Energy Efficient and Distributed Resource Allocation for Wireless Powered OFDMA Multi-cell Networks

Zheng Chang*, Zhongyu Wang†, Xijuan Guo†, Zhu Han‡, and Tapani Ristaniemi*
* University of Jyväskylä, Faculty of Information Technology, P. O. Box 35, FI-40014 Jyväskylä, Finland
† College of Information Science and Engineering, Yanshan University, 066004 Qinhuangdao, China
‡ Electrical and Computer Engineering Department, University of Houston, Houston, TX.
Email: zheng.chang@jyu.fi, zhongyuwang_ysu@sina.com, xjguo@ysu.edu.cn, tapani.ristaniemi@jyu.fi, zhan2@uh.edu

***Abstract*—In this paper, we investigate the energy efficient resource allocation problem for the wireless powered OFDMA multi-cell networks. In the considered system, the users who have data to transmit in the uplink are empowered by the wireless power obtained from multiple base stations (BSs) with a large scale of multiple antennas in the downlink. A time division protocol is considered to divide the time of wireless power transfer (WPT) in the downlink and wireless information transfer (WIT) in the uplink into separate time slot. With the objective to improve the energy efficiency (EE) of the system, we propose the antenna selection, time allocation, subcarrier and power allocation schemes. Due to the non-convexity of the formulated optimization problem, we first apply the nonlinear programming scheme to convert it to a convex optimization problem and then address it through an efficient alternating direction method of multipliers based distributed resource allocation algorithm. Extensive simulations are conducted to show the effectiveness of proposed schemes.**

***Index Terms*—wireless power transfer; antenna selection; resource allocation; time allocation; energy efficiency; ADMM**

I. INTRODUCTION

Energy harvesting (EH) is considered as a potential approach to prolong the lifetime of energy constrained networks in a sustainable way [1]. Apart from the techniques that harvest energy from solar, wind, or other physical phenomena, scavenging from radio frequency (RF) signals offers an alternative way for addressing the problem of energy supply [2]. The resulted wireless power transfer (WPT) via the RF energy harvesting has emerged as a new solution for sustainable wireless network operations, and has the potential to make a great contribution on prolonging the battery life time and improving the energy efficiency (EE) performance of the wireless system.

Recently, the researches on WPT have gained increasing interests from both academia and industry. In [2], the problem of maximizing the throughput of WPT systems are studied when considering a single-user case. In [3], the energy efficient optimization problem in a point-to-point narrowband multiple-input single-output (MISO) simultaneous wireless information and power transfer (SWIPT) system is formulated and addressed with the consideration of the power splitting receiver. For the multiuser MIMO wireless powered networks, the authors of [4] present a throughput optimization scheme. Meanwhile, in order to improve the energy transfer efficiency of multiple antenna system with SWIPT, various beamforming methods are adopted. In [5], the authors study the beamforming strategy for a multiuser MISO system and maximize the weighted sum-power transferred to all the receivers. For the massive MIMO system with SWIPT, the authors of [6] present an optimization method to maximize the throughput and ensure rate fairness among multiple users.

Meanwhile, it is widely acknowledged that the current cellular structure has difficulties in facing the traffic increase as well as the spectrum crunch. To further improve the spectrum utilization, massive multiple input multiple output (massive MIMO) system makes a clean break with current practice through the use of a large excess of service-antennas over active terminals. A large number of extra antennas can focus transmit power into smaller regions of space and correspondingly bring huge improvements in throughput comparing with the current MIMO system. However, one of the disadvantages of employing a large scale of multiple antennas is the associated additional energy consumption which are caused by employing a separate RF chain for every employed antenna [7]. Most of the energy efficient communication techniques typically focus on minimizing the transmit power only, which is reasonable when the transmit power is sufficiently large and the number of used RF chains is small. However, in a massive MIMO system where the circuit power consumption can be comparable to or even dominates the transmit power, it would be worthwhile to investigate whether some of the antennas can be switched off, and spectrum and transmit power can be allocated accordingly to improve the system EE performance. There are different methods to optimize the EE performance of a massive MIMO system, including antenna selection [7] and resource allocation schemes [8]. In [9], with the objective to optimize the EE of a point-to-point MIMO system with a large scale of multiple antennas and SWIPT, the authors present a joint optimization of power and time allocation. In [10], an energy efficient resource allocation problem is investigated for multi-pair massive MIMO amplify-and-forward relay systems.

