized to be 1. The channel vector of all RRHs are represented by

$$\mathbf{g}_k = \mathbf{\Lambda}_k^{1/2}\mathbf{h}_k \tag{1}$$

where $\mathbf{\Lambda}_k = \mathrm{diag}\big([\zeta_{1,k}, \dots, \zeta_{N,k}]\big)\otimes\mathbf{I}_M$, $\mathbf{h}_k = \left[\mathbf{h}_{1,k}^T, \dots, \mathbf{h}_{N,k}^T\right]^T$. Here $(.)^T$ is the transpose and $\zeta_{n,k}$ is the path loss of the channel between the RRH *n* and user *k*. $\otimes$ is the Kronecker product and $\mathbf{h}_{n,k}$ is *M*×1 independent Rayleigh fading coefficients between RRH *n* and user *k*. In the downlink (DL) phase, assuming channel reciprocity, the received signal at user *k* is given by

$$x_k = \sqrt{p_k}\mathbf{g}_k^H\mathbf{w} + \sum_{\substack{j=1 \\ j\neq k}}^{K} q_{j,k}s_j + n_k \tag{2}$$

where p_k is the DL transmission power to the *k*th user, $\mathbf{w} = \sum_{k=1}^{K}\mathbf{u}_k$, and n_k is the zero-mean additive white Gaussian noise with variance σ_d^2. Here $\mathbf{u}_k$ is the DL energy beamforming vector for the *k*th user. The noise power is too small for energy harvesting compared with the received signal power. Therefore, the harvested energy at the kth user is written as

$$E_k = \varepsilon\theta\mathbb{E}[|x_k|^2] = \varepsilon\theta p_k \mathbb{E}[|\mathbf{g}_k^H \mathbf{w}|^2] \tag{3}$$

where $\mathbb{E}[.]$ denotes the statistical expectation and $0 < \varepsilon \leq 1$ is the energy conversion efficiency. The received signal vector for UL phase is given by

$$\mathbf{r} = \mathbf{Gs} + \boldsymbol{z}. \tag{4}$$

Here $\mathbf{G} = [\mathbf{g}_1, \dots, \mathbf{g}_K]$, $\mathbf{s}$ is the information carrying signals of the users, and $\boldsymbol{z}$ is the receiver noise vector with zero mean and variance σ_u^2. The baseband processing unit decodes the received signals from the kth user via a receive beamforming vector denoted by $\mathbf{v}_k$, $k = 1, \dots, K$. Thus, the achievable UL capacity for the kth user can be given by

$$C_k = (1-\theta)\log_2(1+\gamma_k) \tag{5}$$

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

$$\gamma_k = \frac{P_k|\mathbf{v}_k^H \mathbf{g}_k|^2}{\sum_{i=1,i\neq k}^K P_i|\mathbf{v}_k^H \mathbf{g}_i| + |\mathbf{v}_k^H \mathbf{v}_k|\sigma_u^2}. \tag{6}$$

Here P_k denotes the average UL transmit power for the kth user. Thus the energy efficiency of user n can be expressed as

$$\eta_k = \frac{C_k}{P_k}, \forall k \tag{7}$$

We are interested in maximizing the energy efficiency over time allocation, transmit powers, and beamforming vectors, i.e.,

$$\max_{\theta,\mathbf{p},\mathbf{w},\mathbf{V}} \{\eta_1, \eta_2, \dots, \eta_K\} \tag{8}$$

$$\text{C 1: } 0 < \theta < 1 \tag{9}$$

$$\text{C 2: } (1-\theta)\, P_k = E_k, \forall\, k \tag{10}$$

$$\text{C 3: } \sum p_k < p_{\max} \tag{11}$$

$$\text{C 4: } \| \mathbf{w} \| = 1 \tag{12}$$

where $\mathbf{p} = [p_1, \dots, p_K]$ and $\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_K]$.

