User-Centric Energy-Efficient Resource Allocation for Wireless Powered Communications

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***Abstract*—This paper considers wireless powered communication networks (WPCNs), where mobile users first harvest energy from a dedicated power station and then communicate with an information receiving station. We aim to maximize the weighted sum of user-centric energy efficiency (WSUEE) via joint time allocation and power control in both downlink and uplink. The proposed approach provides the flexibility of assigning users different levels of importance so that the individual user EEs can be balanced. The WSUEE maximization problem is investigated for a generalized WPCN where each user is equipped with initial energy and also has a minimum throughput requirement. By exploiting the special structure of the objective function, the considered problem is then transformed into a convex problem that can be solved efficiently. Simulation results verify our theoretical findings and demonstrate the effectiveness of the proposed approach.**

I. Introduction

During the past decades, the battery capacity has been improved at a very slow pace due to the bottleneck of chip technologies. The batteries of wireless devices such as smart phones and tablets, need to be replaced frequently, which has aroused more than 60% of mobile users' complains [1]. As a result, wireless energy transfer (WET) has emerged as a promising solution to prolonging the lifetime of wireless devices, since receivers can be designed to harvest energy from controllable radio frequency (RF) signals. Combined with wireless information transmission (WIT), WET introduces a paradigm shift to the design of conventional wireless communication systems, which has been initially studied in [2]. Therein, the authors established a "harvest-then-transmit" protocol for wireless powered communication networks (WPCNs), where the time allocated to the base station for DL WET and allocated to users for UL WIT were jointly optimized for maximizing the system throughput. In particular, this work focused on the spectral efficiency (SE) of WET for WPCNs while the energy consumption for both energy transfer and information transmission are overlooked, which, however, is a crucial issue in the future wireless communication systems.

Due to rapidly rising energy costs and tremendous carbon footprints, energy efficiency (EE), measured in bits-per-joule, has attracted considerable attention in both academia and industry [3]–[8]. In fact, EE is particularly important in the WPCN since the harvested RF energy is attenuated by signal prorogation which is relatively scarce. Resource allocation for system-centric EE maximization was studied in [9] for simultaneous wireless information and power transfer (SWIPT) systems. Specifically, subcarrier assignment, power allocation, and power splitting ratio were jointly optimized to maximize the system EE, while guaranteeing both the requirements of the minimum harvested energy and also the minimum user data rate. The authors in [10] investigated the energy-efficient power allocation for large-scale multiple-input multiple-output (MIMO) systems under a single-user setup. In our previous work [11], we studied the system-centric EE maximization via joint time allocation and power control. We showed that from a system perspective, only users who has a better energy utilization efficiency can be scheduled while the rest of users keep silent in UL WIT, which leads to starvation in some users and their EEs cannot be guaranteed in practice.

While most of existing works mainly focus on optimizing the system-centric EE from the system perspective [4]–[8], few effort has been made to investigate the user-centric EE from the terminal perspective. Due to capacity limited batteries but increasing demand of heterogeneous user experiences, the individual user EE becomes more and more critical in practical wireless communication systems [1]. However, the resource optimization aiming at improving the system-centric EE makes no distinction among different users in terms of individual user EE, because it is defined as the ratio of the system throughput to the system energy consumption. For wireless powered communication networks (WPCNs) where users harvest energy and transmit data independently, the user-centric EE objective focuses on the EE of each user directly and is thus more interesting than the system-centric EE. Furthermore, if users are specified with high minimum throughput requirements, the user allocated with short transmission time have to increase the transmit power which may result in lower user EE. In contrast, the user allocated with longer transmission time would have higher flexibility to adjust its transmit power in achieving higher user EE. Therefore, how to design the resource allocation policy plays an important role in balancing individual EEs among users.

Different from existing works, we study the user-centric oriented energy-efficient resource allocation in this paper. The time allocation and power control are jointly optimized with the objective of maximizing the weighted sum of user-centric EE (WSUEE) while guaranteeing the minimum user throughput requirements in the WPCN. We show that the power station always transmits with its maximum allowed transmit power. Furthermore, exploiting the sum-of-ratios structure of the objective function, we transform the original non-convex

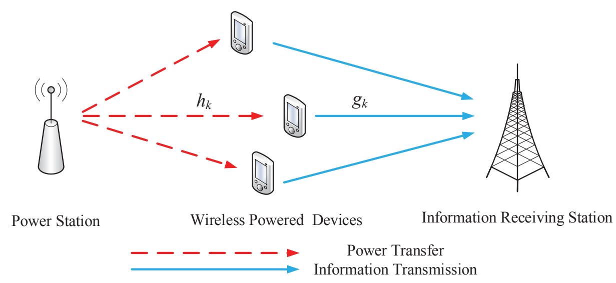

Fig. 1. The system model of a WPCN.

optimization problem into an equivalent parameterized optimization problem which can be solved efficiently.

