Energy-Efficient Resource Allocation in TDMS-Based Wireless Powered Communication Networks

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***Abstract*— This letter considers a wireless powered communication network (WPCN) where users first harvest energy in downlink and then utilize the energy to transmit information signal in uplink simultaneously. Our goal is to maximize the energy efficiency (EE) of the network via joint time allocation and power control. However, directly solving this issue is of significant challenge due to its nonconvex property. By exploiting the nonlinear fractional programming, an iterative resource allocation method based on the Dinkelbach structure is proposed to solve the considered nonconvex optimization problem. In each iteration, we optimize power with fixed time allocation and then optimize time with a given power allocation. Simulation results are presented to show that the system EE is greatly improved by the proposed approach.**

***Index Terms*— Energy efficient, nonconvex, nonlinear fractional programming, wireless powered communication network.**

I. Introduction

OWING to the limited usage time of wireless devices and high operation cost of battery replacement, energy harvesting has become a promising technique in wireless communication networks. Unlike the uncontrollable energy harvesting technique that extracts energy from natural resources, e.g., solar and wind [1], RF-enabled wireless energy transfer (WET) provides an attractive solution by powering wireless devices with continuous and stable energy transmission over the air. In recent years, WET has drawn significant attention because of its capability of prolonging the lifetime of wireless networks. One important application of RF-enabled WET is in wireless powered communication networks (WPCNs), where wireless devices first harvest energy through downlink (DL) WET and then utilize the stored energy to transmit information in the uplink (UL).

Generally, there are two strategies in WPCNs named time division mode switching (TDMS) and time division multiple access (TDMA). The TDMS scheme divides a period of time into two time phases. In the first phase, all users harvest energy from RF signal broadcasted by the power station and then transmit information simultaneously in the second phase. The difference between TDMS and TDMA lies in the second phase. That is, rather than concurrent transmission of all users in TDMS, users transmit their signals one by one in the TDMA, which would decrease the spectrum efficiency. In both the two schemes, numerous works have been done to optimize user throughput [2], [3].

Notice that a great dissipation of energy during the WET phase may considerably decrease the system energy efficiency (EE). Owing to this fact, there is a need to optimize the energy efficiency in WPCNs. Considering initial energy storage and throughput requirements, Wu *et al.* [4] proposed a time and power allocation algorithm to maximize network energy efficiency through the linear fractional programming theory. In [5], the problem of maximizing the system EE is transformed into a linear programming problem, which is solved by a cyclic iteration method. It is worth noting that, all of these works adopt the TDMA scheme in the uplink wireless information tranfer (WIT), which are able to alleviate the spectrum usage, and in particular, generate a mathematically easy case. To our best knowledge, the quality-of-service (QoS) guaranteed energy-efficient resource allocation in the WPCN under the TDMS scheme has not yet been investigated in the literature. Particularly, in a WPCN under the protocol of TDMS, the coupling power allocation among users imposes a great challenge on the algorithm design.

The main contributions of this work are twofold. Firstly, we formulate the EE problems in TDMS as an optimization problem with multiple constraints. Secondly, an alternative method is designed to tackle the energy-efficient resource allocation optimization problem under the protocol of TDMS, which has good performance with the advantages of fast convergence, low complexity and insensitivity to initial values.

II. System Model and Problem Formulation

In this section, we first describe the system model in Section II-A and then formulate the considered problem in Section II-B.

A. System Description

We consider a WPCN, which consists of one hybrid access point (HAP) and K wireless powered users, where the HAP plays the role of power broadcasting in the downlink and information receiving in the uplink. The TDMS scheme is adopted for this network. The DL channel gain from the HAP to user k and its reversed channel are denoted by h_k and g_k, respectively. Without loss of generality, quasi-static channel is considered and perfect channel state information (CSI) is assumed [5], i.e., g_k and h_k are constant during a period of time.