III. THE PROPOSED MULTI-OBJECTIVE ALGORITHM

In this section, we introduce an algorithm to achieve the Pareto optimal EE by converting the MOOP in (8) into a SOOP. The optimization problem for user *k* can be expressed as

$$\max_{\theta,\mathbf{p},\mathbf{w},\mathbf{V}} \eta_k \tag{13}$$

subject to C1–C4. This MOOP function is non-convex due to the coupled variables and UL transmit power constraints, which can be equivalently solved by converting (8) into a SOOP [7], using weighted Tchebycheff method expressed as:

$$\max_{\theta,\mathbf{w},\mathbf{p},\mathbf{V}} \min_{k} \left\{ \varphi_k \left(\eta_k^0 - \eta_k \right) \right\} \tag{14}$$

Here, $\boldsymbol{\varphi} = \{\varphi_1, \ldots, \varphi_K\}$ is weighting vector and η_k^0 is the Utopia EE of user k. Further, the objective function is quasiconvex and can be transformed in an equivalent one by separating $\mathbf{w}$ from others as DL beamformer only affects amount of energy harvesting as per (3). Let $\mathbf{u}_k^*$ represents the optimal beamforming vector for maximizing the harvested energy of user *k* which is the dominant eigenvector of $\mathbf{g}_k \mathbf{g}_k^H$. Thus, the proposed optimal downlink beamforming vector is given by

$$\mathbf{w}^* = \sum_{k=1}^{K} \frac{1}{K} \frac{\mathbf{u}_k^*}{\left\| \mathbf{u}_k^* \right\|} . \tag{15}$$

Next, fixing $\theta = \bar{\theta}$ and substituting for η_k in objective function (14) is equivalent to the following:

$$\min_{\mathbf{p},\mathbf{V}} \max_{k} \left\{ \varphi_k \left(\frac{(\eta_k^0 P_k - C_k)}{P_k} \right) \right\}. \tag{16}$$

The above problem (16) is a generalized fractional programming (GFP), which minimizes the maximum of numerous fractions [7]. Using the following approach, (16) can be transformed to an equivalent and better tractable one, i.e., the objective function (16) is quasiconvex and equivalent to

$$\max_{y\in \mathrm{Y}} \min_{\mathbf{p},\mathbf{V}} f(\mathbf{y},\mathbf{p},\mathbf{V}) = \frac{\sum_{k=1}^{K} y_k \varphi_k (\eta_k^0 P_k - C_k)}{\sum_{k=1}^{K} y_k P_k} \tag{17}$$

where $\mathrm{Y} \triangleq \left\{ (y_1,...,y_K) \middle| y_k \geq 0, \forall k, \sum_{k=1}^{K} y_k = 1 \right\}$. We can solve the problem (17) by iterative algorithm which is summarized in Table I. In the table, steps 2 to 9 solve the first subproblem while steps 10 to 17 solve the second subproblem, respectively.

The Pareto optimal solution $\{\mathbf{p},\mathbf{V}\}$ for a given $\mathbf{y}$ and finding optimal $\mathbf{y}$ can be obtained iteratively, by solving subproblems $\eta(\mathbf{y}) = \min_{\mathbf{p},\mathbf{V}} f(y,\mathbf{p},\mathbf{V})$, and $\eta^* = \max_{\mathbf{y}\in Y} \eta(\mathbf{y})$ respectively, for a function U defined as

$$U(\mathbf{y},\alpha) = \sum_{k=1}^{K} y_k \left(\varphi_k \left((\eta_k^0 C_k - P_k) - \alpha P_k \right) \right). \tag{18}$$

Let $\mathbf{y}^{(n)}$, $n = 0,1,...,$ be a sequence updated by the following equation

$$\mathbf{y}^{(n+1)} = \arg \max_{\mathbf{y}\in \mathrm{Y}} \min_{\mathbf{p},\mathbf{V}} U\left(\mathbf{y}, \gamma\left(\mathbf{y}^{(n)}\right)\right) \tag{19}$$

The optimal solutions can be achieved as follows:

(a) when $\min_{\mathbf{p},\mathbf{V}} U(\mathbf{y},\eta(\mathbf{y})) = 0$, $\eta(\mathbf{y})$ is obtained

(b) when $\eta(\mathbf{y}^{(n+1)}) = \eta(\mathbf{y}^{(n)})$, $\eta^* = \eta(\mathbf{y}^{(n)})$ is obtained

$$U^* \triangleq \max_{\mathbf{y} \in Y} \min_{\mathbf{p},\mathbf{V}} U(\mathbf{y},\eta^*)$$

The above optimization problem is convex and classic convex optimization method is used to solve [8].