II. Preliminaries

A. System Model

We consider a WPCN, which consists of one power station, K wireless-powered users, and one information receiving station, as depicted in Fig. 1. The "harvest and then transmit" protocol is employed as in [2], i.e., all users first harvest energy from the RF signal broadcasted by the power station in the downlink (DL), and then transmit information signals to the information receiving station in the uplink (UL). Assume that both the DL and the UL channels are quasi-static block fading channels. The DL channel gain between the power station and user terminal k and the UL channel gain between user terminal k and the information receiving station are denoted as h_k and g_k, respectively. We also assume that the channel state information (CSI) is perfectly known at the power station as we are interested in obtaining an EE upper bound for practical WPCNs [2]. Signaling overhead and imperfect CSI will result in performance degradation and the study of their impact on the EE is beyond the scope of this paper.

During DL WET, the power station broadcasts the energy signal with transmit power P_0 and transmission time τ_0. The energy harvested from the noise and the received UL WIT signals from other users is assumed to be negligible, since the noise power and the user transmit powers are both much smaller than the transmit power of the power station in practice [2], [12]. Thus, the amount of energy received at user k can be modeled as

$$E_k^h = \eta_k \tau_0 P_0 h_k - \tau_0 p_{\mathrm{r},k}, \tag{1}$$

where $\eta_k \in (0,1]$ is the energy conversion efficiency of user k and $p_{\mathrm{r},k}$ is a constant circuit power consumption accounting for reception hardware processing.

During UL WIT, each user k transmits an independent information signal to the receiving station with transmit power p_k and transmission time τ_k. Then, the achievable throughput of user k, denoted as B_k, is given by

$$B_k = \tau_k W \log_2 (1 + p_k \gamma_k), \tag{2}$$

where $\gamma_k = \frac{g_k}{\sigma^2}$ denotes the equivalent channel gain for UL WIT. Here, W and σ^2 are the bandwidth of the considered system and the Gaussian noise variance, respectively.

B. Power Consumption Model for Mobile Terminals

Here, we adopt the power consumption model from a comprehensive survey of the green mobile networking [1], where the transmission power, transmission circuit power, and reception circuit power are all taken into account for user terminals. In the WPCN, the overall energy consumption of each mobile terminal consists of two parts: the energy consumed in DL WET and UL WIT, respectively. During DL WET, as the mobile terminal is in the reception mode, there is only a constant circuit power consumption which is caused by reception hardware processing, i.e., $p_{\mathrm{r},k}$. During UL WIT, the mobile terminal is in the transmission mode, the power consumption includes not only the over-the-air transmission power, denoted as p_k, but also the circuit power consumed for transmission hardware processing, denoted as $p_{\mathrm{c},k}$. Therefore, the overall energy consumption of user k in the WPCN can be expressed as

$$E_k = \tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}, \tag{3}$$

where $\varepsilon_k \in (0,1]$ is a constant which accounts for the power amplifier (PA) efficiency of user terminal k.

III. WSUEE Maximization

Our goal is to jointly optimize the time allocation and power control in both DL WET and UL WIT for maximizing the WSUEE, i.e., $EE_{\mathrm{sum}} = \sum_{k=1}^K \omega_k EE_k = \sum_{k=1}^K \omega_k \frac{B_k}{E_k}$, where these predefined weights provide the flexibility to achieve the customized green performance for different users. For example, the system designer can assign higher weights for some users with less energy storage but requiring higher throughput so that to make them more energy-efficient. Thus, the WSUEE maximization problem can be formulated as

$$\begin{aligned}
\max_{\substack{P_0,\{p_k\},\\ \tau_0,\{\tau_k\}}} \quad & \sum_{k=1}^K \omega_k EE_k = \sum_{k=1}^K \omega_k \frac{\tau_k W \log_2(1+p_k\gamma_k)}{\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}} \\
\text{s.t. C1: } & P_0 \le P_{\max}, \ \text{C3: } \tau_0 + \sum_{k=1}^K \tau_k \le T_{\max}, \\
& \text{C2: } \tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \le \eta_k P_0 \tau_0 h_k + Q_k, \forall k, \\
& \text{C4: } \tau_k W \log_2(1+p_k\gamma_k) \ge R_{\min}^k, \ \forall k, \\
& \text{C5: } \tau_0 \ge 0, \ \tau_k \ge 0, \ \forall k, \\
& \text{C6: } P_0 \ge 0, \ p_k \ge 0, \ \forall k.
\end{aligned} \tag{4}$$

In problem (4), C1 constrains the DL maximum allowed transmit power of the power station to $P_{\max}$ due to practical hardware limits. C2 guarantees that the overall energy consumed by user k in DL WET and UL WIT does not exceed the total available energy which includes both the harvested energy $\eta_k P_0 \tau_0 h_k$ and the initial energy Q_k. In C3, $T_{\max}$ is the total available transmission time. C4 ensures the minimum required throughput of user k, $\forall k$, i.e., $R_{\min}^k$. C5 and C6 are non-negative constraints on the time allocation and power control variables, respectively.

