Energy-Efficient Optimization for WPCN System Based on User Cooperation

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***Abstract*—This paper presents a user cooperation scheme for wireless-powered communication network (WPCN). Two energy constraints users first harvest RF energy from a dedicated power station (PS) and cooperatively transmit their representative information to an information receiver (IR). We aim to investigate the energy-efficiency (EE) maximization problem while considering the quality of service (QoS) requirements. In order to achieve that, we formulate the maximization problem by jointly optimizing time allocation, power allocation, and energy beamforming vectors. Since the proposed problem is non-convex, variable substitutions, fractional programming, and semidefinite relaxation (SDR) are used to convert it into a convex problem. Finally, an algorithm is proposed for determining the optimal solution. Simulation results show that the proposed user cooperation scheme improves system efficiency by comparing with the non-cooperation scheme as the benchmark.**

***Index Terms*—Energy-efficiency, wireless powered communication network, user cooperation**

I. INTRODUCTION

As the Internet of Things (IoT) grows and offers more services like e-health, smart cities, and massive connectivity, we can expect it to impact all parts of our lives significantly. However, energy limitations are one of the challenges that need to be solved. Because IoT devices are often low-powered devices with limited energy capacity, ensuring sufficient power supply and enabling long-term operation becomes a significant challenge [1], [2]. One way to extend the battery's life is to recharge or replace the battery, and this could be impractical because of the large number of deployed devices.

In order to overcome this challenge, a wireless-powered communication network (WPCN) has been considered a potential solution for increasing the battery life of wireless devices [3]–[5]. The Wireless Power Communication Network (WPCN) is a future wireless communication system in which wireless devices (WD) batteries are remotely recharged using microwave wireless power transfer (WPT) technology and then use this harvested energy for communication purposes [5]. However, the fundamental limitations of WPCN are its relatively short transmission distance and low efficiency [4]. Relaying is an effective method of enhancing communication ranges for power-constrained IoT networks. In [6], a relay cooperation technique was studied, where a hybrid relay node was used to distribute RF energy to multiple users and forward their information in an amplify-and-forward (AF) or decode-and-forward (DF) manner. In [7] the authors investigate double-hop wireless power communication with a hybrid access point (H-AP), multiple users, and multiple energy-constrained relays, combining wireless power transfer (WPT) in the downlink with simultaneous wireless information and power transfer (SWIPT) in the uplink. Even though relay extends communication ranges, employing a dedicated relay station to help transmit information is costly [8]. As an alternative, user cooperation improves information transmission efficiency [9]–[11].In [9], the weighted sum-rate maximization problem was formulated by jointly maximizing the time schedule, power allocation, and energy beamforming techniques for two users with different operation modes cooperating to transmit information was investigated, namely the active and passive communication modes. However, since the passive device depends on signals emanating from an RF source, it is not energy-efficient. The authors in [11], considered Intelligent Reflecting Surface (IRS)-assisted user cooperation to maximize the common throughput of two users by optimizing the IRS's phase shifts, transmission time, and power allocations.

Energy efficiency is vital in IoT because many devices are connected to the Internet with limited energy resources, so it is critical to address the energy consumption issue. This paper presents a user cooperation scheme for wireless-powered communication network (WPCN). We aim to study the energy-efficient optimization problem. The objective is to maximize the EE of the system while jointly optimizing power allocation, time allocation, and energy beamforming vectors. Due to the non-convex nature of the formulated problem, it cannot be solved directly. In order to solve the formulated problem, we need to convert it into a convex problem using variable substitution, fractional programming (FP), and semidefinite relaxation (SDR). Finally, we obtain the optimal solution using an iterative algorithm based on Dinkelbach. According to the simulation results, the proposed user cooperation scheme outperforms the non cooperation benchmark schemes.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System model

As illustrated in Fig.1, we consider a WPCN network consisting of one power station (PS), an information receiver