For a unit period of time, the WET phase occupies the first τ_0 $(0 < \tau_0 < 1)$ of time, during which the HAP broadcast energy with power P_0. Since the noise power and the energy consumed by channel state information feedback is much smaller than P_0, these two parts of energy consumption can be negligible in practice [4]. The amount of energy harvested

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of user k can be expressed as

$$E_k(\tau_0, P_0) = \eta P_0 \tau_0 h_k, \tag{1}$$

where η is a constant energy transformation efficiency at the receiver. After the WET phase, the WIT phase takes the amount of time τ_1, during which all users transmit UL information simultaneously. Apparently, $\tau_0 + \tau_1 \leq 1$ should be satisfied.

Let $\boldsymbol{P}$ denote the power vector $(p_1, p_2, \ldots, p_K)$ and p_j denote the transmit power of user j. Then, the achievable throughout of user k in bits/s is given by

$$R_k(\tau_1, \boldsymbol{P}) = \tau_1 W \log_2\left(1 + \frac{g_k p_k}{n_k + \sum_{j=1, j\neq k}^{K} g_j p_j}\right) \tag{2}$$

where n_k denotes the noise power of user k and W is the system bandwidth. Then, the system throughput, defined as the sum-throughput of all users, is $R_{tot}(\tau_1, \boldsymbol{P}) = \sum_{k=1}^{K} R_k(\tau_1, \boldsymbol{P})$.

The total power consumption of the network is composed of two parts. During the WET, the system energy consumption is

$$E_{\text{WET}}(\tau_0, P_0) = P_0 \tau_0 - \sum_{k=1}^{K} E_k + P_c \tau_0, \tag{3}$$

where P_c is the circuit power of the HAP and $P_0\tau_0 - \sum_{k=1}^{K} E_k$ is the energy loss. During the WIT, the energy consumed by all users can be modeled as

$$E_{\text{WIT}}(\tau_1, \boldsymbol{P}) = \sum_{k=1}^{K} \left(p_k \tau_1 + p_k^c \tau_1\right), \tag{4}$$

where p_k^c is the circuit power of the user terminal. Thus, the total energy consumption of the system is defined as $E_{tot}(\tau_0, \tau_1, \boldsymbol{P}, P_0) = E_{\text{WET}}(\tau_0, P_0) + E_{\text{WIT}}(\tau_1, \boldsymbol{P})$.

Hence, the system EE can be characterized by the ratio of the sum-throughput to the total power consumption of the system, i.e., $q = \frac{R_{tot}(\tau_1, \boldsymbol{P})}{E_{tot}(\tau_0, \tau_1, \boldsymbol{P}, P_0)}$.

B. Problem Formulation

Our goal is to maximize the system EE while guaranteeing the QoS of all users. Therefore, the optimum EE can be achieved by solving the optimization problem given by

$$\begin{aligned}
\max_{\substack{\tau_0, \tau_1, \\ \boldsymbol{P}, P_0}} \quad & \frac{R_{tot}(\tau_1, \boldsymbol{P})}{E_{tot}(\tau_0, \tau_1, \boldsymbol{P}, P_0)} \\
\text{s.t.} \quad & \text{C1}: 0 \leq P_0 \leq P_{\max}, \\
& \text{C2}: \tau_0 + \tau_1 \leq 1, \\
& \text{C3}: p_k \tau_1 + p_k^c \tau_1 \leq \eta P_0 \tau_0 h_k, \quad \forall k, \\
& \text{C4}: R_k(\tau_1, \boldsymbol{P}) \geq B_{\min}^k, \quad \forall k, \\
& \text{C5}: \tau_0, \tau_1 \geq 0, \quad \forall k, \quad \text{C6}: p_k \geq 0. \quad \forall k.
\end{aligned} \tag{5}$$

In the problem (5), C1 denotes the non-negative and peak power $P_{\max}$ constraints, C2 means the constrains of the total available transmission time, and C3 ensures that the energy consumed by user k during the WIT should not exceed the total harvested energy $\eta P_0 \tau_0 h_k$ in the WET. The QoS of users are guaranteed by the constraint C4, i.e., the throughput of user k should be no less than its minimum throughput requirement $B_{\min}^k$. Inequalities C5 and C6 are non-negative constraints on the optimization variables.

