User-Centric Energy Efficiency Maximization for Wireless Powered Communications

Qingqing Wu, *Student Member, IEEE*, Wen Chen, *Senior Member, IEEE*, Derrick Wing Kwan Ng, *Member, IEEE*, Jun Li, *Member, IEEE*, and Robert Schober, *Fellow, IEEE*

***Abstract*— In this paper, we consider wireless powered communication networks (WPCNs) where multiple users harvest energy from a dedicated power station and then communicate with an information receiving station in a time-division manner. Thereby, our goal is to maximize the weighted sum of the user energy efficiencies (WSUEEs). In contrast to the existing system-centric approaches, the choice of the weights provides flexibility for balancing the individual user EEs via joint time allocation and power control. We first investigate the WSUEE maximization problem without the quality of service constraints. Closed-form expressions for the WSUEE as well as the optimal time allocation and power control are derived. Based on this result, we characterize the EE tradeoff between the users in the WPCN. Subsequently, we study the WSUEE maximization problem in a generalized WPCN where each user is equipped with an initial amount of energy and also has a minimum throughput requirement. By exploiting the sum-of-ratios structure of the objective function, we transform the resulting non-convex optimization problem into a two-layer subtractive-form optimization problem, which leads to an efficient approach for obtaining the optimal solution. The simulation results verify our theoretical findings and demonstrate the effectiveness of the proposed approach.**

Manuscript received April 12, 2016; accepted July 3, 2016. Date of publication July 19, 2016; date of current version October 7, 2016. The work of W. Chen was supported by the National 973 Project under Grant 2012CB316106, in part by the National 863 Project under Grant 2015AA01A710, and STCSM Project under Grant 16JC1402900. The work of D. W. Kwan Ng was supported by the Australian Research Council Linkage Project LP under Grant 160100708. The work of J. Li was supported in part by the National Natural Science Foundation of China under Grant 61501238, in part by the Jiangsu Provincial Science Foundation under Project BK20150786, in part by the Specially Appointed Professor Program in Jiangsu Province, 2015, and in part by the Fundamental Research Funds for the Central Universities under Grant 30916011205. The work of R. Schober was supported by the Alexander von Humboldt Professorship Program. The associate editor coordinating the review of this paper and approving it for publication was E. Uysal Biyikoglu.

Q. Wu and W. Chen are with the Shanghai Key Laboratory of Navigation and Position Based Services, Shanghai Jiao Tong University, Shanghai 200240, China, and also with the School of Electronic Engineering and Automation, Guilin University of Electronic Technology, Guilin 541004, China (e-mail: wu.qq@sjtu.edu.cn; wenchen@sjtu.edu.cn).

D. W. Kwan Ng is with the School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney, NSW 2052, Australia (e-mail: wingn@ece.ubc.ca).

J. Li is with the School of Electronic and Optical Engineering, Nanjing University of Science and Technology, Nanjing 210044, China (e-mail: jun.li@njust.edu.cn).

R. Schober is with the Institute for Digital Communications, Friedrich-Alexander-University Erlangen-Nurnberg, Erlangen 91054, Germany (e-mail: frschoberg@ece.ubc.ca).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TWC.2016.2593440

***Index Terms*— User energy efficiency, wireless powered communication networks, resource allocation.**

I. Introduction

Wireless energy transfer (WET), where receivers harvest energy from radio frequency (RF) signals, is considered to be a promising solution for prolonging the lifetime of wireless devices. Combined with wireless information transmission (WIT), WET introduces a paradigm shift for the design of wireless communication systems and has been studied for various system architectures [1]–[14]. In [11], the authors established a "harvest-then-transmit" protocol for wireless powered communication networks (WPCNs), where the time allocated to the base station for downlink (DL) WET and the time allocated to the users for uplink (UL) WIT were jointly optimized for maximization of the system throughput. Similar problems were studied in the contexts of WPCNs with relays [12] and massive multiple-input multiple-output (MIMO) [13]. These works either focused on the spectral efficiency (SE) or the outage probability of WPCNs while the energy consumption of both energy transfer and information transmission was not considered, despite its importance for the design of future wireless communication systems.

The explosive growth of high-data-rate applications and services has triggered a dramatic increase in the energy consumption of wireless communications. Due to the rapidly rising energy costs and tremendous carbon footprints of communication systems [15], energy efficiency (EE), measured in bits-per-joule, has attracted considerable attention as a new performance metric in both academia and industry [16]–[20]. In fact, EE is particularly important in WPCNs since the harvested RF energy is attenuated by signal propagation. Resource allocation for system-centric EE maximization was studied in [8] for simultaneous wireless information and power transfer (SWIPT) systems. Specifically, the subcarrier assignment, power allocation, and power splitting ratio were jointly optimized for maximization of the system EE, while guaranteeing both a minimum amount of harvested energy and also a minimum user data rate. Chen *et al.* [21] investigated energy-efficient power allocation for large-scale MIMO systems for a single-user setup. However, employing large numbers of antennas may not be energy efficient if the energy consumption of the antennas is taken into account.

In our previous work [2], we studied system-centric EE maximization via joint time allocation and power control. We showed that from the system's perspective, only users who have a better energy utilization efficiency than the system itself should be scheduled while the rest of the users should remain silent during UL WIT. However, such a resource allocation algorithm design may lead to starvation of some users and thus their quality of service (QoS) cannot be guaranteed in practice. In fact, most existing works focus on optimizing the system-centric EE from the system's perspective [7], [16]–[19], [22], and little effort has been made to investigate the user-centric EE from the terminals' perspective. Since the capacities of batteries are limited but the demand for heterogeneous user experience increases, the EEs of individual users become increasingly critical for the operation of practical wireless communication systems [23]. However, a resource allocation aiming at optimizing the system-centric EE, which is defined as the ratio of the system throughput to the system energy consumption, is in general suboptimal as far as the EE of the individual users is concerned [1], [19], [24]. In contrast, in WPCNs, where users harvest energy and transmit information signals independently, the user-centric EE focuses on the EE of each user and is thus more relevant for practical user-centric applications than the system-centric EE [1]. In addition, user-centric EE optimization provides insights into the EE tradeoff between different users. For conventional SE optimization, the tradeoff between users is quite obvious and simple: the throughput of one user cannot be improved without decreasing the throughput of the other users. This is because utilizing more resources, such as transmit power and transmission time, is always beneficial for increasing the data rate of a user. However, this simple relationship may not hold for EE optimization. It is well known that exceedingly large transmit power will lead to a lower individual user EE [25], which suggests that users may not always compete for resources with each other. In other words, it may be possible to maximize the EEs of all users simultaneously. Furthermore, if the users have high minimum throughput requirements, users that are allocated short transmission times have to transmit with larger powers in order to meet the throughput requirements which may result in lower user EEs. In contrast, users that are allocated longer transmission times have higher flexibility in adjusting their transmit powers which facilitates higher user EEs. In this case, the EEs of the users may not be maximized simultaneously. Therefore, it is interesting to study the EE tradeoff between different users in WPCNs and it is expected that the adopted resource allocation policy plays an important role in balancing the individual EEs [1].

In this paper, we consider a WPCN where multiple users first harvest energy from a power station and then use the harvested energy to transmit data to an information receiving station. As mentioned before, our previous work [2] focused on evaluating the system EE, which is beneficial for striking a balance between the system throughout and the system energy consumption. In contrast, in this work, we aim to unveil the user EE tradeoff in WPCNs and design a computationally efficient resource allocation algorithm to balance the individual EEs of the users. Furthermore, the resource allocation algorithm proposed in [7] is based on the Dinkelbach method which is only applicable for optimization problems with a single-ratio objective function. Hence, this technique cannot be applied to the problem studied in this work where the system design objective function has a sum-of-ratios structure. The main contributions of this paper are summarized as follows:

- Different from most existing works [2], [5], [7], [8], [21], we study the energy-efficient resource allocation in WPCNs from a user-centric perspective. Time allocation and power control are jointly optimized to maximize the weighted sum of the user energy efficiencies (WSUEE). Thereby, our problem formulation takes also into account the circuit power consumption for WIT and WET. We first investigate the WSUEE maximization problem without minimum user throughput constraints, which provides useful insights into the EE tradeoff between the users of WPCNs. Subsequently, we extend the WSUEE maximization problem to a generalized WPCN where each user has a certain amount of initial energy and also a minimum throughput requirement. This generalization provides more flexibility for users to improve their EEs while guaranteeing QoS.
- For WPCNs without QoS requirements, we reveal that it is optimal to let the power station transmit with the maximum allowed power while letting each user exhaust its own harvested energy using a fixed transmit power. Based on this insight, we derive closed-form expressions for the maximum WSUEE as well as the optimal time allocation and power control, which facilitates the characterization of the EE tradeoff between users in WPCNs. It is found that within a throughput region, all users can achieve their individual maximum EEs simultaneously while only beyond that region, there exists non-trivial tradeoff among user EEs. This is unlike the conventional user SE tradeoff in [11] where users are always competing for resources and a non-trivial user SE tradeoff always exists.
- For generalized WPCNs, the WSUEE maximization problem is more difficult to solve since in contrast to the case without QoS requirements, some users may not exhaust all of their available energies in order to save transmission time for users with high throughput requirements. Exploiting the sum-of-ratios structure of the objective function, we transform the original non-convex optimization problem into an equivalent parameterized optimization problem which can be solved iteratively via solving a two-layer optimization problem. For the inner-layer, we show that the joint time allocation and power control optimization problem in subtractive form is a standard convex optimization problem and can be efficiently solved using Lagrangian dual decomposition. For the outer-layer, the parameters for the equivalent parametric optimization problem are updated with the damped Newton method having a superlinear convergence speed. The proposed two-layer algorithm is guaranteed to converge to the optimal solution.

The remainder of this paper is organized as follows. Section II introduces the WPCN system model. In Section III, we study energy-efficient transmission in WPCNs without

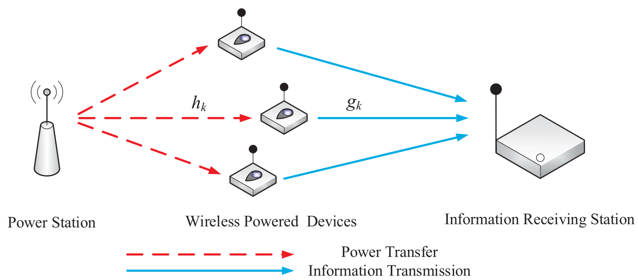


Fig. 1. The system model of a wireless powered communication network (WPCN).

QoS requirements. In Section IV, we consider the WSUEE maximization for generalized WPCNs. Section V provides simulation results for verification of our theoretical findings and the effectiveness of the proposed algorithm. Finally, Section VI concludes the paper.

II. System Model

In this section, we first introduce the WPCN system model. Then, the WPCN power consumption model for the wireless terminals is provided. Finally, we define the objective function, i.e., the WSUEE.