Remark 3.1: Note that in order to meet throughput requirements while maintaining high user EE of some users, other users may not have sufficient time to use up their harvested energy in the current transmission block. From the expectation towards EE, it is favourable to use the energy left from previous transmission blocks in the current transmission block. Therefore, in C2, we assume that each user terminal is configured with an amount of initial energy Q_k. Moreover, Q_k can also be the energy harvested from other sources such as solar and wind, which enables the proposed optimization to accommodate various energy harvesting techniques, combined with WET. Thus, this setup provides users a higher flexibility in utilizing energy and in improving the EE, which thereby is more general than previous works [2], [13]. Furthermore, if each user has sufficient initial energy Q_k, the optimal value of τ_0 can even be zero, which suggests the power transfer technique is not activated. Thus, problem (4) can be simplified to the WSUEE maximization problem in conventional *time division multiplexing access (TDMA)* systems without using WET.

Although problem (4) is quite interesting, it is neither convex nor quasi-convex due to the sum-of-ratios objective function and the products of optimization variables in C2 and C4. In general, there is no standard method for solving non-convex optimization problems efficiently. Nevertheless, in the following, we show that the considered problem can be efficiently solved by exploiting the sum-of-ratios structure of the objective function in (4). The following proposition characterizes the transmit power of the power station.

Proposition 3.1: For problem (4), the maximum WSUEE can always be achieved at $P_0^* = P_{\max}$.

Proof: As the energy transfer may not be activated due to the initial energy of users, we discuss the following two cases. First, if $\tau_0^* > 0$ and $P_0^* < P_{\max}$ hold in the optimal solution $\{P_0^*, \{p_k^*\}, \tau_0^*, \{\tau_k^*\}\}$, then we can construct another feasible solution $\{\widehat{P}_0, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ satisfying $\widehat{P}_0 = P_{\max}$, $\widehat{\tau}_0 = \frac{P_0^*\tau_0^*}{\widehat{P}_0}$, $\widehat{p}_k = p_k^*$, and $\widehat{\tau}_k = \tau_k^*$, which guarantees that C1-C6 still hold. Thus, it follows that $\widetilde{\tau}_0 < \tau_0^*$ and thus $\widehat{\tau}_0 p_{\mathrm{r},k} + \widehat{\tau}_k \frac{\widehat{p}_k}{\varepsilon_k} + \widehat{\tau}_k p_{\mathrm{c},k} < \tau_0^* p_{\mathrm{r},k} + \tau_k^* \frac{p_k^*}{\varepsilon_k} + \tau_k^* p_{\mathrm{c},k}^*$. Then, we can easily check that $EE_k^* < \widehat{EE}_k$, $\forall k$, and thus $P_0^* = P_{\max}$ always holds. Second, if $\tau_0^* = 0$ holds, then the value of the transmit power P_0^* does not affect the maximum system EE, and thus $P_0^* = P_{\max}$ is also optimal. ■

Applying Proposition 3.1 to problem (4), we only have to optimize τ_0, $\{p_k\}$, and $\{\tau_k\}$, $\forall k$. In the next section, we exploit the sum-of-ratios structure of WSUEE to transform the original problem into some more tractable problems, which facilitates the development of a computationally efficient algorithm.

A. Problem Transformation

The following theorem states the equivalence of a sum-of-ratios optimization problem and a parameterized subtractive-form problem.

Theorem 3.1: If $(\tau_0, \{p_k^*\}, \{\tau_k^*\})$ is the optimal solution to problem (4), then there exist $\boldsymbol{\alpha}^* = (\alpha_1, \cdots, \alpha_K)$ and $\boldsymbol{\beta}^* = (\beta_1, \cdots, \beta_K)$ such that $(\tau_0, \{p_k^*\}, \{\tau_k^*\})$ is the optimal solution to the following problem with $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$:

$$\max_{\{\tau_0, \{p_k\}, \{\tau_k\}\} \in \mathcal{F}} \sum_{k=1}^{K} \alpha_k (\omega_k B_k - \beta_k E_k), \tag{5}$$

where $\in \mathcal{F}$ is the feasible set of problem (4). Furthermore, $(\tau_0, \{p_k^*\}, \{\tau_k^*\})$ have to satisfy the following system equations for $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$:

$$\alpha_k E_k - 1 = 0, k \in \{1, \cdots, K\}, \tag{6}$$

$$\beta_k E_k - \omega_k B_k = 0, k \in \{1, \cdots, K\}. \tag{7}$$

Proof: We refer the interested readers to [14] for detailed proof of the equivalence. ■

Theorem 3.1 suggests that for the sum-of-ratios maximization problem (4), there exists an equivalent parameterized subtractive-form problem, i.e., problem (5), with some additional given parameters. In fact, the parameterized objective function of problem (5) has very clear interpretation from the economic perspective: $\boldsymbol{\beta}$ represents the price for the cost of each item in an investment portfolio while $\boldsymbol{\alpha}$ coordinates all items to seek for the maximum profit. Nevertheless, this means that we can obtain the optimal solution to problem (4) by solving problem (5) at $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. Therefore, in the sequel, we first solve problem (5) with given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$, and then we develop an efficient approach to update $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ until (6) and (7) are both satisfied.