In this work, we investigate energy efficient resource allo-

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cation problem for the WPT enabled massive MIMO system. Specifically, an OFDMA multi-cell scenario is considered and our aim is to improve the EE of the system through proposing antenna selection, time allocation, subcarrier and power allocation schemes. In the considered system, the users who have data to transmit in the uplink can only be empowered by the WPT from multiple base stations (BSs) with a large scale of multiple antennas in the downlink. A time division protocol is considered to divide the time of WPT in the downlink and wireless information transfer (WIT) in the uplink into separate time slot. Based on the considered system, the main contributions can be summered as follows,

- The EE optimization problem for a multiuser multi-cell massive MIMO WPT system is presented. In the frequency domain, OFDMA is considered for spectrum utilization and in the time domain, a time division protocol is considered to divide the time of WPT in the downlink and wireless information transfer (WIT) in the uplink into a separate time slot.
- With the objective to improve the EE of the system, a joint antenna selection, time allocation, subcarrier and power allocation problem is presented. As the presented system model consists of multiple cells, we advocate the distributed method to address the formulated problem.
- Due to the non-convex nature of the presented problem, a nonlinear optimization method is first applied to transfer it into a convex problem. Then, we apply a novel alternating direction method of multipliers (ADMM) to turn the original problem into a series of interactive steps and find the optimal solution in a distributed manner.

The remainder of this paper is organized as follows. Section II introduces the considered system model. The problem formation and transformation are presented in Section III. In Section IV, we address the formulated problem and present the ADMM-based solution. Simulation results are illustrated and discussed in Section V. Finally, we conclude this work in Section VI.

II. System Model

We consider an OFDMA multi-cell massive MIMO system with WPT. In the considered multi-cell system, there are in total J cells and we denote M_j as the cell j. In the each cell, there is one BS, K users with single antenna and n_F subcarriers. Consider $\mathcal{L} = [\mathbf{L_1}, \mathbf{L_j}, ..., \mathbf{L_J}]$ as the allocated antenna vector for all users where $\mathbf{L_j} = [L_{j,k,g}]_{k=1}^{K}$, and $L_{j,k,g}$ is the number of antennas of the BS j allocated to user k on subcarrier g. The role of the BS is to charge the users via WPT in the downlink (DL), while the users have the functionality of storing the energy transmitted by the BS so that the energy can be used to transmit data to BS. The considered scenario is typical in a wireless sensor networks application. The channel coefficient between BS j and user k on subcarrier g is denoted by $\mathbf{h_{j,k,g}} \in \mathbb{C}^{L_{j,k,g}\times 1}$. We consider a quasi-static block fading channel model where the channel between BS j and user k is constant for a given transmission block T, and it can vary independently in every transmission block.

We separate the transmission time slot T into two. In the first time slot, the BS charges all the users in its coverage for WPT and each user stores the harvested energy in a rechargeable battery. In the second time slot, each user sends its own data to the BS. In the first time slot $\tau_{j,k,g}$, the BS transmits energy to users by WPT on subcarrier g. In the second time slot $T-\tau_{j,k,g}$, each user transmits its data to the BS by WIT on the same subcarrier. Meanwhile, in order to improve the efficiency of power transfer, we advocate the energy beamforming for WPT in the downlink.