A. Signal and Energy Harvesting Models

We consider a WPCN which consists of a power station, K wireless-powered users, and an information receiving station, as depicted in Fig. 1. The "harvest-then-transmit" protocol is employed [11], i.e., all users first harvest energy from the RF signal broadcasted by the power station in the DL, and then transmit information signals individually to the information receiving station in the UL. For the ease of implementation, the power station and all users are equipped with a single antenna and use time division duplex to transmit in the same frequency band [8], [11]. Both the DL and the UL channels are modeled as quasi-static block fading channels, where the channel coefficients are assumed to be constant during each transmission time block (corresponding to e.g. one data packet), but vary independently from one block to the next [8], [11], [12]. 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 since our goal is to obtain an EE upper bound for practical WPCNs [11]. Once calculated, the resource allocation policy is conveyed to the users to perform energy-efficient transmission. Thereby, we assume that the energy consumed for estimating and exchanging CSI can be drawn from a dedicated battery which does not rely on the harvested RF energy [5].

In the DL WET stage, the power station broadcasts an energy signal with transmission power P_0 during transmission time τ_0. The energy harvested from the noise and the UL WIT signals received from other users is assumed to be negligible, since the thermal noise power and the user transmit powers are both much smaller than the transmit power of the power station in practice [11], [26]. Thus, the amount of energy harvested at user k can be modeled as

$$E_k^H = \eta_k \tau_0 P_0 h_k, \tag{1}$$

where $\eta_k \in (0, 1]$ is the energy conversion efficiency [11].

In the UL WIT stage, user k transmits an independent information signal x_k to the information receiving station with transmission power p_k during transmission time τ_k. Then, the achievable throughput of user k, denoted as B_k, is given by[1]

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

where $\gamma_k = \frac{g_k}{\sigma^2}$ denotes the channel-to-noise-power ratio for UL WIT. Constants W and σ^2 are the bandwidth of the considered system and the variance of the additive white Gaussian noise, respectively.

B. Power Consumption Model for Wireless Terminals

Since we focus on user-centric EE maximization, it is important to properly model the energy consumption of the user terminals in WPCNs. Here, we adopt the power consumption model from [23] and [27], which takes into account the transmit power, transmit circuit power, and receive circuit power of the user terminals for system design.

In WPCNs, the overall energy consumption of each wireless powered terminal consists of two parts: the energies consumed during DL WET and UL WIT, respectively. In the DL WET stage, as the terminal is in reception mode, only a constant circuit power is consumed for receive signal processing, i.e., $p_{\mathrm{r},k}$. Thus, the energy consumption in this stage is $p_{\mathrm{r},k}\tau_0$. Note that $E_k^H - p_{\mathrm{r},k}\tau_0 = (\eta_k P_0\ h_k - p_{\mathrm{r},k})\tau_0 > 0$ should always hold. If $E_k^H - p_{\mathrm{r},k}\tau_0 \le 0$, it means that user k cannot store any energy during energy harvesting. This can be caused by a low energy conversion efficiency η_k, a small transmit power of the power station P_0, a degraded DL channel gain h_k, or a large receive circuit power consumption $p_{\mathrm{r},k}$. In this case, user k should be shut down and not be considered for resource allocation. Hence, in the following, we only consider those users which satisfy $E_k^H - p_{\mathrm{r},k}\tau_0 \ge 0$. In the UL WIT stage, the wireless terminal is in the transmission mode, and the power consumption includes not only the over-the-air information transmit power, denoted as p_k, but also the circuit power consumed for transmit signal processing, denoted as $p_{\mathrm{c},k}$. Therefore, the overall energy consumption of user k 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.

[1]Here, the achievable throughput of user k, $B_k, \forall k$, corresponds to the total number of bits transmitted by user k in the duration of a transmission time block, $T_{\max}$.

C. Objective Function: User-Centric EE

The EE of each user in WPCNs is defined as the ratio of its achievable throughput during UL WIT and its overall energy consumption during both DL WET and UL WIT, i.e.,

$$EE_k = \frac{B_k}{E_k} = \frac{\tau_k W \log_2(1 + p_k\gamma_k)}{\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}}. \quad (4)$$

In this paper, we aim at balancing the EEs of the users in WPCNs. To achieve this goal, we adopt WSUEE as the objective function, which is in fact a scalarization of the EEs of multiple users. This metholodolgy is commonly used for the investigation of possibly conflictling design objectives [19], [28]. The WSUEE of WPCNs can be expressed as

$$EE_{\mathrm{sum}} = \sum_{k=1}^{K} \omega_k EE_k, \quad (5)$$

where the constant weight factors $\omega_k \geq 0$, $\forall k$, are provided by upper layers and reflect the priorities of the different users. These predefined weights introduce a flexibility for customizing the performance of different users. For example, the system designer can assign higher weights to users with less energy storage but higher throughput requirements to make them more energy efficient.

III. WSUEE Maximization xWithout User QoS Requirements

In this section, we investigate the WSUEE maximization problem when QoS constraints are not imposed, which provides useful design insights for energy-efficient transmission and characterization of the user EE tradeoff in WPCNs. Our goal is to jointly optimize time allocation and power control for both DL WET and UL WIT for maximization of the WSUEE, i.e., $EE_{\mathrm{sum}} = \sum_{k=1}^{K} \omega_k EE_k$. The WSUEE maximization problem can be formulated as

$$\begin{aligned}
\max_{\substack{\tau_0,\{\tau_k\},\\ P_0,\{p_k\}}} \quad & \sum_{k=1}^{K} \omega_k EE_k = \sum_{k=1}^{K} \omega_k \frac{\tau_k W \log_2(1 + p_k\gamma_k)}{\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k}} \\
\text{s.t. C1: } & P_0 \leq P_{\max}, \\
\text{C2: } & \tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \leq \eta_k P_0 \tau_0 h_k, \quad \forall k, \\
\text{C3: } & \tau_0 + \sum_{k=1}^{K} \tau_k \leq T_{\max}, \\
\text{C4: } & \tau_0 \geq 0, \quad \tau_k \geq 0, \quad \forall k, \\
\text{C5: } & P_0 \geq 0, \quad p_k \geq 0, \quad \forall k.
\end{aligned} \quad (6)$$

In problem (6), C1 constrains the maximum DL transmit power of the power station to $P_{\max}$. C2 guarantees that the total energy consumed by user k for DL WET and UL WIT does not exceed the available harvested energy $\eta_k P_0 \tau_0 h_k$. In C3, $T_{\max}$ is the total available transmission time. C4 and C5 are non-negativity constraints on the time allocation and power control variables, respectively. Note that problem (6) is neither convex nor quasi-convex due to the sum-of-ratios objective function and the products of optimization variables in C2 and C3. In general, there is no standard method for solving non-convex optimization problems efficiently. Nevertheless, in the following, we first investigate the properties of energy-efficient transmission in WPCNs, and then we derive a closed-form expression for the maximum WSUEE based on these properties.

A. Optimal Solution

We first study the transmit power of the power station in energy-efficient WPCNs.

Proposition 1: For WSUEE maximization, the power station of the WPCN always transmits with the maximum allowed power during DL WET, i.e., $P_0 = P_{\max}$.

Proof: Please refer to Appendix A. ■

The intuition behind Proposition 1 is that letting the power station transmit with the maximum allowed power reduces the reception time needed for DL WET, and thereby reduces the receive energy consumption of the wireless terminals. In addition, this transmission strategy also provides users with more transmission time, and thereby increases their throughputs for UL WIT, which improves the user EEs.

Next, we investigate how the wireless powered users utilize their harvested energy for energy-efficient transmission.

Proposition 2: For WSUEE maximization, each user in the WPCN uses up all of its harvested energy, i.e., $\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} = \eta_k P_0 \tau_0 h_k$, $\forall k$.

Proof: Please refer to Appendix B. ■

Proposition 2 reveals that the optimal strategy for energy utilization by the users of energy-efficient WPCNs is to fully utilize the harvested energy. Since DL WET incurs receive circuit energy consumption for users, if they do not fully utilize the harvested energy during UL WIT, the user EE can always be improved by decreasing the time for DL WET.

The following proposition characterizes the time utilization in energy-efficient WPCNs.

Proposition 3: For WSUEE maximization, the maximum value of the WSUEE can always be achieved by using up all the available transmission time $T_{\max}$.

Proof: Please refer to Appendix C. ■

In fact, if $\tau_0 + \sum_{k=1}^{K} \tau_k < T_{\max}$ holds, we can always increase τ_0 and τ_k by the same factor such that constraint C3 in (6) is satisfied with strict equality, i.e., $\tau_0 + \sum_{k=1}^{K} \tau_k = T_{\max}$. Then, it is easy to check that the scaled τ_0 and τ_k also always satisfy constraint C2 and achieve the same WSUEE. However, it is worth noting that the achieved user throughput increases linearly with τ_k and will be scaled accordingly when we scale τ_0 and τ_k. This has an interesting interpretation: the throughput can be improved without decreasing the EE but at the cost of increasing the transmission time.

In Propositions 1-3, we have revealed some useful properties of WSUEE maximization in WPCNs.Based on these properties, we derive in the following the optimal transmission times and transmit powers and express them in terms of the so-called transmit EEs of the users.

Theorem 4: In WPCNs, the maximum WSUEE, EE^*_{sum}, is given by

$$EE^*_{\mathrm{sum}} = \sum_{k=1}^{K} \left(1 - \frac{p_{\mathrm{r},k}}{\eta_k P_{\max} h_k}\right) \omega_k ee^*_k, \quad (7)$$

where $ee_k^* \triangleq \max_{p_k} \frac{W\log_2(1+p_k g_k)}{\frac{p_k}{\varepsilon_k}+p_{c,k}}$ can be interpreted as the transmit EE of user k for UL WIT. Correspondingly, the optimal power control and time allocation are given by

$$p_k^* = \left[\frac{W\varepsilon_k}{ee_k^* \ln 2} - \frac{1}{\gamma_k}\right]^+, \quad \forall k, \tag{8}$$

$$\tau_k^* = \frac{(\eta_k P_{\max} h_k - p_{\mathrm{r},k}) ee_k^*}{W\log_2(\frac{W\varepsilon_k\gamma_k}{ee_k^*\ln 2})}\tau_0, \quad \forall k, \tag{9}$$

$$\tau_0^* \in \left(0, \frac{T_{\max}}{1+\sum_{k=1}^K \frac{(\eta_k P_{\max} h_k - p_{\mathrm{r},k}) ee_k^*}{W\log_2(\frac{W\varepsilon_k\gamma_k}{ee_k^*\ln 2})}}\right]. \tag{10}$$

Proof: Please refer to Appendix D. ∎

Theorem 4 provides an expression for the maximum WSUEE by using the WPCN system parameters and the defined transmit EE. Since $\eta_k P_{\max} h_k \tau_0$ is the total energy harvested at user k and $p_{\mathrm{r},k}\tau_0$ is the circuit energy consumed during DL WET, then the actual energy stored in the battery is given by $(\eta_k P_{\max} h_k - p_{\mathrm{r},k})\tau_0$. Therefore, if a user has a lower $\frac{p_{\mathrm{r},k}\tau_0}{\eta_k P_{\max} h_k \tau_0} = \frac{p_{\mathrm{r},k}}{\eta_k P_{\max} h_k}$ in (7), it indicates that this user has more energy available for storage in its battery. Then, $\frac{(\eta_k P_{\max} h_k - p_{\mathrm{r},k})\tau_0}{\eta_k P_{\max} h_k \tau_0} = \frac{\eta_k P_{\max} h_k - p_{\mathrm{r},k}}{\eta_k P_{\max} h_k} = 1 - \frac{p_{\mathrm{r},k}}{\eta_k P_{\max} h_k}$ can be interpreted as the receive efficiency which indicates the capability of user k to store energy during DL WET. Hence, the EE of user k, EE_k, can be expressed as the product of the receive efficiency for DL WET, the transmit EE for UL WIT, and the corresponding weight, i.e., $\left(1 - \frac{p_{\mathrm{r},k}}{\eta_k P_{\max} h_k}\right)\omega_k ee_k^*$. Moreover, in (8), we also observe that the optimal transmit power of each user, p_k^*, is solely determined by its own local parameters, i.e., $p_{\mathrm{c},k}$, g_k, and ε_k. This implies that the maximum WSUEE can always be achieved by allowing each user to maximize its own EE. This can be explained as follows. In the absence of minimum user throughput requirements, the optimal strategy is to let each user use up all of its harvested energy, which results in a linear relationship between τ_0 and τ_k as shown in (9). In addition, scaling τ_0 and τ_k with the same factor does not affect the user EE in (4). Thus, the system can always find a sufficiently small τ_0 and τ_k, $\forall k$, to satisfy time constraint C3 in (6) for a given $T_{\max}$, such that the EEs of the different users do not conflict with each other. Note that the user transmit EE, ee_k, $\forall k$, is a quasiconcave function with respect to p_k, $\forall k$. Hence, the maximum value, ee_k^*, can be readily calculated by the simple bisection method [27], [29]. Then, we can obtain the maximum WSUEE as well as the optimal transmission times and transmit powers from (7)-(10).