With Theorem 3.1, problem (4) is transformed into the following one for given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$

$$\begin{aligned} \max_{\tau_0, \{p_k\}, \{\tau_k\}} \quad & \sum_{k=1}^{K} \alpha_k \Big(\omega_k \tau_k W \log_2 (1 + p_k \gamma_k) \\ & - \beta_k \left(\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}\right)\Big) \\ \text{s.t.} \quad & \text{C2, C3, C4, C5, C6.} \end{aligned} \tag{8}$$

Although problem (8) is more tractable than the original problem (4), it is still non-convex due to the products of optimization variables. Hence, we further introduce a set of auxiliary variables, i.e., $\widetilde{E}_k = p_k \tau_k$, for $\forall k$, which can be interpreted as the actual energy consumed for transmitting information signals by user k. Replacing p_k with $\frac{\widetilde{E}_k}{\tau_k}$, problem (8) can be written as

$$\begin{aligned} \max_{\substack{\tau_0, \{\tau_k\}, \\ \{\widetilde{E}_k\}}} \quad & \sum_{k=1}^{K} \alpha_k \left(\omega_k \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k\right) \right. \\ & \left. - \beta_k \left(\tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}\right)\right) \\ \text{s.t.} \quad & \text{C3, C5, C6: } \widetilde{E}_k \geq 0, \ \forall k, \\ & \text{C2: } \tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + p_{\mathrm{c},k} \tau_k \leq \eta_k P_{\max} \tau_0 h_k + Q_k, \forall k, \\ & \text{C4: } \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k\right) \geq R_{\min}^k, \ \forall k. \end{aligned} \tag{9}$$

After this substitution, it is easy to verify that problem (9) is a standard convex optimization problem, which can be solved by the interior-point method [15]. However, this method does not exploit the special structure of the problem itself. Hence, in the following, we employ the Karush-Kuhn-Tucker (KKT) conditions to analyze problem (9), which results in an optimal and efficient approach.

B. Joint Time Allocation and Power Control

The partial Lagrangian function of problem (9) can be written as

$$
\begin{aligned}
&\mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta) \\
&= \sum_{k=1}^{K} \alpha_k \left(\omega_k \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \right. \\
&\left. - \ \beta_k \left(\tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \right) \right) \\
&+ \sum_{k=1}^{K} \lambda_k \left(\eta_k P_{\max} \tau_0 h_k + Q_k - \tau_0 p_{\mathrm{r},k} - \frac{\widetilde{E}_k}{\varepsilon_k} - p_{\mathrm{c},k} \tau_k \right) \\
&+ \sum_{k=1}^{K} \mu_k \left(\tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) - R_{\min}^k \right) \\
&+ \delta \left(T_{\max} - \tau_0 - \sum_{k=1}^{K} \tau_k \right),
\end{aligned} \tag{10}
$$

where $\boldsymbol{\lambda} = (\lambda_1, \cdots, \lambda_K) \succeq \mathbf{0}$ and $\boldsymbol{\mu} = (\mu_1, \cdots, \mu_K) \succeq \mathbf{0}$ are Lagrange multiplier vectors associated with the energy causality constraints C2 and the minimum user throughput constraints C4, respectively. δ is the non-negative Lagrange multiplier corresponding to the total time constraint C3. Note that the boundary constraints of optimization variables, i.e., C5 and C6, will be absorbed into the optimal solution in the following. Accordingly, the associated dual function of problem (9) is given by $\mathcal{G}(\boldsymbol{\lambda}, \boldsymbol{\beta}, \delta) = \max\limits_{(\tau_0, \{p_k\}, \{\tau_k\}) \in \mathcal{D}} \mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$, where $\mathcal{D}$ is the feasible set specified by C4 and C5. The dual problem of (9) is thus given by

$$
\min_{\boldsymbol{\lambda} \succeq \mathbf{0}, \boldsymbol{\beta} \succeq \mathbf{0}, \delta \geq 0} \ \max_{(\tau_0, \{\widetilde{E}_k\}, \{\tau_k\}) \in \mathcal{D}} \mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta). \tag{11}
$$

As original problem (9) is a standard convex optimization problem, the duality gap between problem (9) and its dual problem (11) is zero [15]. This means that the optimal solution of problem (9) can be obtained by solving problem (11) with two iterative optimizations: primary variables optimization which maximizes $\mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ over $(\tau_0, \widetilde{E}_k, \tau_k)$ for given $(\boldsymbol{\lambda}, \boldsymbol{\beta}, \delta)$, and dual variables optimization that minimizes $\mathcal{G}(\boldsymbol{\lambda}, \boldsymbol{\beta}, \delta)$ over $(\boldsymbol{\lambda}, \boldsymbol{\beta}, \delta)$ for given $(\tau_0, \widetilde{E}_k, \tau_k)$. In the following, we discuss in detail these two nested loops respectively.