Table 1: Proposed multi-objective algorithm

1. Initialize $\mathbf{y}^{(0)} \in \mathrm{Y}, \eta, n = 0, \varepsilon_1$ and ε_2
2. Find $\left\{\mathbf{p}^{*}, \mathbf{V}^{*}\right\} = \arg\min_{\mathbf{p},\mathbf{V}} U\left(\mathbf{y}^{(n)}, \eta\right)$.
3. **If** $\left|\sum_{k=1}^{K} y_k^{(n)} \varphi_k \left(\eta_k^0 P_k^{*} - \mathrm{C}_k^{*}\right) - \eta_k P_k^{*}\right| < \varepsilon_1$, **then**
4. set $\eta\left(\mathbf{y}^n\right) = \eta$.
5. **goto** step (10).
6. **else**
7. update $\eta = \dfrac{\sum_{k=1}^{K} y_k^{(n)} \varphi_k (\eta_k^0 P_k^{*} - \mathrm{C}_k^{*})}{\sum_{k=1}^{K} y_k^{(n)} P_k^{*}}$.
8. **goto** step (2).
9. **end**
10. Update $\mathbf{y}^{(n+1)} = \arg\max_{\mathbf{y}\in \mathrm{Y}} \min_{\mathbf{p},\mathbf{V}} U\left(\mathbf{y}, \eta\left(\mathbf{y}^{(n)}\right)\right)$.
11. **If** $\eta\left(\mathbf{y}^{(n+1)}\right) - \eta\left(\mathbf{y}^{(n)}\right) < \varepsilon_2$, **then**
12. set $\eta^{*} = \eta\left(\mathbf{y}^{(n)}\right)$.
13. **exit**.
14. **else**
15. update $n = n + 1$.
16. **goto** step (2).
17. **End**

IV. PERFORMANCE EVALUATION

We assume a hexagonal cell with N= 7 RRHs which are distributed with radius $r_1 = 0, r_2 = \ldots = r_7 = \left(3 - \sqrt{3}\right)/2$ and angles $\theta_1 = 0$, $\theta_2 = \pi/6$, $\theta_3 = 3\pi/6$, $\theta_4 = 5\pi/6$, $\theta_5 = 7\pi/6$, $\theta_6 = 9\pi/6$, $\theta_7 = 11\pi/6$; and fixed P_{max}= 1 Watt, ε = 0.7, and $\sigma_u^2 = \sigma_d^2 = -50$ dBm with 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. RRH is equipped with M = 50 antennas and the total number of antennas is MN = 350, which is assumed same both in CM-MIMO and DM-MIMO. We assumed K = 2 users that are uniformly distributed.

Fig. 1 shows the evolution of EE converges to its maximum within only 5 iterations for DM-MIMO and CM-MIMO. Therefore, it is noticeable that our algorithm has a faster convergence speed for DM-MIMO and CM- MIMO.

Fig. 2 shows the energy efficiency according to the DL total transmission power. It is also observed that the DM-MIMO achieves a considerably higher capacity compared to the CM-MIMO.