Remark 5: It is worth noting that achieving the maximum user EE simultaneously for all users may not always be possible in WPCNs if minimum user throughput constraints have to be fulfilled, see Section IV for details. This is because if user throughput requirements are considered, users may compete for the time resource in order to meet their required throughputs, and thus a non-trivial tradeoff for the time allocation to the users may exist. For instance, if a user is allocated a small τ_k, the only way for it to meet its minimum throughput requirement is to increase its transmit power p_k, which may lead to a lower user EE. In contrast, if a user is allocated a larger τ_k, it has more flexibility in adjusting p_k which helps in achieving a higher user EE as well as in meeting the specified throughput requirement. Therefore, it is of interest to investigate the user EE tradeoff in WPCNs which is considered in the next subsection.

B. User EE Tradeoff

The following corollary characterizes the EE tradeoff between the users of a WPCN.

Corollary 6: The achievable user throughput region, $\mathcal{C}$, in which all users can achieve the maximum user EEs simultaneously, is given by

$$\mathcal{C} = \left\{(B_1, \ldots, B_k, \ldots, B_K) \middle| B_1 \le R_1^{\max}, \ldots, B_k \le R_k^{\max} \ldots, B_K \le R_K^{\max}\right\}, \tag{11}$$

where $R_k^{\max} = \tau_k^* W\log_2(1+p_k^*\gamma_k)$ and $\tau_0^* + \sum_{k=1}^K \tau_k^* = T_{\max}$. B_k is the throughput of user k during UL WIT which has been defined in (2). p_k^*, τ_k^*, and τ_0^* are given in (8), (9), and (10), respectively. If the minimum throughput requirement of any user k exceeds $R_k^{\max}$, then at least one user's EE has to be strictly decreased.

Proof: Please refer to Appendix E. ∎

Corollary 6 indicates that if the users' throughput requirements are inside region $\mathcal{C}$, each user can achieve its own maximum EE without decreasing the EE of other users. In contrast, outside region $\mathcal{C}$, there exists a non-trivial EE tradeoff between the users. It is worth noting that the user EE tradeoff between the users is unlike the conventional user throughput tradeoff for SE maximization [11] where users are always competing for resources, such as power and time, in order to maximize their own throughputs and thus a strict user SE tradeoff always exists. However, for the EE optimization considered in this work, an exceedingly large transmit power may not be beneficial. Thus, the EEs of the users can possibly be maximized simultaneously within a certain user-throughput region of $\mathcal{C}$ in (11). In contrast, in a user-throughput region with non-trivial user EE tradeoff, the EEs of the users can be balanced by assigning different priorities to different users, which results in different time allocation and power control strategies. For practical WPCNs, where users may demand heterogeneous services, it is desirable to investigate the WSUEE maximization problem with QoS constraints for WPCNs. This problem will be addressed in the next section.

Remark 7: It is expected that compared to system-centric EE maximization, maximizing the WSUEE will lead to a lower system EE. For example, for system-centric EE maximization, it was found that the optimal strategy is to schedule only those users whose user EEs are higher than the system EE [2]. This implies that to maintain high system EE, users with low user EEs have to remain silent for UL WIT. In contrast, for WSUEE maximization, we have shown that each user will be assigned a non-zero time interval for UL WIT, c.f. Proposition 3.2. This generally leads to a lower system EE. However, this loss in system EE is unavoidable if fairness among users is desired.

Furthermore, the total system throughput is also degraded due to the similar reason.

IV. WSUEE Maximization With User QoS Requirements

In this section, we study energy-efficient resource allocation for a general WPCN where each user is equipped with a certain amount of initial energy and has a minimum throughput requirement. In this case, the WSUEE maximization problem is formulated as

$$\begin{aligned}
&\max_{\substack{\tau_0,\{\tau_k\},\\ P_0,\{p_k\}}} \sum_{k=1}^{K} \omega_k EE_k \\
&\text{s.t. C1, C4, C5,} \\
&\quad \text{C2: } \tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \le \eta_k P_0 \tau_0 h_k + Q_k, \quad \forall k, \\
&\quad \text{C3: } \tau_0 + \sum_{k=1}^{K} \tau_k \le T_{\max}, \\
&\quad \text{C6: } \tau_k W \log_2(1 + p_k \gamma_k) \ge R_{\min}^k, \quad \forall k, \qquad (12)
\end{aligned}$$

where Q_k in C2 and $R_{\min}^k > 0$ in C6 denote the amount of initial energy and the minimum required throughput of user k, respectively. All other variables, constants, and constraints are identical to those in problem (6).

Remark 8: Note that in order to meet the throughput requirements of some users in C6, other users may not have sufficient time to fully use up their harvested energies in the current transmission block, i.e., $\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \le \eta_k P_0 \tau_0 h_k$ may hold with strict inequality for some k. In other words, at the end of some transmission blocks, some users may have energy left. To achieve a high user EE, it is preferable to use the energy left from previous transmission blocks in the current transmission block. Therefore, in C2, we assume that each user terminal has a certain amount of initial energy Q_k available. Moreover, Q_k could also be the energy harvested from others sources such as solar and wind. Hence, the proposed optimization can account for the effects of various energy harvesting techniques when combined with WET. This setup provides users with a higher flexibility in utilizing the available energy and in improving their individual EEs, and is thereby more general than the setups considered in previous works [5], [11]. Furthermore, if each user has sufficient initial energy Q_k, the optimal value of τ_0 can even be zero which suggests that WET is not needed. Thus, in this case, problem (12) can be simplified to WSUEE maximization in conventional *time division multiple access (TDMA)* systems without WET. In addition, under energy causality constraint C2 in (12), DL WET leads to receive power consumption which reduces user EE, while UL WIT improves user EE. This motivates the system to decrease the time for DL WET and to increase the time for UL WIT. Therefore, for the generalized problem where each user may have some initial energy in the battery, the dependence of UL WIT on DL WET is reduced. However, if the amount of initial energy is not sufficient to meet the minimum required throughput, then there exists a strict tradeoff between DL WET and UL WIT. Thus, the time allocation between DL WET and UL WIT is more complicated than in the case without initial energy and minimum required throughput.

In Section III, we have shown that problem (6) can be solved by exploiting the properties of the problem itself, despite its non-convexity. However, compared to problem (6), problem (12) is more general and hence more interesting. However, problem (12) is also much more challenging to solve for designing a computationally efficient resource allocation algorithm. For example, for given Q_k and $R_{\min}^k$, some users may not use up all of their available energies, which is unlike the conclusion in Proposition 2. The reasons for this are twofold. First, if some user k has large amounts of initial energy, e.g. $Q_k \to +\infty$, it is intuitive that user k cannot use up all of its available energy given the maximum available transmission time $T_{\max}$, otherwise, it has to transmit with an exceedingly large transmit power which results in a low user EE. Second, if some user k has a stringent throughput requirement $R_{\max}^k$, then a large amount of transmission time will be allocated to this user for UL WIT and the other users may not have sufficient time to use up all of their available energies. 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 (12). The following proposition characterizes the transmit power of the power station.

Proposition 9: For problem (12), the maximum WSUEE can always be achieved for $P_0^* = P_{\max}$.

Proof: Please refer to Appendix F. ■

Applying Proposition 9 in problem (12), we only have to optimize τ_0, $\{p_k\}$, and $\{\tau_k\}$, $\forall k$. The commonly used method for solving EE maximization problems is the Dinkelbach method [8], [21], [30]. However, the Dinkelbach method can only solve fractional optimization problems with a single-ratio objective function, and thus is not applicable to problem (12) which has a sum-of-ratios objective function. In the next section, we exploit the sum-of-ratios structure of the WSUEE to transform the original problem into a more tractable problem, which facilitates the development of a computationally efficient resource allocation algorithm.

A. Problem Transformation

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

Theorem 10: If $(\tau_0,\ \{p_k^*\},\ \{\tau_k^*\})$ is the optimal solution to problem (12), 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 $\boldsymbol{\beta} = \boldsymbol{\beta^*}$:

$$\max_{\{\tau_0,\{p_k\},\{\tau_k\}\}\in\mathcal{F}} \sum_{k=1}^{K} \alpha_k(\omega_k B_k - \beta_k E_k), \qquad (13)$$

where $\mathcal{F}$ is the feasible set of problem (12). Furthermore, $(\tau_0,\ \{p_k^*\},\ \{\tau_k^*\})$ have to satisfy the following system of equations for $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$:

$$\alpha_k E_k - 1 = 0, \quad k \in \{1, \cdots, K\}, \tag{14}$$

$$\beta_k E_k - \omega_k B_k = 0, \quad k \in \{1, \cdots, K\}. \tag{15}$$

Proof: We refer the interested reader to [31] for a detailed proof of Theorem 10. ■

Theorem 10 suggests that for the sum-of-ratios maximization problem (12), there exists an equivalent parameterized maximization problem with an objective function in subtractive form, i.e., problem (13), with some additional given parameters. In fact, the parameterized objective function of problem (13) has an interesting interpretation from the economics perspective: $\boldsymbol{\beta}$ represents the price for the cost of each item in an investment portfolio, e.g. the power consumption in the system, while $\boldsymbol{\alpha}$ coordinates all items to seek the maximum profit. By applying Theorem 10 to problem (12), we can obtain the optimal solution to problem (12) by solving problem (13) for $\boldsymbol{\alpha} = \boldsymbol{\alpha}^*$ and $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. Therefore, in the sequel, we first solve problem (13) for given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ and then develop an efficient approach to update $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ until (14) and (15) are both satisfied.