The key challenge in solving problem (5) is the lack of convexity of the problem formulation. Besides, the constraints

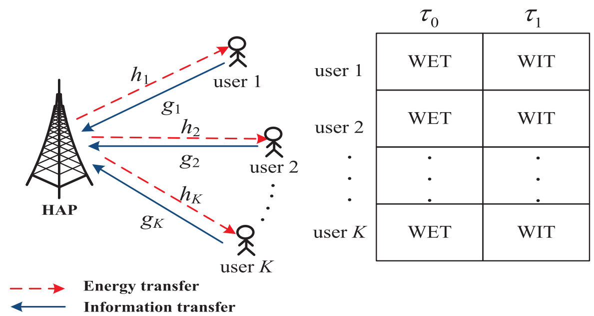

Fig. 1. A WPCN with WET in the DL and WIT in the UL under the protocol of TDMS.

do not span a convex solution set due to the coupled variables of power and time in C3 and C4. To this end, an alternative iteration approach is proposed in next section.

III. Algorithm Design

Although the problem (5) is nonconvex, we observe that the objective funciton has a fractional structure. Therefore, as described in Section III-A, the Dinkelbach method can be applied to tackle this issue. Particularly, we initialize a small EE and update it in terms of iteration. Since the involved problem in each iteration is still a nonconvex issue with respect to the coupled variables of power and time, we solve the power allocation and time allocation problems in each outer loop iteration, separately, which are illustrated in Section III-B and Section III-C.

A. Dinkelbach Based Iterative Algorithm

To begin with, we first investigate the transmit power of the HAP. With an assumption that each user has a fixed energy requirement, a greater energy broadcasting power can reduce the charging time, which results in a lower consumption of circuit power. In other words, increasing the energy transmit power could improve the system EE. Accordingly, as also pointed out in [5], the optimal P_0 must be $P_{\max}$. Therefore, we only need to optimize τ_0, τ_1, and p_k, $\forall k$, for solving the problem (5).

Before presenting our proposed algorithm, we first introduce a proposition given as follows.

Proposition 1: The optimal value of Problem (5) q^*, defined as

$$q^* = \max_{\tau_0, \tau_1, \boldsymbol{P} \in \mathcal{F}} \frac{R_{tot}(\tau_1, \boldsymbol{P})}{E_{tot}(\tau_0, \tau_1, \boldsymbol{P})}, \tag{6}$$

where $\mathcal{F}$ is the feasible set, satisfies the equality given by

$$\max_{\tau_0, \tau_1, \boldsymbol{P} \in \mathcal{F}} \{R_{tot}(\tau_1, \boldsymbol{P}) - q^* E_{tot}(\tau_0, \tau_1, \boldsymbol{P})\} = 0. \tag{7}$$

Proof: The proof is similar to that of [9, Th. 1] and is thus omitted here. ∎

According to Proposition 1, solving the problem (5) is equivalent to finding a q such that zero is the optimal objective value of the problem given by

$$\max_{\tau_0, \tau_1, \boldsymbol{P}} \ R_{tot}(\tau_1, \boldsymbol{P}) - q E_{tot}(\tau_0, \tau_1, \boldsymbol{P}) \tag{8a}$$

$$\text{s.t. C1} - \text{C6} \tag{8b}$$

Then, the Dinkelbach method can solve this issue by initializing a small q and updating it in each iteration of the