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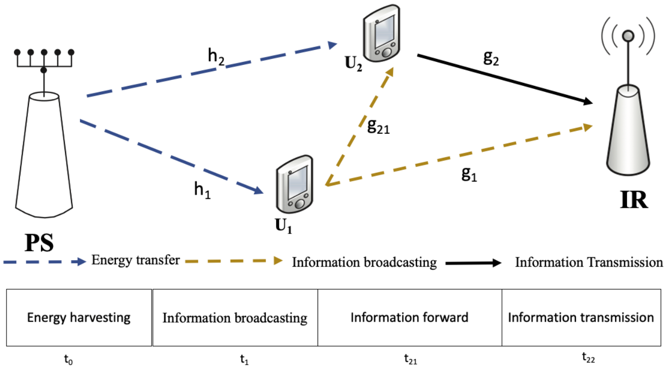

Fig. 1. System model for user cooperation.

(IR), and two users, denoted U1 and U2. The PS is assumed to have M antennas, while both users each have a single antenna. In order to establish communication with IR, both users need to harvest energy from the RF signal radiated by the PS. The channel between the nodes is assumed to be a quasi-static fading channel that remains constant over one transmission block. Accordingly, h_1 and h_2 denote channel vectors between the PS and U$_i$, while g_1, g_2, and g_{21} are channel variables between the U1-IR, U2-IR, and U1-U2, respectively. During WET, PS transmits energy to both U1 and U2 through RF transmission. The received signal at U1 and U2 from PS is given by

$$y_0^{(i)} = \sqrt{P_0}\mathbf{h}_i^H \boldsymbol{\omega} + n_i, \quad \forall i = 1, 2, \tag{1}$$

where P_0 is the transmit power at PS, $\mathbf{h}_i \in \mathbb{C}^{M\times 1}$ shows the complex channel vectors between PS and users, $\omega \in \mathbb{C}^{M\times 1}$ is energy beamforming vector that satisfies $\|\omega\|^2 \leq 1$ and $n_i \sim \mathcal{CN}\left(0, \sigma_i^2\right)$, is additive white Gaussian noise (AWGN). In general, the received noise power is smaller than transmitted power, so it is assumed to be negligible. Hence, during t_0 the amount of energy harvested at users is given by

$$E_i^h = t_0 \eta \left|\mathbf{h}_i^H \boldsymbol{\omega}\right|^2 P_0, \quad \forall i = 1, 2, \tag{2}$$

where $\eta \in \{0, 1\}$ is a constant that indicates the rate of energy conversion, which in this paper, we assumed to be equal for both users. Generally, two users are located at different distances from the IR, and typically, the user closer to the IR has better channel conditions. To assist the information transmission from U1 to IR, U2 works as a relay node. Additionally, U2 has its information to deliver to IR. During t_1, U1 broadcasts information to IR and U2. The received signal at IR and U2 from U1 can be respectively expressed as follows

$$y_1^{(1)} = \sqrt{P_1} g_1 s_0 + n_r, \tag{3}$$

$$y_1^{(2)} = \sqrt{P_1} g_{21} s_o + n_u, \tag{4}$$

where g_1 and g_{21} represents the channel variables between the U1 and IR and between U1 and U2, respectively, n_r and n_u are the additive Gaussian white noises satisfying $n_r \sim \mathcal{CN}\left(0, \sigma_r^2\right)$ and $n_u \sim \mathcal{CN}\left(0, \sigma_u^2\right)$ and s_0 is the information symbol of U1 with unit power. Furthermore, the total energy consumed at U2 denoted by E_{u2} must be less than the amount of energy harvested

$$E_{u2} \leq E_2^h \tag{5}$$

During t_{21}, U2 decodes the information received from U1 and then relays the decoded information to IR. Hence, the received signal at IR from U2 corresponding to the information of U1 is given by

$$y_2^{(1)} = \sqrt{P_{21}} g_2 s_1 + n_r \tag{6}$$

where P_{21} denotes the power consumed at U2 to help the data transmission of U1 and s_1 indicates the transmit signal for this duration. Base on [12], The achievable rate between U1 and IR over the decode-and-forward (DF) relay channel can be derived as

$$R_1 = \min\left\{R^{(10)}, R^{(20)}\right\} \tag{7}$$

where $R^{(10)}$ is the sum information rate from U1-IR and U2-IR which is

$$R^{(10)} = t_1 \log_2\left(1 + \frac{P_1 \left|g_1\right|^2}{\sigma_r^2}\right) + t_{21} \log_2\left(1 + \frac{P_{21} \left|g_2\right|^2}{\sigma_r^2}\right) \tag{8}$$

and $R^{(20)}$ is the information rate over the U1-U2 which is

$$R^{(20)} = t_1 \log_2\left(1 + \frac{P_1 \left|g_{21}\right|^2}{\sigma_u^2}\right) \tag{9}$$