1) Primary Variables Optimization: Since the maximization of $\mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ over $(\tau_0, \widetilde{E}_k, \tau_k)$ for given $(\boldsymbol{\lambda}, \boldsymbol{\beta}, \delta)$ is standard concave optimization problem, the optimal solution can be obtained by KKT conditions. Taking the partial derivative of $\mathcal{L}$ with respect to τ_0, $\widetilde{E}_k$, and τ_k, respectively, we obtain

$$
\frac{\partial \mathcal{L}}{\partial \tau_0} = \sum_{k=1}^{K} \lambda_k (\eta_k P_{\max} h_k - p_{\mathrm{r,k}}) - \sum_{k=1}^{K} \alpha_k \beta_k p_{\mathrm{r,k}} - \delta, \tag{12}
$$

$$
\frac{\partial \mathcal{L}}{\partial \widetilde{E}_k} = \frac{W(\alpha_k \omega_k + \mu_k) \tau_k \gamma_k}{(\tau_k + \widetilde{E}_k \gamma_k) \ln 2} - \frac{\alpha_k \beta_k + \lambda_k}{\varepsilon_k}, \tag{13}
$$

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \tau_k} &= (\alpha_k \omega_k + \mu_k) W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \\
&- \frac{W(\alpha_k \omega_k + \mu_k) \widetilde{E}_k \gamma_k}{(\tau_k + \widetilde{E}_k \gamma_k) \ln 2} - (\alpha_k \beta_k + \lambda_k) p_{\mathrm{c},k} - \delta,
\end{aligned} \tag{14}
$$

Setting $\frac{\partial \mathcal{L}}{\partial \widetilde{E}_k} = 0$, the relationship of $\widetilde{E}_k$ and τ_k can be obtained as

$$
p_k^* = \frac{\widetilde{E}_k}{\tau_k} = \left[\frac{W(\alpha_k \omega_k + \mu_k) \varepsilon_k}{(\alpha_k \beta_k + \lambda_k) \ln 2} - \frac{1}{\gamma_k} \right]^+, \forall\, k, \tag{15}
$$

where $[x]^+ \triangleq \max\{x, 0\}$. From (15), we can see that p_k^* increases with both the PA efficiency ε_k and the UL channel gain γ_k. This suggests that in order to maximize the WSUEE, the user with the higher PA efficiency and the higher UL channel gain should transmit with higher power as this user is more energy-efficient in utilizing energy.

Substituting (15) into (14) and after some manipulations, $\frac{\partial \mathcal{L}}{\partial \tau_k}$ can be expressed as

$$
\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \tau_k} &= (\alpha_k \omega_k + \mu_k) W \log_2 \left(\frac{W(\alpha_k \omega_k + \mu_k) \varepsilon_k}{(\alpha_k \beta_k + \lambda_k) \ln 2} \gamma_k \right) - \delta \\
&- (\alpha_k \beta_k + \lambda_k) \left(\frac{W(\alpha_k \omega_k + \mu_k)}{(\alpha_k \beta_k + \lambda_k) \ln 2} - \frac{1}{\gamma_k \varepsilon_k} + p_{\mathrm{c},k} \right).
\end{aligned} \tag{16}
$$

From (12) and (16), we observe that Lagrangian function $\mathcal{L}$ is a linear function of both τ_0 and τ_k. This means that the optimal values of τ_0 and τ_k can always be found at the vertices of the feasible region [15]. Therefore, in order to obtain τ_0 and τ_k, we substitute (15) into (9), which results in the following optimization problem

$$
\begin{aligned}
\max_{\tau_0, \{\tau_k\}} \ & \sum_{k=1}^{K} \tau_k \left(\alpha_k \omega_k W \log_2 (1 + p_k^* \gamma_k) - \alpha_k \beta_k \left(\frac{p_k^*}{\varepsilon_k} + p_{\mathrm{c},k} \right) \right) \\
& - \tau_0 \sum_{k=1}^{K} \alpha_k \beta_k p_{r,k} \\
\text{s.t.} \ & \text{C3}, \quad \text{C5}, \\
& \text{C2: } \tau_k \left(\frac{p_k^*}{\varepsilon_k} + p_{\mathrm{c},k} \right) \leq \tau_0 (\eta_k P_{\max} h_k - p_{\mathrm{r},k}) + Q_k, \forall\, k, \\
& \text{C4: } \tau_k W \log_2 (1 + p_k^* \gamma_k) \geq R_{\min}^k, \forall\, k.
\end{aligned} \tag{17}
$$

It is easy to observe that problem (17) is a linear programming problem with respect to τ_0 and τ_k. Therefore, standard linear optimization tools, such as the simplex method [15], can be employed to obtain the optimal solution efficiently. Substituting τ_k back to (15), $\widetilde{E}_k$ is obtained immediately.