Based on Theorem 10, problem (12) is transformed into the following optimization problem for given $(\boldsymbol{\alpha}, \boldsymbol{\beta})$

$$\begin{aligned} \max_{\substack{\tau_0,\{\tau_k\},\\ \{p_k\}}} \quad & \sum_{k=1}^{K} \alpha_k \Bigg(\omega_k \tau_k W \log_2 (1 + p_k \gamma_k) \\ & \qquad - \beta_k \left(\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \right) \Bigg) \\ \text{s.t.} \quad & \text{C2, C3, C4, C5, C6.} \end{aligned} \tag{16}$$

Although problem (16) is more tractable than the original problem (12), it is still non-convex due to the products of optimization variables in the objective function, C2, and C6, respectively. 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 information transmission by user k. Replacing p_k with $\frac{\widetilde{E}_k}{\tau_k}$, problem (16) can be written as

$$\begin{aligned} \max_{\substack{\tau_0,\{\tau_k\},\\ \widetilde{E}_k}} \quad & \sum_{k=1}^{K} \alpha_k \left(\omega_k \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \right. \\ & \qquad \left. - \beta_k \left(\tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \right) \right) \\ \text{s.t.} \quad & \text{C3,} \quad \text{C4,} \quad \text{C5: } \widetilde{E}_k \geq 0, \quad \forall k, \\ & \text{C2: } \tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + p_{\mathrm{c},k} \tau_k \leq \eta_k P_{\max} \tau_0 h_k + Q_k, \ \forall k, \\ & \text{C6: } \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \geq R_{\min}^k, \quad \forall k. \end{aligned} \tag{17}$$

After this substitution, it can be easily verified that problem (17) is a standard convex optimization problem. Hence, in the following, we analyze the Karush-Kuhn-Tucker (KKT) conditions of problem (17) which leads to an optimal and computationally efficient algorithm.

B. Joint Time Allocation and Power Control

The partial Lagrangian function for problem (17) can be written as

$$\begin{aligned} & \mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta) \\ & = \sum_{k=1}^{K} \alpha_k \left(\omega_k \tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \right. \\ & \quad \left. - \ \beta_k \left(\tau_0 p_{\mathrm{r},k} + \frac{\widetilde{E}_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} \right) \right) \\ & \quad + \sum_{k=1}^{K} \lambda_k \left(\eta_k P_{\max} \tau_0 h_k + Q_k - \tau_0 p_{\mathrm{r},k} - \frac{\widetilde{E}_k}{\varepsilon_k} - p_{\mathrm{c},k} \tau_k \right) \\ & \quad + \sum_{k=1}^{K} \mu_k \left(\tau_k W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) - R_{\min}^k \right) \\ & \quad + \delta \left(T_{\max} - \tau_0 - \sum_{k=1}^{K} \tau_k \right), \end{aligned} \tag{18}$$

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 constraint C2 and the minimum user throughput constraint C6, respectively. δ is the non-negative Lagrange multiplier corresponding to the total time constraint C3. Note that the non-negativity constraints of the optimization variables, i.e., C4 and C5, will be absorbed into the optimal solution in the following. Accordingly, the associated dual function of problem (17) is given by $\mathcal{G}(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta) = \max_{(\tau_0,\{p_k\},\{\tau_k\}) \in \mathcal{D}} \mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$, where $\mathcal{D}$ is the feasible set specified by C4 and C5. The dual problem of (17) is thus given by

$$\min_{\boldsymbol{\lambda} \succeq \mathbf{0}, \boldsymbol{\mu} \succeq \mathbf{0}, \delta \geq 0} \ \max_{(\tau_0, \{\widetilde{E}_k\}, \{\tau_k\}) \in \mathcal{D}} \mathcal{L}(\tau_0, \widetilde{E}_k, \tau_k, \boldsymbol{\lambda}, \boldsymbol{\mu}, \delta). \tag{19}$$

Since the original problem (17) is a standard convex optimization problem which also satisfies SlaterâŁ™s constraint qualification, the duality gap between problem (17) and its dual problem (19) is zero [32]. This means that the optimal solution of problem (17) can be obtained by solving two optimization problems iteratively: the primal variable 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 $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$, and the dual variable optimization that minimizes $\mathcal{G}(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ over $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ for given $(\tau_0, \widetilde{E}_k, \tau_k)$. In the following, we discuss the solution methodology in detail.

1) Primal Variable 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 $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ is a standard concave optimization problem, the optimal solution can be obtained from the KKT conditions. Taking the partial derivative of $\mathcal{L}$ with respect to τ_0, $\widetilde{E}_k$, and τ_k, respectively, yields

$$\frac{\partial \mathcal{L}}{\partial \tau_0} = \sum_{k=1}^{K} \lambda_k (\eta_k P_{\max} h_k - p_{\mathrm{r,k}}) - \sum_{k=1}^{K} \alpha_k \beta_k p_{\mathrm{r,k}} - \delta, \tag{20}$$

$$\frac{\partial \mathcal{L}}{\partial \widetilde{E}_k} = \frac{W(\alpha_k \omega_k + \mu_k) \tau_k \gamma_k}{(\tau_k + \widetilde{E}_k \gamma_k) \ln 2} - \frac{\alpha_k \beta_k + \lambda_k}{\varepsilon_k}, \tag{21}$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \tau_k} & = (\alpha_k \omega_k + \mu_k) W \log_2 \left(1 + \frac{\widetilde{E}_k}{\tau_k} \gamma_k \right) \\ & \quad - \frac{W(\alpha_k \omega_k + \mu_k) \widetilde{E}_k \gamma_k}{(\tau_k + \widetilde{E}_k \gamma_k) \ln 2} - (\alpha_k \beta_k + \lambda_k) p_{\mathrm{c},k} - \delta. \end{aligned} \tag{22}$$

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

$$p_k^* = \frac{\widetilde{E}_k}{\tau_k} = \left[\frac{W(\alpha_k\omega_k + \mu_k)\varepsilon_k}{(\alpha_k\beta_k + \lambda_k)\ln 2} - \frac{1}{\gamma_k}\right]^+, \quad \forall k, \tag{23}$$

where $[x]^+ \triangleq \max\{x, 0\}$. From (23), 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, a user with the higher PA efficiency and a higher UL channel gain should transmit with higher power as this user is more efficient in utilizing energy.

Substituting (23) into (22) and after some manipulations, $\frac{\partial \mathcal{L}}{\partial \tau_k}$ can be expressed as

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \tau_k} &= (\alpha_k\omega_k + \mu_k)W\log_2\left(\frac{W(\alpha_k\omega_k + \mu_k)\varepsilon_k}{(\alpha_k\beta_k + \lambda_k)\ln 2}\gamma_k\right) - \delta \\ &\quad - (\alpha_k\beta_k + \lambda_k)\left(\frac{W(\alpha_k\omega_k + \mu_k)}{(\alpha_k\beta_k + \lambda_k)\ln 2} - \frac{1}{\gamma_k\varepsilon_k} + p_{c,k}\right).\end{aligned} \tag{24}$$

From (20) and (24), we observe that the 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 [32]. Therefore, in order to obtain τ_0 and τ_k, we substitute (23) into (17), which yields the following optimization problem

$$\begin{aligned}\max_{\tau_0,\{\tau_k\}} \quad & \sum_{k=1}^{K}\tau_k\left(\alpha_k\omega_k W\log_2(1+p_k^*\gamma_k) - \alpha_k\beta_k\left(\frac{p_k^*}{\varepsilon_k}+p_{c,k}\right)\right) \\ & - \tau_0\sum_{k=1}^{K}\alpha_k\beta_k p_{r,k} \\ \text{s.t.}\ & \text{C3},\ \text{C4}, \\ & \text{C2: } \tau_k\left(\frac{p_k^*}{\varepsilon_k} + p_{c,k}\right) \le \tau_0(\eta_k P_{\max} h_k - p_{r,k}) + Q_k, \quad \forall k, \\ & \text{C6: } \tau_k W\log_2\left(1 + p_k^*\gamma_k\right) \ge R_{\min}^k, \quad \forall k.\end{aligned} \tag{25}$$

We observe that problem (25) is a linear programming problem with respect to τ_0 and τ_k. Therefore, standard linear optimization tools, such as the simplex method [32], can be employed to obtain the optimal solution efficiently. Substituting τ_k back into (23), $\widetilde{E}_k$ is obtained immediately.

2) Dual Variable Optimization: After computing the primal variables $(\tau_0, \widetilde{E}_k, \tau_k)$, we now proceed to solve dual problem (19), i.e., $\min_{\boldsymbol{\lambda}\succeq\mathbf{0},\boldsymbol{\mu}\succeq\mathbf{0},\delta\ge 0} \mathcal{G}(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$. Since a dual function is always convex by definition, we adopt the gradient method for updating $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$. The Lagrange multiplier update equations are given by

$$\begin{aligned}\lambda_k(n+1) = \Bigg[\lambda_k(n) - \epsilon_1 \times \Bigg(&\eta_k P_{\max}\tau_0 h_k + Q_k \\ &- \tau_0 p_{r,k} - \frac{\widetilde{E}_k}{\varepsilon_k} - p_{c,k}\tau_k\Bigg)\Bigg]^+, \quad \forall k,\end{aligned} \tag{26}$$

$$\mu_k(n+1) = \left[\mu_k(n) - \epsilon_2 \times \left(\tau_k W\log_2\left(1 + \frac{\widetilde{E}_k}{\tau_k}\gamma_k\right) - R_{\min}^k\right)\right]^+, \quad \forall k, \tag{27}$$

$$\delta(n+1) = \left[\delta(n) - \epsilon_3 \times \left(T_{\max} - \tau_0 - \sum_{k=1}^{K}\tau_k\right)\right]^+, \tag{28}$$

where index $n \ge 0$ is the iteration index and ϵ_i, $i \in \{1, 2, 3\}$, are positive step sizes. A discussion regarding the choice of the step size for gradient methods is provided in [32] and is thus omitted here for brevity. The updated Lagrange multipliers in (26)-(28) can be used for updating the time allocation and power control variables in the primary variable optimization. Due to the concavity of primary problem (17), the iterative optimization of $(\tau_0, \widetilde{E}_k, \tau_k)$ in *1)* and $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \delta)$ in *2)* is guaranteed to converge to the optimal solution of (17).

C. Updating $(\boldsymbol{\alpha}, \boldsymbol{\beta})$

Having obtained $(\tau_0, \widetilde{E}_k, \tau_k)$ in Section IV-B, we are now ready to develop an algorithm for updating $(\boldsymbol{\alpha}, \boldsymbol{\beta})$. Let $\psi_k(\alpha_k) = \alpha_k E_k - 1$ and $\psi_{k+K}(\beta_k) = \beta_k E_k - \omega_k B_k$, $k = 1, \cdots, K$. It is shown in [31] 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, i.e., (14) and (15) hold. Thus, the well-known damped Newton method [19], [31], defined by (29)-(31), can be employed to update $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ as follows

$$\boldsymbol{\alpha}^{n+1} = \boldsymbol{\alpha}^n + \zeta^n \boldsymbol{q}^n, \tag{29}$$

$$\boldsymbol{\beta}^{n+1} = \boldsymbol{\beta}^n + \zeta^n \boldsymbol{q}^n, \tag{30}$$

$$\boldsymbol{q}^n = [\boldsymbol{\psi}'(\boldsymbol{\alpha}, \boldsymbol{\beta})]^{-1}\boldsymbol{\psi}(\boldsymbol{\alpha}, \boldsymbol{\beta}), \tag{31}$$

where $\boldsymbol{\psi}'(\boldsymbol{\alpha}, \boldsymbol{\beta})$ is the Jacobian matrix of $\boldsymbol{\psi}(\boldsymbol{\alpha}, \boldsymbol{\beta})$, n is the iteration index, and ζ^n is the greatest ξ satisfying

$$\|\boldsymbol{\psi}(\boldsymbol{\alpha}^n + \xi\boldsymbol{q}^n, \boldsymbol{\beta}^n + \xi\boldsymbol{q}^n)\| \le (1 - \varsigma\xi)\|\boldsymbol{\psi}(\boldsymbol{\alpha}^n, \boldsymbol{\beta}^n)\|, \tag{32}$$

where $\xi \in (0, 1)$, $\varsigma \in (0, 1)$, and $||\cdot||$ denotes the standard Euclidean norm. Specifically, for the problem at hand, the pointwise update equations for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can be expressed as

$$\alpha_k^{n+1} = (1 - \zeta^n)\alpha_k^n + \zeta^n\frac{1}{E_k^n}, \tag{33}$$

$$\beta_k^{n+1} = (1 - \zeta^n)\beta_k^n + \zeta^n\frac{\omega_k B_k^n}{E_k^n}. \tag{34}$$

The details of obtaining the optimal solution to problem (12) are summarized in Algorithm 1. A flow chart for Algorithm 1 is presented in Figure 2.