Algorithm 1 Energy-Efficient Resource Allocation Algorithm

Initialization set the maximum tolerance ε and $q = q^0$;
repeat
  Initialize $n = 0$, set the initial value of τ_0, τ_1, $\boldsymbol{P}$ and $I^0 = 0$;
  repeat
    Set $n = n + 1$;
    Solve the problem (8) for the given q, τ_0, τ_1 and obtain the power allocation $\boldsymbol{P}^n$;
    Solve the problem (8) under the condition of q, $\boldsymbol{P}^n$ and obtain the time allocation policy τ_0^n and τ_1^n;
    Calculate $I^n = R_{tot}(\tau_1^n, \boldsymbol{P}^n) - qE_{tot}(\tau_0^n, \tau_1^n, \boldsymbol{P}^n)$;
    Set $\boldsymbol{P} = \boldsymbol{P}^n$, $\tau_0 = \tau_0^n$ and $\tau_1 = \tau_1^n$;
  until $\left|I^n - I^{n-1}\right| < \varepsilon$
  Update $q = \frac{R_{tot}(\tau_1, \boldsymbol{P})}{E_{tot}(\tau_0, \tau_1, \boldsymbol{P})}$;
until q converge;

outer loop. Unfortunately, the coupling variables of power and time entangle the problem (8) involved in each iteration. To circumvent this problem, an alternative procedure is adopted in the inner loop, i.e., a pure power optimization issue and a pure time optimization issue are solved circularly. For the power optimization with a fixed time, we transform the problem (8) to a D.C. (difference of two concave functions) programming problem [10]. For the time allocation with fixed power allocation, we solve (8) by one-dimensional linear programming. The specific energy-efficient resource allocation algorithm is described in Algorithm 1. The parameters are defined as follows: n is the iteration index, q^0 is a small positive constant, which denotes the initial value of q, I^n is the objective function value of τ_0^n, τ_1^n and $\boldsymbol{P}^n$ which are the time and power allocation after the n-th inner loop iteration.

B. Power Allocation

In this subsection, an iterative gradient method based on the D.C. programming is developed for solving power allocation optimization problem under fixed q and time allocation.

It is easy to see that C3, C6 are linear constraints. On the other hand, we can rearrange C4 as

$$p_k g_k + \left(1 - 2^{B_{\min}^k / W\tau_1}\right)\left(n_k + \sum\nolimits_{j=1, j\neq k}^{K} p_j g_j\right) \geq 0, \quad \forall k, \tag{9}$$

which is linear as well. Therefore, all constraints are linear. Let us now shift our attention to the objective function (8a), which can be converted to

$$f(\boldsymbol{P}) - h(\boldsymbol{P}), \tag{10}$$

where

$$f(\boldsymbol{P}) = \tau_1 W \sum_{k=1}^{K} \log_2\left(\sum_{j=1}^{K} p_j g_j + n_k\right) - qE_{tot}(\tau_0, \tau_1, \boldsymbol{P}) \tag{11}$$

and

$$h(\boldsymbol{P}) = \tau_1 W \sum_{k=1}^{K} \log_2\left(\sum\nolimits_{j=1, j\neq k}^{K} p_j g_j + n_k\right). \tag{12}$$

Particularly, for given τ_0, τ_1, the problem (8) is equivalently transformed to

$$\max \; f(\boldsymbol{P}) - h(\boldsymbol{P}) \tag{13a}$$
$$\text{s.t. C3, C6, (9).} \tag{13b}$$

Algorithm 2 Iterative Gradient Method for Power Allocation

Initialization
- Set $\boldsymbol{P}^0$, calculate $D^0 = f(\boldsymbol{P}^0) - h(\boldsymbol{P}^0)$;
- Set $i = 0$ and maximum tolerance $\phi > 0$;

repeat
  Obtain $\boldsymbol{P}^*$ by solving the problem (15);
  Set $i = i + 1$ and $\boldsymbol{P}^i = \boldsymbol{P}^*$;
  Calculate $D^i = f(\boldsymbol{P}^i) - h(\boldsymbol{P}^i)$;
until $\left|D^i - D^{i-1}\right| < \phi$;

It is worth noting that (13a) is a D.C. function. Thus, it can be efficiently solved by a sequence of convex programming procedures.