2) Dual Variables Optimization: After computing primary variables (τ_0, $\widetilde{E}_k$, τ_k), we now proceed to solve dual problem (11), i.e., $\min\limits_{\boldsymbol{\lambda}\succeq\mathbf{0},\boldsymbol{\beta}\succeq\mathbf{0},\delta\geq 0} \mathcal{G}(\boldsymbol{\lambda},\boldsymbol{\beta},\delta)$. Since a dual function is always convex by definition, we adopt the subgradient method to update $(\boldsymbol{\lambda},\boldsymbol{\beta},\delta)$ towards optimal with global convergence. The subgradients required are given by

$$\begin{cases} \Delta\lambda_k &= \eta_k P_{\max}\tau_0 h_k + Q_k - E_k, \\ \Delta\mu_k &= \tau_k W \log_2\left(1+\frac{\widetilde{E}_k}{\tau_k}\gamma_k\right) - R_{\min}^k, \forall\, k, \\ \Delta\delta &= T_{\max} - \tau_0 - \sum_{k=1}^{K}\tau_k, \end{cases} \tag{18}$$

The discussion on choosing the step size can be found in [15] and we thus omit it here for brevity. Then, the updated Lagrange multipliers by (18) can be used for updating the time allocation and power control in primary variables optimization. Due to the concavity of primary problem (9), the iterative optimization between $(\tau_0, \widetilde{E}_k, \tau_k)$ in *1)* and $(\boldsymbol{\lambda},\boldsymbol{\beta},\delta)$ in *2)* is guaranteed to converge to the optimal solution of (9).

C. Updating ($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$) for Given Time Allocation and Power Control

After obtaining $(\tau_0, \widetilde{E}_k, \tau_k)$ in Section III-B, we develop an algorithm to update ($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$) for problem (5). Let $\psi_k(\alpha_k) = \alpha_k E_k - 1$ and $\psi_{k+K}(\beta_k) = \beta_k E_k - \omega_k B_k$, $k = 1, 2, \cdots, K$. It has been shown in [14] that the unique optimal solution of $(\boldsymbol{\alpha},\boldsymbol{\beta})$ is obtained if and only if $\boldsymbol{\psi}(\boldsymbol{\alpha},\boldsymbol{\beta}) = [\psi_1, \psi_2, \cdots, \psi_{2k}] = \mathbf{0}$ is satisfied as (6) and (7). Thus, the well-known damped Newton method [8], [14], defined by (19)-(21), can be employed to update $(\boldsymbol{\alpha},\boldsymbol{\beta})$ as follows

$$\boldsymbol{\alpha}^{n+1} = \boldsymbol{\alpha}^n + \zeta^n \boldsymbol{q}^n, \tag{19}$$

$$\boldsymbol{\beta}^{n+1} = \boldsymbol{\beta}^n + \zeta^n \boldsymbol{q}^n, \tag{20}$$

$$\boldsymbol{q}^n = [\boldsymbol{\psi}'(\boldsymbol{\alpha},\boldsymbol{\beta})]^{-1}\boldsymbol{\psi}(\boldsymbol{\alpha},\boldsymbol{\beta}), \tag{21}$$

where n is the iteration index and ζ^n is the step size in the nth iteration which can be chosen by a diminishing manner [15]. Specifically, the pointwise updating equations of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can be expressed as

$$\alpha_k^{n+1} = (1-\zeta^n)\alpha_k^n + \zeta^n \frac{1}{E_k^n}, \tag{22}$$

$$\beta_k^{n+1} = (1-\zeta^n)\beta_k^n + \zeta^n \frac{\omega_k B_k^n}{E_k^n}. \tag{23}$$

The details of obtaining the optimal solution to problem (4) is summarized in Algorithm 1.

The computational complexity of Algorithm 1 derives from two-layered optimizations, i.e., the damped Newton method in the outer layer and the Lagrangian dual decomposition in the inner layer. As shown in [14], the damped Newton method has superlinear convergence speed while the Lagrangian dual decomposition only has polynomial complexity. Thus, the proposed algorithm is guaranteed to converge to the optimal solution quickly.