According to the law of conservation of energy, the amount of power that user k can obtain from BS j can be given as follows [4],

$$E_{j,k,g} = \eta\tau_{j,k,g}\left(\alpha_{j,k}^2\left|\mathbf{b_{j,k,g}^H}\mathbf{h_{j,k,g}}\right|^2 P_j\right), \tag{1}$$

where $\alpha_{j,k}(\leq 1)$ denotes path loss between BS j and user k, $\mathbf{b_{j,k,g}}$ is an energy beamforming vector of BS j, and $\mathbf{h_{j,k,g}}$ is the DL channel. Moreover, the transmit power of BS j is P_j. η ($\eta \leq 1$) is the conversion efficiency from harvested energy into electric energy stored by the user. Beamforming vector can appropriately adjust energy transfer direction. Further, we consider maximum ratio transmission (MRT) beamforming, i.e., $\mathbf{b_{j,k,g}} = \frac{\mathbf{h_{j,k,g}}}{\|\mathbf{h_{j,k,g}}\|}$.

During the second time slot $T-\tau_{j,k,g}$, user k transmits its data to BS j using the harvested energy, and the information signal that received by BS j is as follows,

$$y_{j,k,g}^{ID} = \sqrt{\frac{E_{j,k,g}}{T-\tau_{j,k,g}}}\alpha_{j,k}\mathbf{h_{j,k,g}^H}\mathbf{x_{j,k,g}} + \Gamma_{j,k,g} + n_{j,k,g}, \tag{2}$$

where $\mathbf{x_{j,n,g}}$ is the transmitted signal. $n_{j,k,g}$ is an additive white Gaussian noise (AWGN), $n_{j,k,g} \sim \mathcal{CN}\left(0,\sigma^2\right)$, and we consider the noise on UL is of same kind as the one on DL. $\frac{E_{j,k,g}}{T-\tau_{j,k,g}}$ denotes the transmit power of user k. $\Gamma_{j,k,g}$ is the interference from other users to user k and we have

$$\begin{aligned}\Gamma_{j,k,g} = &\sum_{n\neq k}\sqrt{\frac{E_{j,n,g}}{T-\tau_{j,n,g}}}\alpha_{j,n,g}\mathbf{h}_{j,n,g}\mathbf{x_{j,n,g}} \\ &+\sum_{s\neq j}\sum_{k=1}^{K}\sqrt{\frac{E_{s,k,g}}{T-\tau_{s,k,g}}}\alpha_{s,k,g}\mathbf{h_{s,k,g}}\mathbf{x_{s,k,g}},\end{aligned} \tag{3}$$

According to the above analysis and properties of a massive MIMO system [7], i.e., channel hardening phenomenon [11], the channel capacity from user k to BS j is denoted by (4), where $\beta_{j,k,g} \in \{0,1\}$ is the subcarrier allocation indicator on subcarrier g for user k in BS j. There is mutual interference inside the cell, and $\sum_{n=1,n\neq k}^{K}\frac{E_{j,n,g}\alpha_{j,n,g}^2\beta_{j,n,g}}{T-\tau_{j,n,g}}$ is the variance of subcarrier reuse interference inside the cell. At the same time, there are some interferences from outside the other cells, and $\sum_{s=1,s\neq j}^{J}\sum_{n=1}^{K}\frac{E_{s,n,g}\alpha_{s,n,g}^2,\beta_{s,n,g}}{T-\tau_{s,n,g}}$ is the variance of subcarrier reuse interference outside the cell. For the sake of simplicity, we denote $\rho_{j,k,g}$ as the signal to interference plus noise ratio (SINR), of which the expression is presented in (5).

$$C_{j,k,g} = (T-\tau_{j,k,g})\log_2\left(1+L_{j,k,g}\frac{\frac{E_{j,k,g}}{T-\tau_{j,k,g}}\alpha_{j,k,g}^2}{\sigma^2+\sum\limits_{n=1,n\neq k}^{K}\frac{E_{j,n,g}\alpha_{j,n,g}^2\beta_{j,n,g}}{T-\tau_{j,n,g}}+\sum\limits_{s=1,s\neq j,}^{J}\sum\limits_{n=1}^{K}\frac{E_{s,n,g}\alpha_{s,n,g}^2\beta_{s,n,g}}{T-\tau_{s,n,g}}}\right). \tag{4}$$

$$\rho_{j,k,g} = \frac{\frac{E_{j,k,g}}{T-\tau_{j,k,g}}\alpha_{j,k,g}^2}{\sigma^2+\sum\limits_{n=1,n\neq k}^{K}\frac{E_{j,n,g}\alpha_{j,n,g}^2\beta_{j,n,g}}{T-\tau_{j,n,g}}+\sum\limits_{s=1,s\neq j,}^{J}\sum\limits_{n=1}^{K}\frac{E_{s,n,g}\alpha_{s,n,g}^2\beta_{s,n,g}}{T-\tau_{s,n,g}}}. \tag{5}$$