During t_{22}, U2 transmits its own information to IR. The received signal at IR can be expressed as

$$y_2^{(2)} = \sqrt{P_{22}} g_2 s_2 + n_r \tag{10}$$

where P_{22} indicates the power consumed at U2 to transmit its information and s_2 indicates its information symbol where $\mathbb{E}\left[\left|s_2\right|^2\right] = 1$. Consequently, the achievable information rate between U2 and IR is

$$R_2 = t_{22} \log_2\left(1 + \frac{P_{22} \left|g_2\right|^2}{\sigma_r^2}\right) \tag{11}$$

The total system throughput, denoted by R_{sum} is given by

$$R_{\text{sum}} = R_1 + R_2 \tag{12}$$

B. Energy Consumption Model

According to this system model, we consider the total energy consumed by the WET and WIT phases. Thus, the amount of energy consumed by the PS can be expressed as follows

$$E_{ps} = P_0 t_0 + P_c^{ps} t_0 \tag{13}$$

where P_c^{ps} is the circuit power consumption of the PS. The energy consumption of the U1 and U2 is denoted as E_{u1} and E_{u2} respectively, are given

$$E_{u1} = P_1 t_1 + P_c t_1 - E_1^h \tag{14}$$

$$E_{u2} = P_{21} t_{21} + P_c t_{21} + P_{22} t_{22} + P_c t_{22} - E_2^h \tag{15}$$

where P_c denotes the circuit power consumption of the users, the total energy consumption of the system denoted as E_{sum} is given by

$$E_{\text{sum}} = E_{ps} + E_{u1} + E_{u2} \tag{16}$$

Thus, the system overall EE denoted by Φ_{EE} is the total system throughput to the total consumed energy.

$$\Phi_{EE} = \frac{R_{\text{sum}}}{E_{\text{sum}}} \tag{17}$$

C. Problem Formulation

This section aims to maximize the total system EE by jointly optimizing the power allocation, time allocation, and energy beamforming vector. Therefore, the optimization problem can be expressed as follows

$$\begin{aligned}
\max_{\boldsymbol{\omega},\boldsymbol{P},\boldsymbol{t}} \quad & \Phi_{EE} \\
\text{s.t.}\ C1 &: P_0 \le P_{max}, \\
C2 &: P_1 t_1 + P_c t_1 \le E_1^h; \\
C3 &: P_{21} t_{21} + P_c t_{21} + P_{22} t_{22} + P_c t_{22} \le E_2^h, \\
C4 &: P_0, P_1, P_{21}, P_{22} \ge 0, \\
C5 &: t_0 + t_1 + t_{21} + t_{22} \le T, \\
C6 &: t_0, t_1, t_{21}, t_{22} \ge 0, \\
C7 &: \|\boldsymbol{\omega}\|^2 \le 1 \\
C8 &: R_1 \ge R_{min}^1, \\
C9 &: R_2 \ge R_{min}^2,
\end{aligned} \tag{$\mathbf{P1}$}$$

where $\boldsymbol{t} = [t_0, t_1, t_{21}, t_{22}]$, $\boldsymbol{P} = [P_0, P_1, P_{21}, P_{22}]$, R_{min}^1, R_{min}^2 are the minimum transmission rates at the users. C1 indicates the amount of maximum transmitted power of the PS need to be within the limits of P_{max}, where C2 and C3 ensure that users won't consume more energy than they harvest, C4 maintains non-negative power allocation variables, C5 indicates the total time constraint, C6 shows the time allocation variables are non-negative, C7 restricts the power of energy beamforming vector, C8 and C9 ensure the quality of service (QoS) for the users. Clearly, Problem P1 is non-convex due to its fractional objective function and coupling constraints. This makes it difficult to solve using standard convex optimization techniques.