Hence, we can obtain a sequence of $\boldsymbol{P}$ by initializing a feasible $\boldsymbol{P}^0$ and update it in each iteration by solving the following convex programming

$$\max \; f(\boldsymbol{P}) - \left[h\left(\boldsymbol{P}^i\right) + \nabla h^T\left(\boldsymbol{P}^i\right)\left(\boldsymbol{P} - \boldsymbol{P}^i\right)\right] \tag{14a}$$
$$\text{s.t. C3, C6, (9).} \tag{14b}$$

Here, $\boldsymbol{P}^i$ is the value of $\boldsymbol{P}$ in the i-th iteration, $\nabla h(\boldsymbol{P})$ denotes the gradient of $h(\boldsymbol{P})$, which is

$$\nabla h(\boldsymbol{P}) = \sum\nolimits_{k=1}^{K} \frac{\tau_1 W}{\sum_{j=1, j\neq k}^{K} p_j g_j + n_k} d_k, \tag{15}$$

where d_k is a K-dimensional column vector with $d_k(k) = 0$, $d_k(j) = \frac{g_j}{\ln 2}$, $j \neq k$ and $h(\boldsymbol{P})$ is approximated by its first order Taylor expansion $h\left(\boldsymbol{P}^i\right) + \nabla h^T\left(\boldsymbol{P}^i\right)\left(\boldsymbol{P} - \boldsymbol{P}^i\right)$ in the i-th iteration.

The specific method for power allocation is described in Algorithm 2, in which D^i denotes the objective function value of the problem (13) in the i-th iteration.

C. Time Allocation

In this subsection, we focus on solving the problem (8) under fixed q and $\boldsymbol{P}$. This time allocation issue can actually be regarded as a two-dimensional linear programming respect to τ_0 and τ_1. Although off-the-shelf solvers, such as the simplex method [9], can handle this issue, the computationally complexity increases with the number of users. Before proceeding, let us introduce a theorem below, which is needed in deriving the optimal strategy for time allocation.

Theorem 1: For the problem (5), the maximum EE can always be achieved at $\tau_0 + \tau_1 = 1$.

Proof: If $\tau_0^* + \tau_1^* < 1$ holds in the optimal solution $\{P_0^*, \boldsymbol{P}^*, \tau_0^*, \tau_1^*\}$, then we can construct another feasible point $\{\tilde{P}_0, \tilde{\boldsymbol{P}}, \tilde{\tau}_0, \tilde{\tau}_1\}$ with $\tilde{\tau}_0 + \tilde{\tau}_1 = 1$, $\tilde{P}_0 = P_0^*$, $\tilde{\boldsymbol{P}} = \boldsymbol{P}^*$ and $\tilde{\tau}_0/\tilde{\tau}_1 = \tau_0^*/\tau_1^*$, which guarantees C1-C6 still hold. Then, we can easily conclude that $\widetilde{EE} = EE^*$ and thus the maximum EE can always be achieved when $\tau_0 + \tau_1 = 1$. ■

Based on Theorem 1, we can replace τ_0 by $1 - \tau_1$ and further transform the problem (8) to an one-dimensional linear optimization problem, denoted as

$$\max_{\tau_1} \; c\tau_1 - b \tag{16a}$$
$$\text{s.t. } \tau_1 \leq \frac{\eta P_0 h_k}{p_k + p_k^c + \eta P_0 h_k}, \quad \forall k, \tag{16b}$$
$$R_k(\tau_1, \boldsymbol{P}) \geq B_{\min}^k, \quad \forall k, \tag{16c}$$

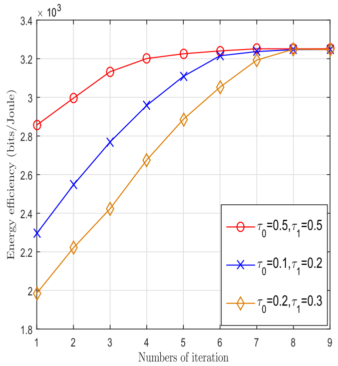

Fig. 2. Convergence of Algorithm 1.