Thus, the throughput from user k to BS j can be presented as follows [11],

$$C_{j,k,g} = (T-\tau_{j,k,g})\log_2\left(1+L_{j,k,g}\rho_{j,k,g}\right), \tag{6}$$

and the total throughput is

$$C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) = \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{g=1}^{n_F}\beta_{j,k,g}C_{j,k,g}, \tag{7}$$

where $\boldsymbol{P}$, $\boldsymbol{\tau}$, $\boldsymbol{A}$, and $\boldsymbol{\beta}$ are the power, time, antenna, and subcarrier allocation policies, respectively. Meanwhile, the total energy consumption in the system is expressed as [7] [12],

$$E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) = \sum_{j=1}^{J}\left\{\left[P_{bs}\max_{k}\{L_{j,k,g}\}+KP_{user}\right]T + \sum_{g=1}^{n_F}P_j\beta_{j,k,g}\max\tau_{j,k,g}\right\}, \tag{8}$$

where P_{bs} is the power consumption for each antenna on BS j, i.e., $P_{bs} = P_{DAC} + P_{mix} + P_{filt}$. P_{user} represents the power consumption of the each user equipment, i.e., $P_{user} = P_{syn} + P_{LNA} + P_{mix} + P_{IFA} + P_{filr} + P_{ADC}$. P_{DAC}, P_{mix}, P_{filt}, P_{syn}, P_{LNA}, P_{IFA}, P_{filr}, P_{ADC} denotes the power consumption of the DAC, the mixer, the transmit filter, the frequency synthesizer, the low noise amplifier, the frequency amplifier, the receiver filter and ADC, respectively. Based on the above analysis, we can get the energy efficiency (EE) metic in bits/J/Hz as follows,

$$\Sigma\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) = \frac{C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right)}{E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right)}. \tag{9}$$

III. Problem formation and transformation

A. Problem formation

In order to maximize EE, in this work, we jointly optimize transmit power and time, subcarrier and number of used antennas. With the above analysis, the EE problem can be formulated as follows,

$$\mathbf{P1}: \max_{\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}} \ \Sigma\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right), \tag{10}$$

$$\begin{aligned} s.t.\quad & \mathbf{C1}: && 0\le P_j \le P_{bs,\max},\\ & \mathbf{C2}: && 0\le \tau_{j,k,g}\le T,\\ & \mathbf{C3}: && 0\le \frac{E_{j,k,g}}{T-\tau_{j,k,g}}\le P_{user,\max},\\ & \mathbf{C4}: && \frac{C_{j,k,g}}{T-\tau_{j,k,g}}\ge R_{\min},\\ & \mathbf{C5}: && L_{j,k,g}\in\{L_{j,k,g}^{\min},L_{j,k,g}^{\min+1},...,L_{j,k,g}^{\max}\},\\ & \mathbf{C6}: && \beta_{j,k,g}\in\{0,1\}. \end{aligned} \tag{11}$$

In (11), $\mathbf{C1}$ is the transmit power constraint for BS j and $\mathbf{C3}$ is the power constraint for user k. $\mathbf{C2}$ is the WPT time constraint and $\mathbf{C4}$ can ensure that Quality of Service (QoS) R_{min}. $\mathbf{C5}$ ensures on the number of antennas allocated to each user to preserve the fairness between users, satisfies the channel hardening and improves the system EE. $\mathbf{C6}$ is a combinatorial constraint on the subcarrier assignment.