III. ENERGY-EFFICIENT RESOURCE ALLOCATION ALGORITHM

In this section, we focus on using variable substitution approaches and the Dinkelbach method [13] to solve the problem. In order to deal with coupled variables, first, we introduce auxiliary variables, and then we use Dinkelbach's method, which converts a fractional expression into a non-fractional expression. Subsequently, we apply the SDR technique to relax the rank-one constraint on the energy beamforming [14]. $\boldsymbol{Q} = t_0 \boldsymbol{\omega}\boldsymbol{\omega}^{\boldsymbol{H}}$, $\tilde{R}$, $\gamma_0 = P_0 t_0$, $\gamma_1 = P_1 t_1$, $\gamma_{21} = P_{21} t_{21}$ and $\gamma_{22} = P_{22} t_{22}$. thus R_1, R_2 and E_{sum} can recast as

$$\tilde{R} \le t_1 \log_2 \left(1 + \frac{\gamma_1 \left|g_1\right|^2}{t_1 \sigma_r^2}\right) + t_{21} \log_2 \left(1 + \frac{\gamma_{21} \left|g_2\right|^2}{t_{21} \sigma_r^2}\right) \tag{18}$$

$$\tilde{R} \le t_1 \log_2 \left(1 + \frac{\gamma_1 \left|g_{21}\right|^2}{t_1 \sigma_u^2}\right) \tag{19}$$

$$R_2 = t_{22} \log_2 \left(1 + \frac{\gamma_{22} \left|g_{21}\right|^2}{t_{22} \sigma_u^2}\right) \tag{20}$$

$$\begin{aligned}
E_{\text{sum}} \ =& \gamma_0 + P_c^{ps} t_0 + \gamma_1 + P_1^c t_2 + \gamma_{21} + P_2^c t_2 \\
& + \gamma_{22} + P_2^c t_2 - \eta \operatorname{Tr}\left(\boldsymbol{h}_i h_i^H \mathbf{Q}\right). \quad \forall i = 1, 2
\end{aligned} \tag{21}$$

Where $\tilde{R}$ is represented as the equivalent epigraph of P1. thus, we reformulated problem P1 as follows

$$\begin{aligned}
\max_{\mathbf{Q},\boldsymbol{\Gamma},\boldsymbol{t},\tilde{R}} \quad & \Phi_{EE} = \tfrac{R_{\text{sum}}}{E_{\text{sum}}} \\
\text{s.t.}\, C10 &: \gamma_0 \le P_{max}, \\
C11 &: \gamma_1 + P_c t_1 \le \eta \operatorname{Tr}\left(\boldsymbol{h}_1 \boldsymbol{h}_1^H \mathbf{Q}\right), \\
C12 &: \gamma_{21} + P_c t_{21} + \gamma_{22} + P_c t_{22} \le \eta \operatorname{Tr}\left(\boldsymbol{h}_2 \boldsymbol{h}_2^H \mathbf{Q}\right), \\
C13 &: \gamma_0, \gamma_1, \gamma_{21}, \gamma_{22} \ge 0, \\
C14 &: \operatorname{Tr}(\mathbf{Q}) \le \gamma_0, \\
C15 &: \boldsymbol{Q} \succeq 0, \\
C16 &: \operatorname{rank}(\boldsymbol{Q}) = 1, \\
C17 &: \tilde{R} \le t_1 \log_2 \left(1 + \tfrac{\gamma_1 |g_1|^2}{t_1 \sigma_r^2}\right) + t_{21} \log_2 \left(1 + \tfrac{\gamma_{21} |g_2|^2}{t_{21} \sigma_r^2}\right) \\
C18 &: \tilde{R} \le t_1 \log_2 \left(1 + \tfrac{\gamma_1 |g_{21}|^2}{t_1 \sigma_u^2}\right),
\end{aligned} \tag{$\mathbf{P2}$}$$

where $\mathbf{\Gamma}$= $[\gamma_0, \gamma_1, \gamma_{21}, \gamma_{22}]$. Since the objective function is a fractional expression, it is hard to solve it directly. However, we will use the Dinkelbach method to solve this, which converts fractional expressions into non-fractional expressions. As a result, we define q^* as the optimal value.