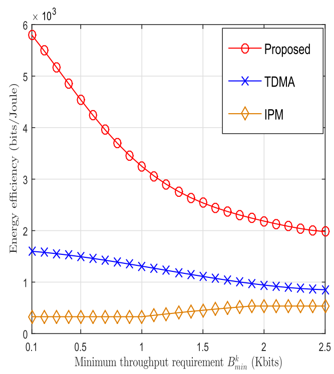

Fig. 3. EE for different $B_{\min}^k$.

where b and c are defined as

$$b = -q\left(P_0\left(1-\sum\nolimits_{k=1}^{K}\eta h_k\right)+P_c\right)$$

$$c = -q\left(\sum\nolimits_{k=1}^{K}\left(p_k+p_k^c\right) - P_0\left(1-\sum\nolimits_{k=1}^{K}\eta h_k\right) - P_c\right) + W\sum_{k=1}^{K}\log_2\left(1+\frac{g_k p_k}{n_k+\sum_{j=1,j\neq k}^{K} g_j p_j}\right). \tag{17}$$

Owing to the one-dimensional linear structure of the problem (16), we can easily draw the conclusion that the optimal solution of this problem can be achieved at one of the start/end points which relies on the sign of the constant c. Then, the optimal time allocation is given by

$$\tau_1 = \begin{cases} \min\limits_k \dfrac{\eta P_0 h_k}{p_k + p_k^c + \eta P_0 h_k}, & c > 0 \\ \max\limits_k \dfrac{B_{\min}^k}{W\log_2\left(1+\dfrac{g_k p_k}{n_k+\sum_{j=1,j\neq k}^{K} g_j p_j}\right)}, & c \leq 0. \end{cases} \tag{18}$$

It is worth noting that our Dinkelbach based iterative algorithm has a fast convergence speed. The result follows from the convergence analysis of the Dinkelbach method [7]. Furthermore, Since the Dinkelbach method in the main loop for updating q is regardless of the number of users K, the total complexity of the proposed algorithm is $O(K^3)$ [10].

IV. Simulation Results

In this section, we present simulation results to demonstrate the performance of proposed resource allocation. It is assumed that the channel reciprocity holds for DL and UL and thus $h_k = g_k, k = 1, \cdots, K$. Accordingly, both the DL and UL channel power gains are modeled as $h_k = g_k = 10^{-3}\rho^2 D_k{}^{-\alpha}, k = 1, \cdots, K$, where α is the pathloss exponent and ρ^2 is an exponentially distributed random variable with unit mean [3]. Five users are randomly distributed on the right side of the HAP with the reference distance $d_1 = 1$m, $d_2 = 1.2$m, $d_3 = 1.3$m, $d_4 = 2$m, $d_5 = 2.4$m. Other parameters are set as $\alpha = 2$, $W = 20$Khz, $\eta = 0.9$, $P_c = 500$mW, $p_c = 10$mW, $\sigma^2 = -50$dBm, $P_{\max} = 40$dBm [5].

Fig. 2 depicts the convergence speed of our method with $B_{\min}^k = 1$Kbits. It is seen that the proposed method not only converges fast but also is not sensitive to the selection of the initial points of time allocation. Fig. 3 reveals that the EE decreases with the increase of $B_{\min}^k$. Here, we assume that the minimum throughput requirement $B_{\min}^k$ is the same for all users. Moreover, we provide a comparison among the standard interior-point methods (IPM) [8], TDMA [5] and our proposed algorithm. It can be observed that the performance of our method is much better than those of IPM and TDMA, especially in the region of low minimum throughput requirement. It is easy to understand the numerical results because in the case of lower minimum throughput requirement, the energy of interference which is caused by information transfer simultaneously in the up-link is close to the noise power, and therefore the longer information transfer time will achieve higher energy efficiency.

V. Conclusion

This letter addressed a wireless powered communication networks where the energy access point and information access point are co-located. Under the TDMS protocol, the system EE is maximized by a joint optimization of UL-DL time allocation and power allocation. Simulation results demonstrate that the proposed algorithm can improve the system EE significantly.

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