The complexity of Algorithm 1 can be evaluated as follows. First, the complexity for obtaining τ_0, p_k, and $\tau_k, \forall k$, linearly increases with the number of users, K. Second, since there are $2K + 1$ dual variables, the complexity of the subgradient method is $\mathcal{O}(K^2)$ [32] where $\mathcal{O}(x)$ means that there is an upper bound for the complexity which grows with order x. Finally, the complexity for updating $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is independent of K [31]. Therefore, the total complexity of the proposed algorithm is $\mathcal{O}(K^3)$.

V. Numerical Results

In this section, we present simulation results to validate our theoretical findings and to demonstrate the user EE. 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

Algorithm 1 Energy-Efficient Resource Allocation Algorithm for WPCNs

1: Initialize the algorithm accuracy indicator t;
2: Initialize $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, and set $n = 0$;
3: **repeat**
4: Initialize $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ;
5: **repeat**
6: Obtain the time allocation variables τ_0 and τ_k by solving problem (25);
7: Obtain the power control variables p_k from (23);
8: Update the dual variables $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ in (26), (27), and (28), respectively;
9: **until** $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, and δ converge;
10: Compute B_k and E_k from (2) and (3);
11: Compute $\boldsymbol{q}^n$ from (31);
12: Compute the largest ξ satisfying (24);
13: Update $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ in (33) and (34);
14: $n = n + 1$;
15: **until** $||\boldsymbol{\psi}(\boldsymbol{\alpha}, \boldsymbol{\beta})|| \le t$.

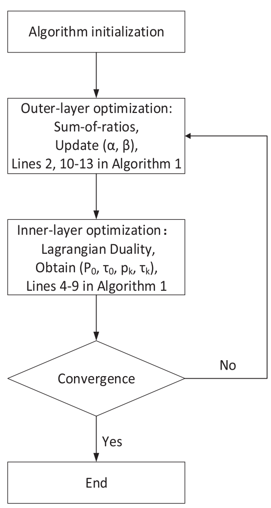


Fig. 2. Flow chart of the proposed Algorithm 1.

station. The system bandwidth is set to 20 kHz and the time duration is set as 1 s [11]. 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. For the purpose of comparison, the maximum transmit powers of the power stations are set as 30 dBm and 46 dBm in Figure 4-5 and Figure 6-9 [11]. Unless specified otherwise, we assume that all users have the same receive and transmit circuit power consumption as well as the same weight, the same energy conversion efficiency, and the same PA efficiency. The corresponding values are set to $p_{\mathrm{r},k} = p_{\mathrm{r}} = 30$ mW, $\omega_k = \omega = 1$, $p_{\mathrm{c},k} = p_{\mathrm{c}} = 50$ mW, $\eta_k = \eta = 0.9$, and $\varepsilon_k = \varepsilon = 0.9$, $\forall k$, respectively [8].

A. WSUEE Versus Maximum Transmit Power

In Figure 3, we compare the performance of the following schemes: 1) WSUEE optimal: proposed approach; 2) System EE optimal: maximization of the system EE which is defined as a ratio of the system throughput and the system energy consumption [2]; 3) Throughput optimal: conventional throughput maximization [11]; 4) Partial utilization: each user consumes only part of its harvested energy, i.e., $\tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} = \rho\ (\eta_k P_{\max} h_k - p_{\mathrm{r},k})\tau_0$, where ρ $(0 < \rho < 1)$ can be adjusted to strike a balance between the energy consumed in

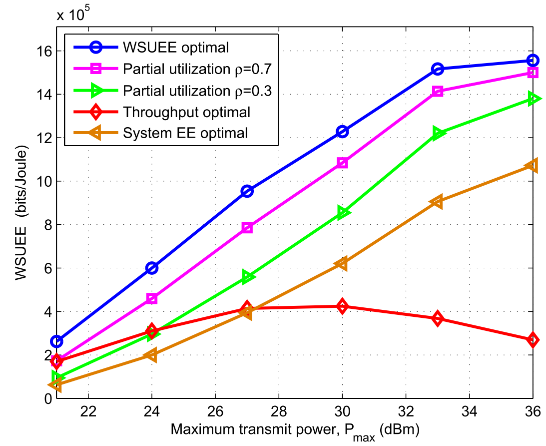


Fig. 3. WSUEE versus the maximum allowed transmit power of the power station.

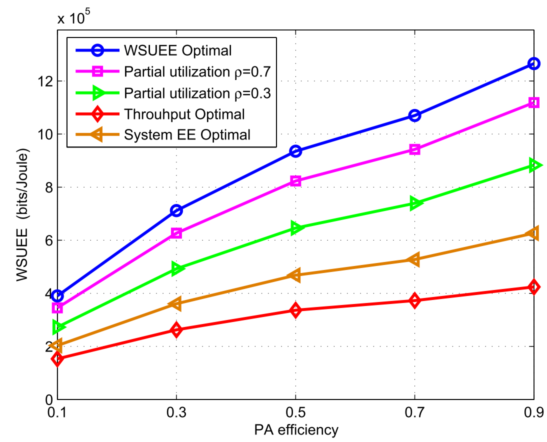


Fig. 4. The impact of the PA efficiency on WSUEE.

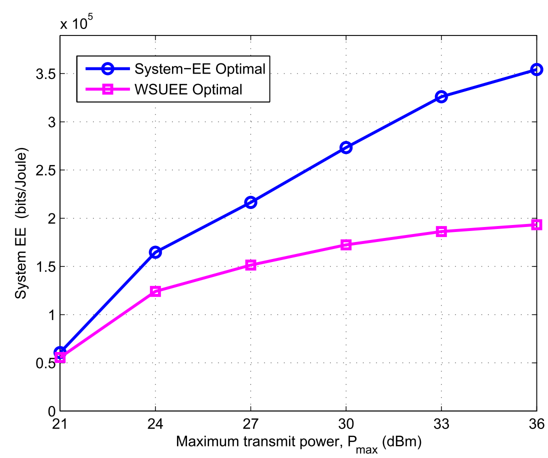
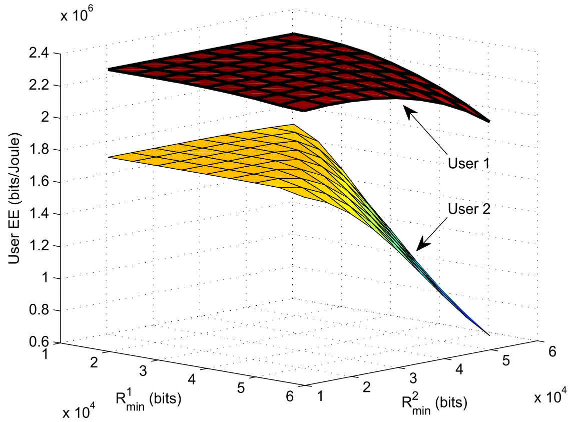
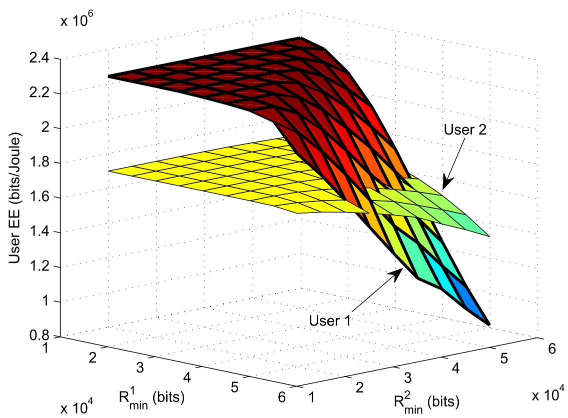


Fig. 5. Average system EE performance of the system EE optimal scheme and the WSUEE optimal scheme.



(a) User EE versus $R^1_{\min}$ and $R^2_{\min}$ for $\boldsymbol{\omega} = [5\ 1]$.



(b) User EE versus $R^1_{\min}$ and $R^2_{\min}$ for $\boldsymbol{\omega} = [1\ 5]$.

Fig. 6. User EE versus the minimum throughput requirement for different weights, $\boldsymbol{\omega} = [\omega_1\ \omega_2]$.

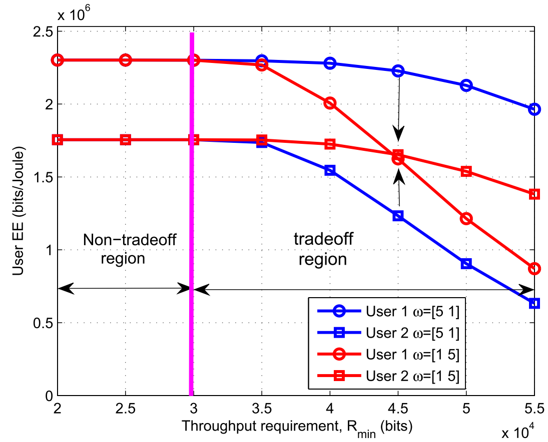


Fig. 7. User EE versus the minimum throughput requirement for different weights when $R^1_{\min} = R^2_{\min} = R_{\min}$.

the current transmission block and the energy stored for the next transmission block.

From Figure 3, we observe that the WSUEE of the proposed approach first increases quickly with the transmit power of the power station and then experiences marginal increases in the high transmit power region. This is because when $P_{\max}$ is low, to transfer a certain amount of energy, a small increase of $P_{\max}$ can significantly reduce the time needed for DL WET and thus reduce the receive circuit energy consumption. Therefore, the user EE improves quickly. On the other hand, in the high $P_{\max}$ region, the time needed for DL WET is already so short that the receive circuit energy consumption does no longer have a large impact on the total user energy consumption, and thus, further increasing the transmit power leads only to a marginal increase in the WSUEE.