B. Problem Transformation

As we can observe, $\mathbf{P1}$ is a non-convex fractional programming problem. Particularly, for the considered optimization problem with an objective function in the fractional form, there exists an equivalent optimization problem with an objective function in the subtractive form. According to [13], we firstly convert fractional problem into a linear form, namely,

$$\begin{aligned} \mathbf{P2}: & \max_{\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}} \ C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) - q^{*}E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right),\\ & s.t.\quad \mathbf{C1}-\mathbf{C6}, \end{aligned} \tag{12}$$

where q^* is regarded as the global optimal solution of EE, i.e.,

$$q^* = \frac{C\left(\boldsymbol{P}^*,\boldsymbol{\tau}^*,\boldsymbol{A}^*,\boldsymbol{\beta}^*\right)}{E_{tot}\left(\boldsymbol{P}^*,\boldsymbol{\tau}^*,\boldsymbol{A}^*,\boldsymbol{\beta}^*\right)} = \max_{\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}}\frac{C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right)}{E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right)}. \tag{13}$$

To address the formulated fractional programming problem, we can transform it into a subtractive form and solve it accordingly. First, we have **Theorem 1** as follows,

Theorem 1. *q can reach its optimal value if and only if*

$$\max_{\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}} \ C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) - q^{*}E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A},\boldsymbol{\beta}\right) = 0.$$

Proof. The proof is according to the one presented in Theorem in [13] . □

Theorem 1 presents the necessary and sufficient condition w.r.t. the optimal solution. Particularly, for the considered optimization problem with an objective function in the fractional form, there exists an equivalent optimization problem with an objective function in the subtractive form, and both formulations result in the same resource allocation solutions. In order to obtain the q^*, an iterative algorithm with guaranteed convergence [5] can be applied and it can be found in Alg. 1.

Algorithm 1 Iterative Algorithm for Obtaining q^*

```
1: Set maximum tolerance δ;
2: while (not convergence) do
3:   Solve the problem (14) for a given q and obtain resource
     allocation policies {P', τ', A', β'};
4:   if C(P', τ', A', β') − qE_tot(P', τ', A', β') ≤ δ then
5:     Convergence = true;
6:     return {P*, τ*, A*, β*} = {P', τ', A', β'} and
       obtain q*_c by Theorem 1;
7:   else
8:     Convergence = false;
9:     return Obtain q = C(P', τ', A', β') / E_tot(P', τ', A', β');
10:  end if
11: end while
```

In order to obtain a low-complexity solution to problem $\mathbf{P2}$, we revisit the combinatorial constraints in $\mathbf{C5}$ and $\mathbf{C6}$ by relaxing the corresponding variable such that $L_{j,k,g}$ and $\beta_{j,k,g}$ are positive real numbers [14]. For facilitating the derivation of the resource allocation algorithm, we introduce two auxiliary continuous variables to replace $L_{j,k,g}$ and $\beta_{j,k,g}$, and define them as $L^{\dagger}_{j,k,g} = \left[L^{\min}_{j,k,g}, L^{\max}_{j,k,g}\right]$, and $\beta^{\dagger}_{j,k,g} = [0,1]$. Then we substitute them into (12) and obtain a new problem $\mathbf{P3}$,

$$\mathbf{P3}: \max_{\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A}^{\dagger},\boldsymbol{\beta}} \quad C\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A}^{\dagger},\boldsymbol{\beta}^{\dagger}\right) - q^* E_{tot}\left(\boldsymbol{P},\boldsymbol{\tau},\boldsymbol{A}^{\dagger},\boldsymbol{\beta}^{\dagger}\right), \tag{14}$$

$$\begin{aligned} s.t. \quad & \overrightarrow{C1}: \quad 0 \le P_j \le P_{bs,\max}, \\ & \overrightarrow{C2}: \quad 0 \le \tau_{j,k,g} \le T, \\ & \overrightarrow{C3}: \quad 0 \le \frac{E_{j,k,g}}{T-\tau_{j,k,g}} \le P_{user,\max}, \\ & \overrightarrow{C4}: \quad \frac{C_{j,k,g}}{T-\tau_{j,k,g}} \ge R_{\min}, \\ & \overrightarrow{C5}: L^{\dagger}_{j,k,g} \in \left[L^{\min}_{j,k,g}, L^{\max}_{j,k,g}\right], \\ & \overrightarrow{C6}: \beta^{\dagger}_{j,k,g} \in [0,1]. \end{aligned} \tag{15}$$

To make the problem $\mathbf{P3}$ of (14) tractable and solvable, we will introduce an ADMM-based distributed solution and address the formulated problem in a distributed manner.