$$q^* = \max_{\mathbf{Q},\boldsymbol{\Gamma},\mathbf{t},\tilde{R}} \frac{\tilde{R} + R_2}{E_{\text{sum}}} \tag{22}$$

By applying nonlinear fractional programming theory [13], it can be rewritten equivalently as a subtractive function.

$$\max_{\mathbf{Q},\boldsymbol{\Gamma},\mathbf{t},\tilde{R}} \left\{\tilde{R} + R_2 - q^* E_{\text{sum}}\right\} = 0. \tag{23}$$

The optimal Φ_{EE} can be obtained under the optimal variables ($\mathbf{Q}^*, \boldsymbol{\Gamma}^*, \mathbf{t}^*, \tilde{R}^*$), and q^* can be typically solved by an iteration. As a result of the rank-one constraint C16, the problem remains non-convex. Using SDR [14], non-convex problems can be approximated as convex by removing rank-one C16. Consequently, the problem P2 has been relaxed as follows

$$\begin{aligned}
\max_{\mathbf{Q},\boldsymbol{\Gamma},\mathbf{t},\tilde{R}} \quad & \tilde{R} + R_2 - q E_{\text{sum}} \\
\text{s.t.} \quad & C5, C6, C8, C9, C10, C11 \\
& C12, C13, C14, C15, C17, C18
\end{aligned} \tag{$\mathbf{P3}$}$$

Proposition 1: Problem P3 is a convex problem.

proof: Both $\tilde{R}$ and R_2 belong to the convex function [15]. In addition, E_{sum} is a linear function. Constraint C17 is the perspective function of concave functions. Furthermore, constraint C18 is convex since it has a similar form to constraint C17. Other constraints are linear. Thus, problem P3 is convex. As a result, proposition 1 is proved.

The optimal solution $\{\boldsymbol{Q}^*, \boldsymbol{\Gamma}^*, \boldsymbol{t}^*, \tilde{R}^*\}$ of Problem P3 can be derived by using CVX tools [16]. In this study, we aim

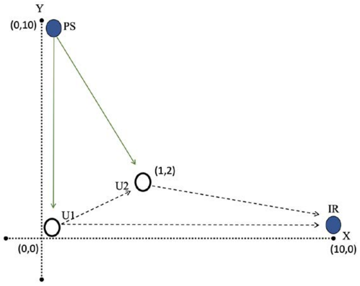

Fig. 2. User cooperation network structure model

to determine the optimal beamforming vector ω^* Instead of $\mathbf{Q}^*$. Accordingly, if $\mathbf{Q}^*$ satisfies the rank-one constraint, ω^* is the optimal energy beamforming vector during t_0, and can be estimated by using eigenvalue decomposition $\mathbf{Q}^*/P_0^* t_0^*$. The optimal solutions of problem P3 denoted as $P_0^* = \gamma_0^*/t_0^*, P_1^* = \gamma_1^*/t_1^*, P_{21}^* = \gamma_{21}^*/t_{21}^*, P_{22}^* = \gamma_{22}^*/t_{22}^*$. We use an iterative algorithm, which is detailed in Algorithm 1, to obtain the optimal solutions for problem P3. In the following proposition, we prove that $\mathbf{Q}^*$ always has the rank-one property.