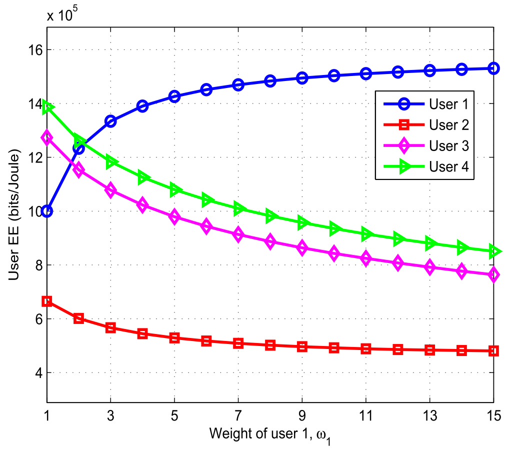
We also observe from Figure 3 that the proposed approach outperforms all other considered schemes which can be explained as follows. First, the partial utilization scheme is based on the assumption that each user has harvested more energy during DL WET than it utilizes during UL WIT. Since the DL transmit power of the power station is fixed to $P_{\max}$, it implies that users consume more time during DL WET and hence consume more receive circuit energy than the optimal amount, which thereby leads to low user EEs. Therefore, not fully utilizing the harvested energy is suboptimal. However, as $P_{\max}$ increases, the receive circuit energy consumed for RF energy harvesting decreases due to the short energy harvesting time. Thus, the partial utilization scheme gradually converges to the optimal scheme. Second, as mentioned in [11], although the throughput optimal scheme also lets each user utilize all of its harvested energy, the time allocation between the DL power station and the UL users is not EE oriented which thus leads to a strictly suboptimal performance in terms of user-centric EE. Finally, the system-centric EE seeks to improve the system EE by exploiting multiuser diversity [2]. This kind of optimization leads to starvation of some users which may not be scheduled at all. This leads to an unsatisfactory WSUEE.

B. WSUEE Versus User PA Efficiency

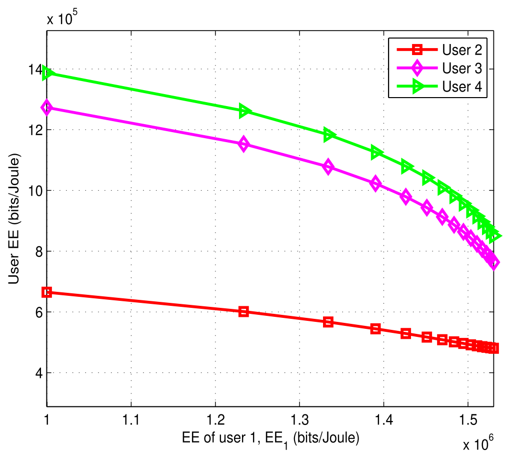
Figure 4 illustrates the impact of the user PA efficiency on the WSUEE of the considered schemes. As can be observed, the performance of all schemes increases with the PA efficiency, as expected from the analytical expression for the WSUEE in (7). In addition, the performance gains of the proposed approach compared to the other schemes are also enhanced as the PA efficiency increases. This can be attributed to the fact that a higher PA efficiency allows a user to have more energy for information transmission, which provides the proposed optimization approach with more degrees of freedom for improving the user-centric EE.

C. System EE Versus Maximum Transmit Power

In Figure 5, we illustrate the achieved system EE of the proposed WSUEE optimal resource allocation, which is generated by taking the result of the WSUEE optimal approach into the system EE expression. As can be seen, WSUEE maximization incurs a performance loss in terms of system EE compared to system-centric EE maximization and the performance loss increases with increasing maximum transmit power. This is due to the following two reasons. First, WSUEE maximization does not take into account the energy loss caused by signal



(a) User EE versus the weight of user 1.



(b) User EE tradeoff.

Fig. 8. Illustration of EE tradeoff between four users.

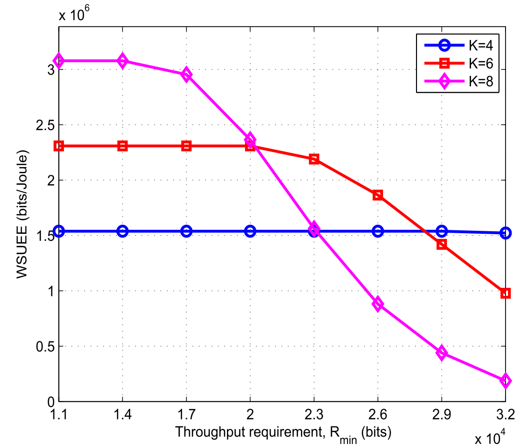


Fig. 9. WSUEE versus the minimum user throughput requirement.

attenuation during DL WET and thus, the obtained time allocation between DL WET and UL WIT is not optimal in terms of the system EE. Second, as revealed in Proposition 3.2, for WUSEE maximization, each user is assigned a non-zero time interval for UL WIT, which is not beneficial for the overall system throughput and limits the system's ability to exploit multi-user diversity. In contrast, system-centric EE maximization selectively schedules only those users whose user EEs are higher than the system EE while forcing the rest of the users to be silent. Therefore, the system EE gain of the system-centric EE maximization approach over the WSUEE maximization approach is at the expense of sacrificing user fairness, which is not desirable from the perspective of the end users.

D. User EE Tradeoff Region

In Figure 6, we illustrate the findings of Corollary 6. A WPCN with two users is considered. Specifically, we set $\boldsymbol{h} \triangleq [h_1, h_2] = [0.1, 0.1]$ and $\boldsymbol{\gamma} \triangleq [\gamma_1, \gamma_2] = [1000, 500]$. We plot the achieved user EE versus the user throughput requirements for different weights. In Figure 6(b), we switch the weights of the two users in (12) compared to Figure 6(a), and then evaluate the individual user EEs respectively to illustrate the effect of the weights on the user EEs. Comparing Figure 6(a) and Figure 6(b), we can see that when the required throughputs of the two users are small, both of their EEs are constant with respect to the required throughputs, which suggests that changing the weights has no impact on the EE of either user. This is because both users achieve their own maximum EE simultaneously. However, when the throughput requirements become stringent, the user EEs of the two users can be adjusted by selecting different weights for different users. Particularly, in Figure 6(b), by assigning a larger weight to user 2 which has the worse UL WIT channel, we can improve its user EE significantly compared to Figure 6(a). To make this point clearer, in Figure 7, we show the non-tradeoff and tradeoff regions in terms of the user throughput when $R_{\min} = R^k_{\min}$, $k = 1, 2$. Specifically, for $\boldsymbol{\omega} = [5\ 1]$, we observe that the EE of user 1 decreases slowly while the EE of user 2 decreases sharply as $R_{\min}$ increases. In contrast, for $\boldsymbol{\omega} = [1\ 5]$, the EEs of user 1 and user 2 show the opposite behaviours. In particular, for $R_{\min} = 4.5 \times 10^4$ bits, user 1 and user 2 achieve almost identical EEs. This suggests that in the user EE tradeoff region, assigning different weights to different users can indeed enforce a certain notion of fairness among users and help improve the individual EEs of users having degraded channels.

E. Illustration of EE Tradeoff Between Users

Figure 8 illustrates the tradeoff between four users where users 1, 2, 3, and 4 are located at distances of 80 m, 70 m, 90 m, and 95 m from the power station, respectively. Without loss of generality, we assume that all users have the same minimum throughput requirement, i.e., $R^k_{\min} = R_{\min} = 2 \times 10^4$ bits, $\forall k$. We assign the same weights to users 2, 3, and 4, i.e., $\omega_2 = \omega_3 = \omega_4 = 1$, and vary the weight of user 1, ω_1, between 1 and 15. As can be seen from Figure 8(a), as ω_1 increases, the EE of user 1 increases while the EEs of users 2, 3, and 4, decrease, which further demonstrates that assigning higher weights to some users indeed helps improve their EEs.

In addition, it is worth noting that as ω_1 increases, the EE of user 1 first gradually increases and finally approaches a constant value, which is the maximum EE that user 1 can achieve. The user EE tradeoff is further studied in Figure 8(b), where the EEs of users 2, 3, and 4 versus the EE of user 1 are depicted. As the EE of user 1 increases, the EE of the other users strictly decreases, which illustrates the non-trivial tradeoff between the EEs of individual users.

F. WSUEE Versus Minimum User Throughput Requirement

In Figure 9, we consider a symmetric network where all users have the same minimum throughput requirement, i.e., $R_{\min} = R_{\min}^k$, $\forall k$, and show the WSUEE versus $R_{\min}$. We observe that for all considered numbers of users, the WSUEE first remains constant and then decreases as $R_{\min}$ increases, which further illustrates the fundamental tradeoff between EE and SE. In addition, as $R_{\min}$ increases, the WSUEE for a larger number of users decreases more rapidly than that for a small number of users. This is because for a smaller number of users, a longer UL WIT transmission time is available for each user, and thus the achieved throughput of each user is also larger. However, for a larger number of users, the available UL WIT transmission time allocated for each user is shorter, and the achieved throughput of each user is thus smaller. Therefore, as $R_{\min}$ increases, the WSUEE of a larger number of users decreases faster than that of a smaller number of users. Besides, when $R_{\min}$ is relatively high, users have to compete for time resources more fiercely and thus have to transmit with larger powers during UL WIT in order to meet their throughput requirements, which thus leads to a faster decay in the user EE and thereby the WSUEE.

VI. CONCLUSIONS

In this paper, we investigated the energy-efficient resource allocation in WPCNs from a user-centric perspective. The time allocation and power control of DL WET and UL WIT were jointly optimized to maximize the WSUEE. For the WUSEE maximization problem without minimum user throughput requirements, we derived a closed-form expression for the WSUEE by carefully studying the properties of energy-efficient transmission. For the WUSEE maximization problem with minimum user throughput requirements, we proposed a computationally efficient resource allocation algorithm to obtain the optimal solution by exploiting the sum-of-ratios structure of the objective function. Simulation results demonstrated the gains in EE achieved by the proposed joint optimization approach and also unveiled the tradeoff between the EEs of different users in WPCNs. In particular, (1) for low user throughput requirements, all users can achieve their individual maximum EEs simultaneously; (2) for high user throughput requirements, the individual user EEs can be balanced by assigning different weights to different users; (3) neither the system-centric EE scheme nor the throughput optimal scheme are user-centric EE optimal and the performance loss caused by adopting traditional schemes for user-centric EE systems is higher for larger power station transmit powers and for smaller user receive circuit powers.

APPENDIX A
PROOF OF PROPOSITION 1

We prove Proposition 1 by contradiction. Suppose that $\{P_0^*, \{p_k^*\}, \tau_0^*, \{\tau_k^*\}\}$ achieves the maximum WSUEE of problem (6) satisfying $P_0^* < P_{\max}$. The corresponding EE of user k is denoted as EE_k^*. Then, we construct another 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 $\widehat{\tau}_k = \tau_k^*$, respectively. The corresponding EE of user k is denoted as $\widehat{EE}_k$. It is easy to check that $\{\widehat{P}_0, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ does not violate any of the constraints and is thus a feasible solution. Furthermore, since $\widehat{P}_0 = \widehat{P}_{\max} > P_0^*$, it follows that $\widehat{\tau}_0 < \tau_0^*$. Then, the energy consumption of user k satisfies

$$\widehat{\tau}_0 p_{\mathrm{r},k} + \widehat{\tau}_k \frac{\widehat{p}_k}{\varepsilon_k} + \widehat{\tau}_k p_{\mathrm{c},k} < \tau_0^* p_{\mathrm{r},k} + \tau_k^* \frac{p_k^*}{\varepsilon_k} + \tau_k^* p_{\mathrm{c},k}. \quad (35)$$

Thus, from (35) and (4), it follows that $EE_k^* < \widehat{EE}_k$, $\forall k$. Therefore, we have $\sum_{k=1}^K \omega_k EE_k^* < \sum_{k=1}^K \omega_k \widehat{EE}_k$. Hence, $\{P_0^*, \{p_k^*\}, \tau_0^*, \{\tau_k^*\}\}$ cannot be the optimal solution.