IV. Distributed Resource Allocation Via Alternating Direction Method of Multipliers

As we know, ADMM is a simple but powerful algorithm that is well suited to distributed convex optimization. Following the approach in [15], we introduce local copies of the global optimal resource allocation policies. Each local variable can be considered as the preference of each BS about the resource allocation. Let us introduce a set of new variables to represent the local variables. Firstly, we define local variable $\tilde{\tau}_{j,k,g} = \tau_{j,k,g}$, $\tilde{l}_{j,k,g} = L^{\dagger}_{j,k,g}$, $\tilde{\beta}_{j,k,g} = \beta^{\dagger}_{j,k,g}$, there exists an equivalent formulation of problem $\mathbf{P3}$ of (14) as follows,

$$\mathbf{P4}: \max_{\boldsymbol{P},\tilde{\boldsymbol{\tau}},\tilde{\boldsymbol{A}},\tilde{\boldsymbol{\beta}}} C\left(\boldsymbol{P},\tilde{\boldsymbol{\tau}},\tilde{\boldsymbol{A}},\tilde{\boldsymbol{\beta}}\right) - q^* E_{tot}\left(\boldsymbol{P},\tilde{\boldsymbol{\tau}},\tilde{\boldsymbol{A}},\tilde{\boldsymbol{\beta}}\right) \tag{16}$$

$$\begin{aligned} s.t. \quad & \widetilde{\mathbf{C1}}: \quad 0 \le P_j \le P_{bs,\max}, \\ & \widetilde{\mathbf{C2}}: \quad 0 \le \tilde{\tau}_{j,k,g} \le T \\ & \widetilde{\mathbf{C3}}: \quad 0 \le \frac{\tilde{E}_{j,k,g}}{T-\tilde{\tau}_{j,k,g}} \le P_{user,\max}, \\ & \widetilde{\mathbf{C4}}: \quad \frac{\tilde{C}_{j,k,g}}{T-\tilde{\tau}_{j,k,g}} \ge R_{\min}, \\ & \widetilde{\mathbf{C5}}: \quad L^{\min}_{j,k,g} \le \tilde{l}_{j,k,g} \le L^{\max}_{j,k,g}, \\ & \widetilde{\mathbf{C6}}: \quad 0 \leqslant \tilde{\beta}_{j,k,g} \leqslant 1. \end{aligned} \tag{17}$$

To this end, the primal non-convex optimization problem $\mathbf{P2}$ is transformed into a suboptimal convex problem $\mathbf{P4}$. Holding well-known perspective function [16], it can be observed that it is easy to find that $\mathbf{P4}$ is convex w.r.t. the variables P_j, $\tilde{\tau}_{j,k,g}$ and $\tilde{L}_{j,k,g}$. The proof of the convexity of $\mathbf{P4}$ is shown in Appendix A. As P_j in $\mathbf{P4}$ is not separable with respect to different BS j, to apply ADMM to resource allocation problem $\mathbf{P4}$, this coupling must be handled appropriately. Therefore, the local copy of P_j at BS j is denoted as $\tilde{P}_j$. By means of the local variables $\tilde{P}_j$, $\tilde{\tau}_{j,k,g}$, $\tilde{L}_{j,k,g}$, $\tilde{\beta}_{j,k,g}$, let us define a feasible local variable set for each BS j,

$$X_j = \left\{ \tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g} \,\middle|\, \widetilde{\mathbf{C2}}, \widetilde{\mathbf{C3}}, \widetilde{\mathbf{C4}}, \widetilde{\mathbf{C5}}, \widetilde{\mathbf{C6}} \right\} \tag{18}$$

where the associated local function defined in (19), respectively. By such, the global consensus problem of problem $\mathbf{P4}$ can be rewritten as,

$$\begin{aligned} \mathbf{P5}: \quad \min \quad & \sum_{j=1}^{J} g_j\left(\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right), \\ s.t. \quad & \tilde{P}_j = P_j \qquad 1 \le j \le J. \end{aligned} \tag{20}$$