Algorithm 1 Energy-Efficient Transmission Algorithm for the WPCN

Initialize the algorithm accuracy indicator t;
Initialize $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, and set $n = 0$;
repeat
  Initialize $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ;
  repeat
    Obtain the time allocation τ_0 and τ_k by solving problem (17);
    Obtain the power control p_k from (15);
    Update the dual variables $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ from (18);
  until $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ converge;
  Compute B_k and E_k from (2) and (3);
  Compute $\boldsymbol{q}^n$ from (21);
  Update $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ from (22) and (23);
  $n = n + 1$;
until $||\boldsymbol{\psi}(\boldsymbol{\alpha},\boldsymbol{\beta})|| \leq t$.

IV. Numerical Results

In this section, we present simulation results to validate our theoretical findings, and to demonstrate the user EE of WPCN. Four users are randomly and uniformly distributed on the right hand side of the power station with a reference distance of 2 meters and a maximum service distance of 10 meters. The information receiving station is located 100 meters away from the power station. The system bandwidth is set as 20 kHz. The path loss exponent is 2.4 and the thermal noise power is -110 dBm. The small scale fading for WET and WIT is Rician fading with Rician factor 7 dB and Rayleigh fading, respectively. Without loss of generality, we assume that all the users have the same reception and transmission circuit power consumption as well as the energy conversion efficiency and the PA efficiency, which are set as $p_{\rm r} = 30$ mW, $p_{\rm c} = 50$ mW, $\eta = 0.9$, and $\varepsilon = 0.9$, $\forall\, k$, respectively. Unless specified otherwise, the remaining system parameters are set as $T_{\max} = 1\,$s, and $P_{\max} = 46$ dBm.

A. Demonstration of the Proposed Approach

In Fig. 2, we provide a concrete example to demonstrate the proposed approach for balancing the EEs among users. A two-user scenario is assumed for the WPCN. Specifically, we set $\boldsymbol{h} \triangleq [h_1, h_2] = [0.1, 0.1]$ and $\boldsymbol{\gamma} \triangleq [\gamma_1, \gamma_2] = [1000, 500]$, respectively. We plot the achieved user EE versus the user throughput requirements under different weights. From Fig. 2 to Fig. 3, we exchange the weights of two users and then evaluate the individual user EE, respectively, by solving the WSUEE maximization problem. It is observed from both Fig. 2 and Fig. 3 that the EE of each user first remains constant within a user-throughput regime and then begins to decrease when [$R_{\min}^1$, $R_{\min}^2$] is beyond the regime. This is in essence due to the fundamental tradeoff between EE and SE. In the user EE non-tradeoff regime, adjusting the weights has no impact on the EE of any user, which indicates that these two users can achieve their own maximum EE simultaneously. However, when the throughput requirement becomes stringent,

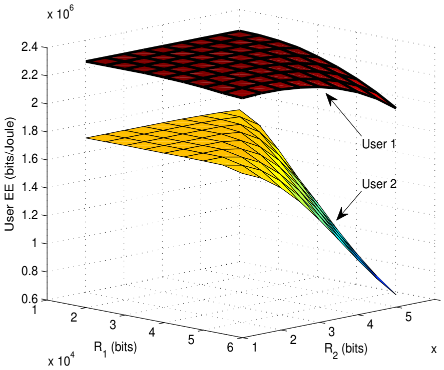

Fig. 2. User EE versus R_1 & R_2 for $\boldsymbol{\omega} = [5\ 1]$.

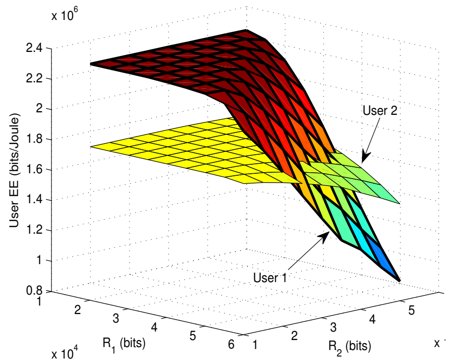

Fig. 3. User EE versus R_1 & R_2 for $\boldsymbol{\omega} = [1\ 5]$.

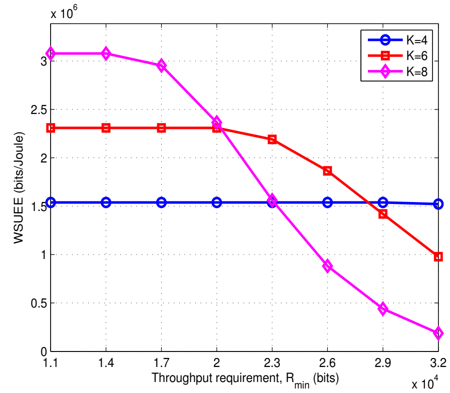

Fig. 4. WSUEE versus the user QoS.

adjusting the weights can realize the user EE balance between user 1 and user 2. Particularly in Fig. 3, by assigning the higher weight to user 2 who has the worse UL WIT channel, we can improve its user EE significantly compared with Fig. 2. This suggests that in the trade-off regime, assigning different weights to different users can indeed enforce a certain notion of fairness among users and help to improve the EE of some channel degraded users.