Proposition 2: According to P3, the optimal value of $\mathbf{Q}^*$ is a rank-one. In order to demonstrate $\mathbf{Q}^*$ has rank-one, the following optimization problem is presented

$$\begin{aligned} &\min_{\mathbf{Q}} \quad \operatorname{Tr}(\mathbf{Q}) \\ \text{s.t.} \quad & \gamma_1^* \leq \eta \operatorname{Tr}\left(\boldsymbol{h}_1 \boldsymbol{h}_1^H \mathbf{Q}\right), \\ & \gamma_{21}^* + \gamma_{22}^* \leq \eta \operatorname{Tr}\left(\boldsymbol{h}_2 \boldsymbol{h}_2^H \mathbf{Q}\right), \\ & \boldsymbol{Q} \succeq 0, \end{aligned} \qquad (\mathbf{P4})$$

Suppose that the optimal solution for problem P4 is $\mathbf{Q}^+$. Which is also a feasible solution for P3. to prove that $\operatorname{Tr}(\mathbf{Q}^+) \leq t_0^*$ since $\mathbf{Q}^*$ is feasible for P3 it is also feasible for P4. we can show that $\operatorname{Tr}(\mathbf{Q}^+) \leq Tr(\mathbf{Q}^*) \leq t_0^*$, thus, $\mathbf{Q}^+$ is also feasible for P3. since the objective function of P3 is a function of $\mathbf{Q}, \boldsymbol{\Gamma}, \mathbf{t}, \text{and } \tilde{R}$. we can derive that $(\mathbf{Q}^+, \boldsymbol{\Gamma}^*, \mathbf{t}^*, \tilde{R}^*)$, is also the optimal solution for P3. which indicates that rank-one $\mathbf{Q}^+$ always exists. Hence, as stated in the Lemma [17, Lemma. 3.2] it is possible to show optimal solution $\mathbf{Q}^+$ such that $(\mathbf{rank}(\mathbf{Q}^+)^2) \leq 2$. Therefore, satisfies $\mathbf{Q}^+ \neq 0$ and thus $\mathbf{rank}(\mathbf{Q}^+) = 1$ Hence, *Proposition 2:* is proved.

Here, we examine the complexity of the proposed algorithm. Since we solved problem P3 using the Dinkelbach method algorithm [13], the computational complexity is $\mathcal{O}(1/\epsilon \log(L_{max}))$, where ϵ and L_{max} are the maximum error tolerance and the maximum number of iterations, respectively.

Algorithm 1 Algorithm for energy-efficient maximization based on Dinkelbach's method

```
Initialization:
  • $\varepsilon = 10^{-2}$; the maximum error tolerance
  • $L_{max}$; the maximum number of iterations.
  • $q = 0$; maximum $\Phi_{EE}$.
  • $k = 0$; the iteration index.
repeat
  solve problem P3 with a given $q$ and find the optimal
      solution $(\boldsymbol{Q}^*, \boldsymbol{\Gamma}^*, \boldsymbol{t}^*, \tilde{R}^*)$;
  if $|\tilde{R} + R_2 - q_{E_{sum}}| \leq \varepsilon$ then
      Set $(\boldsymbol{Q}^*, \boldsymbol{\Gamma}^*, \boldsymbol{t}^*, \tilde{R}^*) = (\boldsymbol{Q}, \boldsymbol{\Gamma}, \boldsymbol{t}, \tilde{R})$.
      $q^* = \frac{\tilde{R}+R_2}{E_{sum}}$
      Convergence = true.
  Else
      set $q = \frac{\tilde{R}+R_2}{E_{sum}}$
      $k = k + 1$
    Convergence = false
  End if
until Convergence = true or $k = L_{max}$
```

IV. SIMULATION RESULTS

In this section, the simulation results are presented to evaluate the performance of the proposed algorithm for user cooperation scheme. The network structure model is depicted in Fig. 2. Consequently, the PS, IR, and two users' coordinates are (0,10), (10,0), (0,0), and (2,1), respectively. The simulation parameters are provided below. All channels follow Rayleigh fading with distribution $\mathcal{CN}\left(0, d_{a,b}^{-\kappa}\right)$ where a, b represents the distance between any two nodes and the path loss exponent κ = 2. Additionally, we set the noise power $\sigma_u^2 = \sigma_r^2$ = -40 dBm. The energy conversion efficiency is η = 0.7, and the circuit powers of the PS and both users are set to P_c^{ps} = 0.5W and p_c = 5mW, respectively. we set the number of antennas at the PS $M = 10, M = 5$, and the total transmission time is T=1s.