As we can see [15], $\mathbf{P5}$ is a global consensus problem. To address such a problem, the initial step is that an augmented Lagrangian with corresponding global consensus constraints should be formed. Let λ_j, $\forall j \in [1,J]$ be the Lagrange multipliers corresponding to consensus constraints in problem $\mathbf{P5}$. The augmented Lagrangian for $\mathbf{P5}$ is,

$$g_j = \begin{cases} \left(\sum_{g=1}^{n_F}\sum_{k=1}^{K}\tilde{\beta}_{j,k,g}\tilde{C}_{j,k,g}\right) - q_j^* \left\{ \left[P_{bs}\max\{\tilde{L}_{j,k,g}\} + KP_{user}\right]T + \sum_{g=1}^{n_F}\tilde{P}_j\tilde{\beta}_{j,k,g}\max_k \ \tilde{\tau}_{j,k,g} \right\}, \tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g} \in X_j, \\ \infty, \qquad otherwise. \end{cases} \tag{19}$$

$$\mathcal{L}_\rho\left(\left\{\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right\}, \{P_j\}, \{\lambda_j\}\right) = \sum_{j=1}^{J} g_j\left(\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right) + \sum_{j=1}^{J}\lambda_j\left(\tilde{P}_j - P_j\right) + \frac{\rho}{2}\sum_{j=1}^{J}\left(\tilde{P}_j - P_j\right)^2, \tag{21}$$

where λ_j is the vector of the Lagrange multipliers and $\rho \in R_{++}$ is a positive constant parameter for adjusting the convergence speed of the ADMM [15]. Based on the iteration of ADMM with consensus constraints [15], the ADMM method applied to problem **P5** consists of following sequential optimization steps as shown in (22)-(24).

With the above analysis, the proposed distributed resource allocation algorithm can be summarized into following steps.

1) $\{\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\}_{j\in J}$-update: In the first step, local association, radio resource allocation strategies are separable across each BS j. Therefore, $\{\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\}_{j\in J} - update$ can be decomposed into J subproblems, which can be solved locally at each BS. Thus, BS j solves the optimization problem at iteration t in equation (22).
2) $\{P_j\}$-update and $\{\lambda_j\}$-update: Compared with the updating of local variables, $\{P_j\} - update$ and $\{\lambda_j\} - update$ are quite simple since they are only an unconstrained quadratic optimization problems. We refer to the formula (23) and (24) to solve the specific update process.
3) Stop Criteria and Convergence: Based on the discussion in [15], our ADMM-based algorithm iterates satisfy residual convergence, objective convergence and dual variable convergence as $t \to \infty$, because our objective function $\sum_{j=1}^{J} g_j\left(\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right)$ is closed, proper and convex and Lagrangian $\mathcal{L}_\rho$ has saddle point.

V. Performance Evaluations

In this section, the performance of the proposed scheme is evaluated and illustrated. Simulation parameters are mainly from [12]. For the sake of simplicity, we use PA to denote the proposed distributed resource allocation algorithm.

Fig. 1 illustrates the EE versus the transmit distance with/without (w./wo.) antenna selection (AS) and subcarrier allocation (SA). The scheme without AS can be considered as the one modified from [9]. As we can observe, firstly, by enlarging the average distance between BS j and users, the EE of considered system has decreased in general, despite of the use of AS and SA. This is mainly because as the distance increases, more transmit power is needed for providing QoS for the users. Secondly, the system performance of the PA is higher than the others, which generally shows the impact of the proposed resource allocation schemes. In addition, we can also observe that the system performance of the one with AS is higher than the one without AS. That is mainly because without antenna selection, more transmit power is needed, which deteriorates the EE performance.