B. WSUEE versus Minimum User Throughput Requirement

In Fig. 4, we assume a symmetric case where all users have the same minimum throughput requirement, i.e., $R_{\min} = R^k_{\min}$, $\forall k$ We observe that the WSUEE of all cases first remains constant and then decreases, which in essence is due to the fundamental trade-off of EE and SE. Furthermore, as $R_{\min}$ increases, the WSUEE of a large K is more likely to decrease than that of a small K. This is because for small K, the UL WIT time allocated to each user will be longer, and thus the achieved throughput of each user while maintaining the maximum WSUEE is larger. However, for large K, the UL WIT time allocated to each user will be shorter, and the achieved throughput of each user while maintaining the maximum WSUEE is smaller, which makes the WSUEE more likely to decrease as $R_{\min}$ increases. When $R_{\min}$ is relatively high, users compete time resource more fiercely and have to transmit with larger power in UL WIT in order to meet ones own throughput requirement, which thus leads to fast decrease in the user EE and thereby the WSUEE.

V. Conclusions

In this paper, we have investigated the energy-efficient resource allocation in WPCN from a user-centric perspective. The time allocation and power control of DL WET and UL WIT are optimized to maximize the WSUEE where the weights of users can be adjusted to achieve the EE balance among individual users. Simulation results verify our theoretical findings and demonstrate that assigning different weights to different users can indeed enforce a certain notion of fairness among users and help to improve the EE of some channel degraded users.

References

[1] M. Ismail, W. Zhuang, E. Serpedin, and K. Qaraqe, "A survey on green mobile networking: From the perspectives of network operators and mobile users," *IEEE Commun. Surveys Tuts.*, vol. 49, no. 6, pp. 30–37, Dec. 2014.

[2] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 418–428, Jan. 2014.

[3] L. Zhou, R. Hu, Y. Qian, and H.-H. Chen, "Energy-spectrum efficiency tradeoff for video streaming over mobile ad hoc networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 5, pp. 981–991, May. 2013.

[4] Q. Wu, M. Tao, and W. Chen, "Joint Tx/Rx energy-efficient scheduling in multi-radio wireless networks: A divide-and-conquer approach," *Proc. IEEE ICC*, 8-12 Jun. 2015.

[5] Q. Wu, W. Chen, M. Tao, J. Li, H. Tang, and J. Wu, "Resource allocation for joint transmitter and receiver energy efficiency maximization in downlink OFDMA systems," *IEEE Trans. Commun.*, vol. 63, no. 2, pp. 416–430, Feb. 2015.

[6] C. Xiong, G. Li, S. Zhang, Y. Chen, and S. Xu, "Energy-efficient resource allocation in OFDMA networks," *IEEE Trans. Commun.*, vol. 60, no. 12, pp. 3767–3778, Dec. 2012.

[7] H. Li, L. Song, and M. Debbah, "Energy efficiency of large-scale multiple antenna systems with transmit antenna selection," *IEEE Trans. Commun.*, vol. 62, no. 2, pp. 638–647, Feb. 2014.

[8] G. Yu, Q. Chen, R. Yin, H. Zhang, and G. Li, "Joint downlink and uplink resource allocation for energy-efficient carrier aggregation," *IEEE Trans. Wireless Commun.*, vol. 14, no. 6, pp. 3207–3218, Jun. 2015.

[9] D. W. K. Ng, E. S. Lo, and R. Schober, "Wireless information and power transfer: Energy efficiency optimization in OFDMA systems," *IEEE Trans. Wireless Commun.*, vol. 12, no. 12, pp. 6352–6370, Dec. 2013.

[10] X. Chen, X. Wang, and X. Chen, "Energy-efficient optimization for wireless information and power transfer in large-scale MIMO systems employing energy beamforming," *IEEE Wireless Commun. Lett.*, vol. 2, no. 6, pp. 667–670, Dec. 2013.

[11] Q. Wu, M. Tao, D. W. K. Ng, W. Chen, and R. Schober, "Energy-efficient transmission for wireless powered multiuser communication networks," *Proc. IEEE ICC*, 8-12 Jun. 2015.

[12] Q. Shi, L. Liu, W. Xu, and R. Zhang, "Joint transmit beamforming and receive power splitting for MISO SWIPT systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3269–3280, Jun. 2014.

[13] H. Ju and R. Zhang, "Optimal resource allocation in full-duplex wireless-powered communication network," *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3528–3540, Oct. 2014.

[14] Y. Jong, "An efficient global optimization algorithm for nonlinear sum-of-ratios problem," 2012. [Online]. Available: http://www.optimization-online.org/DB HTML/2012/08/3586.html.

[15] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.