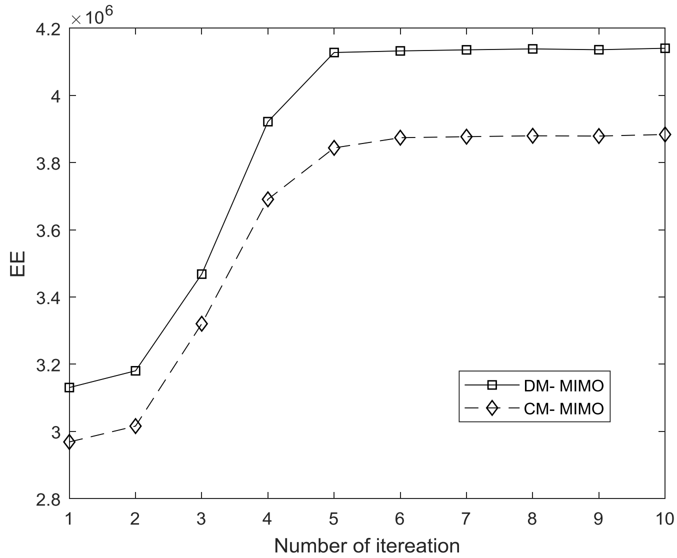

Fig. 1 Convergence of EE for DM- MIMO and CM-MIMO

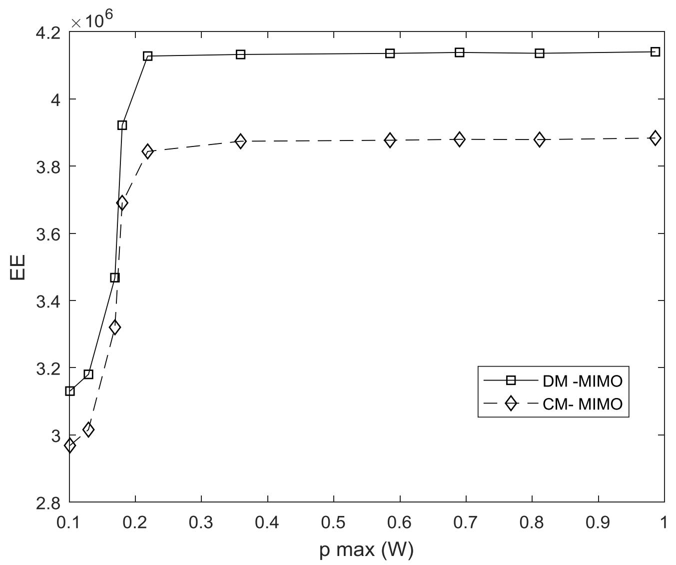

Fig. 2 Comparison of user’s capacity versus $p_{\max}$ for CM-MIMO and DM-MIMO

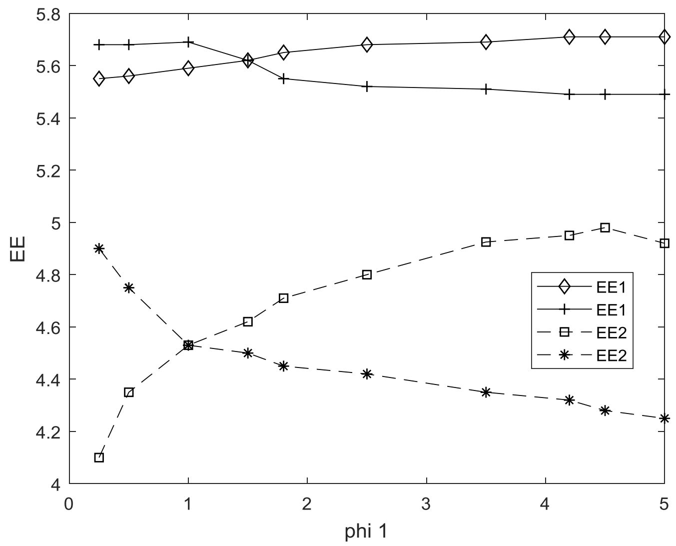

Fig. 3 EE versus φ_1 in the symmetric scenario (φ_2 =1)

Fig. 3 illustrates EE versus the weight of two users 1 and 2 where the users are located randomly from the RRH. Without loss of generality, it is assumed that all users have the same minimum throughput requirement. We assign the same weights to user 2 = 1, and vary the weight of user 1 between 0 and 5. As φ_1 increases, the EE of user 1 increases while the EE of users 2 decreases, which further demonstrates that assigning higher weights to some users indeed improves their EEs. In addition, it is worth noting that as φ_1 increases, the EE of user 1 first gradually increases and finally approaches a constant value.

V. CONCLUSION

In this paper, we have considered the multiobjective optimization for energy efficiency in WPCN network. To find Pareto optimal, the optimization problem is converted into single objective using Tchebycheff method. Then it is solved by iterative algorithm. Performance evaluation shows a fast convergence rate. It is shown that the present scheme achieves a higher EE for both CM-MIMO and DM-MIMO. Further, the EE of the DM-MIMO is significantly higher compared to that of the CM-MIMO

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