APPENDIX B
PROOF OF PROPOSITION 2

We prove Proposition 2 by contradiction. Suppose that $\{P_{\max}, \{p_k^*\}, \tau_0^*, \{\tau_k^*\}\}$ achieves the maximum WSUEE of problem (6) while there exists a user m who does not use up all of its harvested energy, i.e., $\tau_0 p_{\mathrm{r},m} + \tau_k \frac{p_m}{\varepsilon_m} + \tau_m p_{\mathrm{c},m} < \eta_m P_{\max} \tau_0 h_m$ and $\tau_0 p_{\mathrm{r},k} + \tau_k \frac{p_k}{\varepsilon_k} + \tau_k p_{\mathrm{c},k} = \eta_k P_{\max} \tau_0 h_k$ for $k \neq m$. The corresponding EE of user k, denoted as EE_k^*, is given by

$$EE_k^* = \frac{\tau_k^* W \log_2\left(1 + p_k^* \gamma_k\right)}{\tau_0^* p_{\mathrm{r},k} + \tau_k^* \frac{p_k^*}{\varepsilon_k} + \tau_k^* p_{\mathrm{c},k}}, \quad \forall k. \quad (36)$$

Then, we construct another solution $\{P_{\max}, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ satisfying $\widehat{p}_k = p_k^*$, $\forall k$, $\widehat{\tau}_0 = \beta \tau_0^*$, $\widehat{\tau}_m = \alpha \tau_m^*$, and $\widehat{\tau}_k = \beta \tau_k^*$ for $k \neq m$, respectively, where $0 < \beta < 1$ and $\alpha > 1$. Note that for $\beta \to 0$, it follows that $\eta_m P_{\max} \widehat{\tau}_0 h_m - \widehat{\tau}_0 p_{\mathrm{r,m}} = \beta \tau_0^* (\eta_m P_{\max} h_m - p_{\mathrm{r},m}) \to 0$; while as α increases, $\widehat{\tau}_m \frac{\widehat{p}_m}{\varepsilon_m} + \widehat{\tau}_m p_{\mathrm{c},m} = \alpha \tau_m^* (\frac{\widehat{p}_m}{\varepsilon_m} + p_{\mathrm{c},m})$ increases. Thus, there always exist α and β such that both $\alpha \tau_m^* (\frac{\widehat{p}_m}{\varepsilon_m} + p_{\mathrm{c},m}) = \beta \tau_0^* (\eta_m P_{\max} h_m - p_{\mathrm{r},m})$ and $\widehat{\tau}_0 + \sum_{k=1}^K \widehat{\tau}_k = \beta \left(\tau_0^* + \sum_{k \neq m}^K \tau_k^*\right) + \alpha \tau_m^* \leq T_{\max}$ are satisfied. It is also easy to verify that $\widehat{\tau}_0 p_{\mathrm{r},k} + \widehat{\tau}_k \frac{\widehat{p}_k}{\varepsilon_k} + \widehat{\tau}_k p_{\mathrm{c},k} = \eta_k P_{\max} \widehat{\tau}_0 h_k$ still holds. Thus, the corresponding user EEs, $\widehat{EE}_m$ and $\widehat{EE}_k$ for $\forall k \neq m$, can be expressed as

$$\begin{aligned} \widehat{EE}_m &= \frac{\widehat{\tau}_m W \log_2\left(1 + \widehat{p}_m \gamma_m\right)}{\widehat{\tau}_0 \widehat{p}_{\mathrm{r},m} + \widehat{\tau}_m \frac{\widehat{p}_m}{\varepsilon_m} + \widehat{\tau}_m \widehat{p}_{\mathrm{c},m}} \\ &= \frac{\alpha \tau_m^* W \log_2\left(1 + p_m^* \gamma_m\right)}{\beta \tau_0^* p_{\mathrm{r},m}^* + \alpha \left(\tau_m^* \frac{p_m^*}{\varepsilon_m} + \tau_m^* p_{\mathrm{c},m}^*\right)}, \end{aligned} \quad (37)$$

$$\begin{aligned} \widehat{EE}_k &= \frac{\widehat{\tau}_k W \log_2\left(1 + \widehat{p}_k \gamma_k\right)}{\widehat{\tau}_0 \widehat{p}_{\mathrm{r},k} + \widehat{\tau}_k \frac{\widehat{p}_k}{\varepsilon_k} + \widehat{\tau}_k \widehat{p}_{\mathrm{c},k}} \\ &= \frac{\beta \tau_k^* W \log_2\left(1 + p_k^* \gamma_k\right)}{\beta \tau_0^* p_{\mathrm{r},k}^* + \beta \left(\tau_k^* \frac{p_k^*}{\varepsilon_k} + \tau_k^* p_{\mathrm{c},k}^*\right)}, \quad \forall k \neq m. \end{aligned} \quad (38)$$

Comparing (36) with (37) and (38), we observe that $\widehat{EE}_m > EE_m^*$ and $\widehat{EE}_k = EE_k^*$ for $\forall k \neq m$, as $\alpha > 1$ and $0 < \beta < 1$. Therefore, we have $\sum_{k=1}^K \omega_k \widehat{EE}_k > \sum_{k=1}^K \omega_k EE_k^*$, which contradicts that user m does not use up all of its harvested energy. This completes the proof.

Appendix C
Proof of Proposition 3

Suppose that $\{P_{\max}, \{p_k^*\}, \tau_0^*, \{\tau_k^*\}\}$ achieves the maximum WSUEE, EE_{sum}^*, and satisfies $0 \leq \tau_0^* + \sum_{k=1}^K \tau_k^* < T_{\max}$. Then, we can construct another solution $\{\widehat{P}_0, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ with $\widetilde{P}_0 = P_{\max}$, $\widehat{p}_k = p_k^*$, $\widehat{\tau}_0 = \alpha\tau_0^*$, $\widehat{\tau}_k = \alpha\tau_k^*$, respectively, where $\alpha = \frac{T_{\max}}{\tau_0^* + \sum_{k=1}^K \tau_k^*} > 1$ such that $\widehat{\tau}_0 + \sum_{k=1}^K \widehat{\tau}_k = T_{\max}$. The corresponding WSUEE is denoted as $\widehat{EE}_{\text{sum}}$. First, it is easy to verify that $\{\widehat{P}_0, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ still satisfies constraints C1-C3. Then, substituting $\{\widehat{P}_0, \{\widehat{p}_k\}, \widehat{\tau}_0, \{\widehat{\tau}_k\}\}$ into problem (6) yields $\widehat{EE}_{\text{sum}} = EE_{\text{sum}}^*$, which means that the maximum WSUEE can always be achieved by using up all the available time, i.e., $T_{\max}$.

Appendix D
Proof of Theorem 4

From Proposition 2, we obtain

$$\tau_k = \frac{(\eta_k P_{\max} h_k - p_{r,k})\tau_0}{\frac{p_k}{\varepsilon_k} + p_{c,k}}. \tag{39}$$

Substituting (39) into the objective function of problem (6) yields

$$\begin{aligned} EE_{\text{sum}} &= \sum_{k=1}^K \omega_k \frac{\frac{(\eta_k P_{\max} h_k - p_r)\tau_0}{\frac{p_k}{\varepsilon_k} + p_{c,k}} W \log_2(1 + p_k\gamma_k)}{p_r\tau_0 + \frac{(\eta_k P_{\max} h_k - p_r)\tau_0}{\frac{p_k}{\varepsilon_k} + p_{c,k}}\left(\frac{p_k}{\varepsilon_k} + p_{c,k}\right)} \\ &= \sum_{k=1}^K \omega_k \left(1 - \frac{p_r}{\eta_k P_{\max} h_k}\right) \frac{W \log_2(1 + p_k\gamma_k)}{\frac{p_k}{\varepsilon_k} + p_{c,k}}. \end{aligned} \tag{40}$$

From (40), we observe that $\omega_k\left(1 - \frac{p_r}{\eta_k P_{\max} h_k}\right)$ is a constant for each user k. Let $ee_k \triangleq \frac{W \log_2(1+p_k\gamma_k)}{\frac{p_k}{\varepsilon_k} + p_{c,k}}$, which can be interpreted as the transmit EE of user k. Thus, to maximize EE_{sum}, we only have to maximize ee_k. It is easy to prove that ee_k is a strictly quasiconcave function of p_k and its unique stationary point is also the maximum point. Thus, by setting the derivative of ee_k with respect to p_k to zero, we obtain the following relationship between ee_k^* and p_k^*

$$p_k^* = \left[\frac{W\varepsilon_k}{ee_k^* \ln 2} - \frac{1}{\gamma_k}\right]^+, \tag{41}$$

where ee_k^* is the maximum transmit EE of user k. The numerical values for ee_k^* and p_k^* can be easily obtained by the bisection method [32].

Appendix E
Proof of Corollary 6

From (7) in Theorem 4, we know that the maximum value of WSUEE does not depend on the value of τ_0 in the feasible region while the achieved throughput R_k increases linearly with the transmit time τ_k as p_k is given by (8). Therefore, τ_0 and τ_k, $\forall k$, reach their maximum feasible values if and only if

$$\tau_0^* + \sum_{k=1}^K \tau_k^* = T_{\max}. \tag{42}$$

Thus, the maximum achieved throughput at the maximum WSUEE, denoted as $R_k^{\max}$, is given by

$$\begin{aligned} R_k^{\max} &= \tau_k^* W \log_2(1 + p_k^*\gamma_k) \\ &= (\eta_k P_{\max} h_k - p_r)\tau_0^* \frac{W \log_2(1 + p_k^*\gamma_k)}{\frac{p_k^*}{\varepsilon_k} + p_{c,k}} \\ &= (\eta_k P_{\max} h_k - p_r)\tau_0^* ee_k^*. \end{aligned} \tag{43}$$

Thus, if the minimum throughput requirement of any user k exceeds $R_k^{\max}$, we can see from (43) that the only way to meet the requirement is to increase the DL WET time τ_0^* as ee_k already assumes its maximum value ee_k^*. Then, from (42), it follows that $\sum_{k=1}^K \tau_k^*$ has to be decreased which suggests that at least one user's τ_k^* has to be decreased. As EE_k increases with τ_k and decreases with τ_0, we conclude that at least one user's EE has to be decreased.

Appendix F
Proof of Proposition 9

As the power transfer may not always be activated due to the initial energy of the users, we discuss the following two cases. First, if the power transfer is activated for the optimal solution, i.e., $\tau_0^* > 0$, then we can show $P_0^* = P_{\max}$ following a similar proof as for Proposition 1. Second, if $\tau_0^* = 0$ holds true, then the value of the power station's transmit power P_0^* does not affect the maximum value of WSUEE, and thus $P_0 = P_{\max}$ is also an optimal solution.

References

[1] Q. Wu and W. Chen, "User-centric energy-efficient resource allocation for wireless powered communications," in *Proc. IEEE WCSP*, Oct. 2015, pp. 1–6.