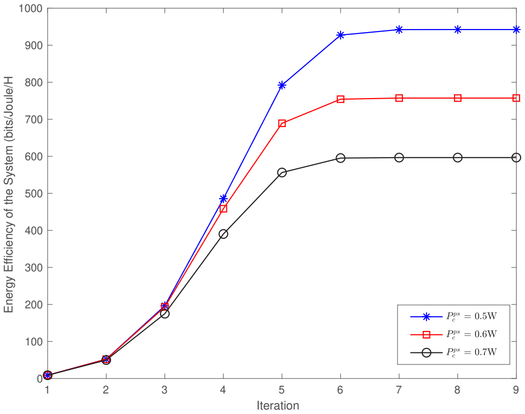

Fig. 3. Energy efficiency versus the number of iterations.

Fig. 3 illustrates the EE of the system versus the number of iterations obtained from the proposed algorithm. For comparison, we evaluate the results for different circuit powers of PS, of which the maximum transmit power of PSmax is 40dbm. The figure shows that energy efficiency converges within a few iterations for all three cases. Furthermore, it appears that as the circuit power of PS increases from 0.5w to 0.9w, the EE of the system decreases.

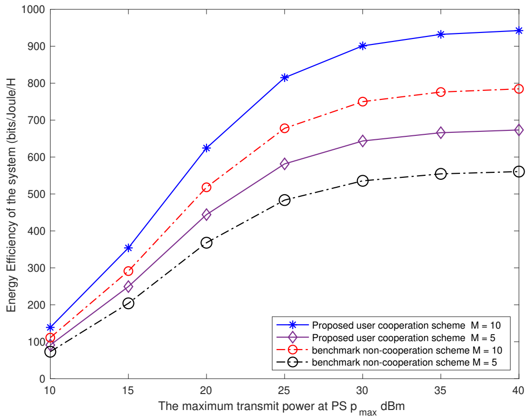

Fig. 4. Energy efficiency of the system versus the maximum transmit power

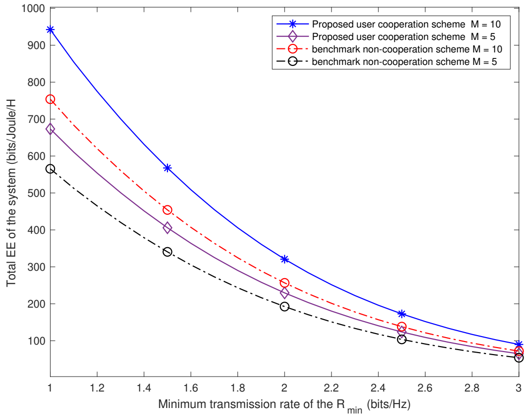

Fig. 5. Energy efficiency of the system versus the minimum transmit rate

Fig. 4 shows the results of evaluating the system EE versus the maximum transmit power at the PS. As Pmax increases, the EE increases and stays mostly constant. Moreover, the proposed schemes outperform the non-cooperation benchmark scheme, indicating that user cooperation can improve the system's efficiency. Additionally, the efficiency of the energy transmission mechanism can be increased by using more antennas.

Fig. 5 shows the system EE versus the minimum transmission rate, $R^1_{min} = R^2_{min} = 1$ bit/Hz. We observe that the proposed scheme has better performance than the non-cooperation benchmark. However, as Rmin increases, the system EE decreases more rapidly. The reason is to ensure the quality of service (QoS) requirement, users need more time to harvest energy. Increasing t_0 will lead to more energy consumption at PS.

V. CONCLUSION

In this paper, we propose a user cooperation scheme for WPCN. We solved the EE maximization problem by optimizing the energy beamforming vector, the time allocation, and the power allocation together while considering the user's quality of service (QoS) requirements. The formulated problem is non-convex because of the fractional objective function and coupling variables. We introduce auxiliary variables and apply semidefinite relaxation to solve the problem. Finally, an algorithm is proposed for determining the optimal solution. The simulation results show that the proposed scheme provides better system efficiency than the non-cooperation benchmark.

ACKNOWLEDGMENT

This work was partially supported by the National Natural Science Foundation of P. R. China (No.61701064), the Chongqing Natural Science Foundation (cstc2019jcyj-msxmX0264).

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