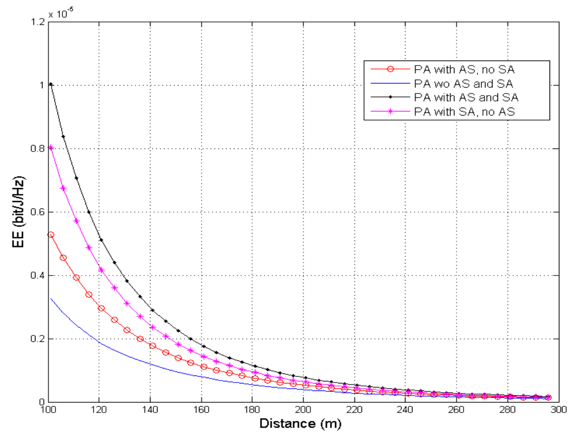

Fig. 1. EE w./wo. antenna selection and subcarrier allocation

In Fig. 2, the system EE performance is presented by jointly varying the transmit power and the duration of first time slot. We can see that there is an optimal value of first time slot $\tau_{j,k,g}$ for certain transmit power to maximize the EE. In general, with the increase of $\tau_{j,k,g}$, the system EE first increases, then reaches its optimal value and finally decreases, which shows the necessity of the allocation of two time slot protocol. As we can observe, when the first time slot is close to zero, with the increase of transmit power, the EE first ascends rapidly and then remains unchanged. However, when the first time slot is close to one, with the increase of transmit power, the EE keeps descending. Therefore, the joint optimization of transmit power P_j and $\tau_{j,k,g}$ is necessary to obtain the maximum of system EE. Fig. 2 validates the energy efficient resource algorithm by jointly optimizing the transmit power and the time.

$$\left\{\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right\}^{[t+1]} := \arg\min \left\{g_j\left(\tilde{P}_j, \tilde{\tau}_{j,k,g}, \tilde{L}_{j,k,g}, \tilde{\beta}_{j,k,g}\right) + \lambda_j\left(\tilde{P}_j - P_j^{[t]}\right) + \frac{\rho}{2}\left(\tilde{P}_j - P_j^{[t]}\right)^2\right\}, \quad (22)$$

$$\{P_j\}^{[t+1]} := \arg\min \left\{\sum_{j=1}^{J} \lambda_j^{[t]}\left(\tilde{P}_j^{[t+1]} - P_j\right) + \frac{\rho}{2}\sum_{j=1}^{J}\left(\tilde{P}_j^{[t+1]} - P_j\right)^2\right\}, \quad (23)$$

$$\{\lambda_j\}^{[t+1]} := \{\lambda_j\}^{[t]} + \rho\left(\tilde{P}_j^{[t+1]} - P_j^{[t+1]}\right). \quad (24)$$

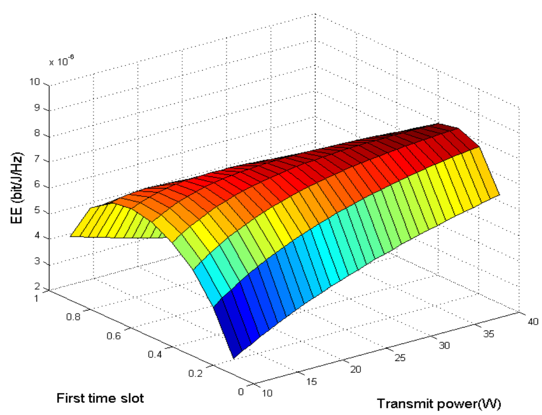

Fig. 2. EE vs transmit power and first time slot.

VI. Conclusion

In this work, we investigated energy efficient resource allocation problem for the WPT enabled OFDMA multi-cell networks. With the objective to improve the EE of the system, we propose antenna selection, time allocation, subcarrier and power allocation schemes. The nonlinear programming and ADMM schemes are applied to address the resource allocation algorithm in a distributed manner. Extensive simulations are conducted to show the effectiveness of proposed schemes. Simulation results are presented to validate the effectiveness of the proposed scheme.

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