[2] Q. Wu, M. Tao, D. W. K. Ng, W. Chen, and R. Schober, "Energy-efficient transmission for wireless powered multiuser communication networks," in *Proc. IEEE ICC*, Jun. 2015, pp. 154–159.

[3] Z. Ding, I. Krikidis, B. Sharif, and H. V. Poor, "Wireless information and power transfer in cooperative networks with spatially random relays," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4440–4453, Aug. 2014.

[4] X. Chen, C. Yuen, and Z. Zhang, "Wireless energy and information transfer tradeoff for limited-feedback multiantenna systems with energy beamforming," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 407–412, Jan. 2014.

[5] C. Zhong, H. A. Suraweera, G. Zheng, I. Krikidis, and Z. Zhang, "Wireless information and power transfer with full duplex relaying," *IEEE Trans. Commun.*, vol. 62, no. 10, pp. 3447–3461, Oct. 2014.

[6] C. Zhong, G. Zheng, Z. Zhang, and G. K. Karagiannidis, "Optimum wirelessly powered relaying," *IEEE Signal Process. Lett.*, vol. 2, no. 10, pp. 1728–1732, Oct. 2015.

[7] Q. Wu, M. Tao, D. W. K. Ng, W. Chen, and R. Schober, "Energy-efficient resource allocation for wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 2312–2327, Mar. 2016.

[8] 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.

[9] D. W. K. Ng, E. S. Lo, and R. Schober, "Robust beamforming for secure communication in systems with wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4599–4615, Aug. 2014.

[10] H. Chen, Y. Li, Y. Jiang, Y. Ma, and B. Vucetic, "Distributed power splitting for SWIPT in relay interference channels using game theory," *IEEE Trans. Wireless Commun.*, vol. 14, no. 1, pp. 410–420, Jan. 2015.

[11] 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.

[12] H. Chen, Y. Li, J. L. Rebelatto, B. F. Uchôa-Filho, and B. Vucetic, "Harvest-then-cooperate: Wireless-powered cooperative communications," *IEEE Trans. Signal Process.*, vol. 63, no. 7, pp. 1700–1711, Apr. 2015.

[13] G. Yang, C. K. Ho, R. Zhang, and Y. L. Guan, "Throughput optimization for massive MIMO systems powered by wireless energy transfer," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 8, pp. 1640–1650, Aug. 2015.

[14] K. Huang and V. K. N. Lau, "Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 902–912, Feb. 2014.

[15] J. Wu, S. Rangan, and H. Zhang, Eds., *Green Communications: Theoretical Fundamentals, Algorithms and Applications*. Boca Raton, FL, USA: CRC Press, 2012.

[16] 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.

[17] G. Y. Li *et al.*, "Energy-efficient wireless communications: Tutorial, survey, and open issues," *IEEE Wireless Commun.*, vol. 18, no. 6, pp. 28–35, Dec. 2011.

[18] 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.

[19] G. Yu, Q. Chen, R. Yin, H. Zhang, and G. Y. 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.

[20] Q. Wu, G. Y. Li, W. Chen, and D. W. K. Ng, "Energy-efficient small cell with spectrum-power trading," *IEEE J. Sel. Areas Commun.*, to be published.

[21] 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.

[22] C. Xiong, G. Y. 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.

[23] 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. 17, no. 3, pp. 1535–1556, 3rd Quart., 2014.

[24] G. Yu, Y. Jiang, L. Xu, and G. Y. Li, "Multi-objective energy-efficient resource allocation for multi-RAT heterogeneous networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 10, pp. 2118–2127, Oct. 2015.

[25] C. Xiong, G. Y. Li, S. Zhang, Y. Chen, and S. Xu, "Energy- and spectral-efficiency tradeoff in downlink OFDMA networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 11, pp. 3874–3886, Nov. 2011.

[26] 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.

[27] Q. Wu, M. Tao, and W. Chen, "Joint Tx/Rx energy-efficient scheduling in multi-radio wireless networks: A divide-and-conquer approach," *IEEE Trans. Wireless Commun.*, vol. 15, no. 4, pp. 2727–2740, Apr. 2016.

[28] E. Björnson and E. Jorswieck. (2013). *Optimal Resource Allocation in Coordinated Multi-Cell Systems*. [Online]. Available: http://www.laneas.com/sites/default/files/publications/387/0100000069-Bjornson-Vol9-CIT-069.pdf

[29] G. Miao, N. Himayat, and G. Y. Li, "Energy-efficient link adaptation in frequency-selective channels," *IEEE Trans. Commun.*, vol. 58, no. 2, pp. 545–554, Feb. 2010.

[30] W. Dinkelbach, "On nonlinear fractional programming," *Manage. Sci.*, vol. 13, no. 7, pp. 492–498, Mar. 1967.

[31] Y.-C. Jong. (2012). *An Efficient Global Optimization Algorithm for Nonlinear Sum-of-Ratios Problem*. [Online]. Available: http://www.optimization-online.org/DB_HTML/2012/08/3586.html

[32] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

Qingqing Wu (S'13) received the B.S. degree in electronics engineering from the South China University of Technology, Guangzhou, China, in 2012. He is currently pursuing the Ph.D. degree with the Network Coding and Transmission Laboratory, Shanghai Jiao Tong University. Since 2015, he has been a Visiting Scholar with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, USA. His current research interests include energy-efficient optimization and wireless information and power transfer. He serves as a TPC member of Chinacom 2015, the IEEE ICCC 2016, the IEEE Globecom 2016, and the IEEE VTC 2017. He was a recipient of the International Conference on Wireless Communications and Signal Processing Best Paper Award in 2015.

Wen Chen (M'03–SM'11) received the B.S. and M.S. degrees from Wuhan University, Wuhan, China, in 1990 and 1993, respectively, and the Ph.D. degree from The University of Electro-Communications, Tokyo, Japan, in 1999. From 1999 to 2001, he was a Researcher with the Japan Society for the Promotion of Sciences. In 2001, he joined the University of Alberta, Edmonton, AB, Canada, starting as a Post-Doctoral Fellow with the Information Research Laboratory and continuing as a Research Associate with the Department of Electrical and Computer Engineering. Since 2006, he has been a Full Professor with the Department of Electronic Engineering, Shanghai Jiao Tong University (SJTU), Shanghai, China, where he is also the Director of the Institute for Signal Processing and Systems. From 2014 to 2015, he was the Dean of the School of Electronic Engineering and Automation with the Guilin University of Electronic Technology, China. Since 2016, he has been the Chairman of SJTU Intelligent Property Management Corporation. He is the author of 74 papers in the IEEE journals and transactions and more than 110 papers in IEEE conference publications. His research interests include network coding, cooperative communications, multiple access technique, and multiple-input multiple-output orthogonal-frequency-division multiplexing systems.

Derrick Wing Kwan Ng (S'06–M'12) received the bachelor's degree (Hons.) and the M.Phil. degree in electronics engineering from the Hong Kong University of Science and Technology in 2006 and 2008, respectively, and the Ph.D. degree from the University of British Columbia (UBC) in 2012. In the summer of 2011 and spring of 2012, he was a Visiting Scholar with the Centre Tecnològic de Telecomunicacions de Catalunya–Hong Kong. He was a Senior Post-Doctoral Fellow with the Institute for Digital Communications, Friedrich-Alexander-University Erlangen-Nürnberg , Germany. He is a Lecturer with the University of New South Wales, Sydney, Australia. His research interests include convex and non-convex optimization, physical layer security, wireless information and power transfer, and green (energy-efficient) wireless communications.

Dr. Ng has served as an Editorial Assistant to the Editor-in-Chief of the IEEE TRANSACTIONS ON COMMUNICATIONS since 2012. He is currently an Editor of the IEEE COMMUNICATIONS LETTERS. He was a Co-Chair for the Wireless Access Track of the 2014 IEEE 80th Vehicular Technology Conference. He has been a TPC member of various conferences, including the Globecom, WCNC, ICC, VTC, and PIMRC. He was honored as an Exemplary Reviewer of the IEEE TRANSACTIONS ON COMMUNICATIONS in 2015, the Top Reviewer of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY in 2014, and an Exemplary Reviewer of the IEEE WIRELESS COMMUNICATIONS LETTERS in 2012, 2014, and 2015. He received best paper awards at the IEEE International Conference on Computing, Networking and Communications 2016, the IEEE Wireless Communications and Networking Conference (WCNC) 2012, the IEEE Global Telecommunication Conference (Globecom) 2011, and the IEEE Third International Conference on Communications and Networking in China 2008. He also received IEEE student travel grants to attend the IEEE WCNC 2010, the IEEE International Conference on Communications (ICC) 2011, and the IEEE Globecom 2011. He was a recipient of the 2009 Four Year Doctoral Fellowship from the UBC, the Sumida & Ichiro Yawata Foundation Scholarship in 2008, and the R&D Excellence Scholarship from the Center for Wireless Information Technology at HKUST in 2006.

Jun Li (M'09) received the Ph.D. degree in electronics engineering from Shanghai Jiao Tong University, Shanghai, China, in 2009. In 2009, he was with the Department of Research and Innovation, Alcatel Lucent Shanghai Bell, as a Research Scientist. From 2009 to 2012, he was a Post-Doctoral Fellow with the School of Electrical Engineering and Telecommunications, University of New South Wales, Australia. From 2012 to 2015, he was a Research Fellow with the School of Electrical Engineering, University of Sydney, Australia. Since 2015, he has been a Professor with the School of Electronic and Optical Engineering, Nanjing University of Science and Technology, Nanjing, China. His research interests include network information theory, channel coding theory, wireless network coding, and cooperative communications.

Robert Schober (S'98–M'01–SM'08–F'10) was born in Neuendettelsau, Germany, in 1971. He received the Diploma (Univ.) and Ph.D. degrees in electrical engineering from the University of Erlangen–Nuermberg in 1997 and 2000, respectively. From 2001 to 2002, he was a Post-Doctoral Fellow with the University of Toronto, Canada, sponsored by the German Academic Exchange Service (DAAD). Since 2002, he has been with the University of British Columbia (UBC), Vancouver, Canada, where he is a Full Professor. Since 2012, he has been an Alexander von Humboldt Professor and the Chair of Digital Communication with the Friedrich Alexander University, Erlangen, Germany. His research interests fall into the broad areas of communication theory, wireless communications, and statistical signal processing.

Dr. Schober is a fellow of the Canadian Academy of Engineering and the Engineering Institute of Canada. From 2012 to 2015, he served as the Editor-in-Chief of the IEEE TRANSACTIONS ON COMMUNICATIONS. Since 2014, he has been the Chair of the Steering Committee of the IEEE TRANSACTIONS ON MOLECULAR, BIOLOGICAL AND MULTISCALE COMMUNICATION. Furthermore, he is a Member-at-Large of the Board of Governors of the IEEE Communications Society. He received several awards for his work, including the 2002 Heinz MaierLeibnitz Award of the German Science Foundation (DFG), the 2004 Innovations Award of the Vodafone Foundation for Research in Mobile Communications, the 2006 UBC Killam Research Prize, the 2007 Wilhelm Friedrich Bessel Research Award of the Alexander von Humboldt Foundation, the 2008 Charles McDowell Award for Excellence in Research from UBC, a 2011 Alexander von Humboldt Professorship, and a 2012 NSERC E.W.R. Steacie Fellowship. In addition, he has received several best paper awards for his research.